MANAGEMENT OF OFFSHORE STRUCTURES UNDER MICROBIOLOGICALLY INFLUENCED CORROSION (MIC)

By

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Dedication

This research is dedicated to all clinicians, nurses, and health service staff worldwide, and want to save this thesis in honor of their efforts and selflessly work around the clock to provide care for patients affected by COVID-19.

ABSTRACT

Offshore systems suffer from excessive corrosion damage in the marine environment because of the dynamic operational and environmental contributing factors. Such situations enhance the serious integrity and safety concerns, systems degradation, and associated risks, especially in harsh environmental conditions. The microbiologically influenced corrosion as an essential corrosion category has considerable characteristic complexity because of the interactions between the bacteria and the corrosion contributing factors. The microbial corrosion and the interconnected system safety management plan are impacted by the stochastic behavior of microbial metabolism and operational parameters. To have a robust and reliable corrosion management plan in offshore systems, the dynamic microbial corrosion features, as well as the corresponding risk factors, must be taken into account.

The present thesis proposes a dynamics-based approach for risk-based safety and integrity management of marine and offshore systems that suffer from microbial corrosion. First of all, a literature review is presented for the identification of microbial corrosion shortages, challenges, and requirements in the risk-based decision-making framework. The study is focused on the four tasks, including characteristics, mechanisms, modeling, and management of microbial corrosion. Secondly, a new probabilistic model is proposed to estimate the corrosion rate of a subsea pipeline by assessing the failure time and probability. The microbial corrosion monitoring and management activities are achieved using the Continuous Bayesian Network technique with the integration of Hierarchical Bayesian Analysis. The analysis outcomes indicate that the interdependencies between the contributing factors of microbial corrosion could raise the rate of corrosion and reduce the failure time of engineered corroded systems. Thirdly, new reliability is proposed to assess the optimum maintenance strategy time-interval for a subsea system impacted by multiple microbial corrosion defects. The different probabilistic models, including the non-homogeneous Markov processes, non-homogeneous Poisson, and homogeneous gamma, are utilized to model the maximum and average pit depth and multiple defects generations. The results show the influence of multiple microbial corrosion defects on the subsea pipeline considering several scenarios and recommend the optimal intervention time and management practices. Finally, a novel risk-based safety and integrity management framework is recommended to evaluate the subsea pipeline's failure. A multi-objective functional optimization methodology is developed to minimize the operational risk associated with microbial corrosion. The research results highlight an actual safety and integrity management plan consistent with the industrial practices. An innovative and dynamic Bayesian Network-based approach is proposed to assess the subsea system's resilience under MIC as a function of time. The subsea system is designed with sufficient resilience to maintain its performance under the time-varying interdependent stochastic conditions. The proposed methodology assists decision-makers in considering the resilience of the system design and operation. The present thesis investigates the mechanisms of microbial corrosion and explores the dynamic risk-based methodologies for several operating scenarios to manage the safety and integrity of marine and offshore systems.

ACKNOWLEDGEMENT

I would like to express my profound gratitude to my supervisor, Prof. Faisal Khan, for his guidance, and patience during my PhD study at the Memorial University. It is a great pleasure to have worked under his supervision. I truthfully acknowledge my co-supervisor, Dr. Rouzbeh Abbassi, for his valuable contribution. He is always available to provide support whenever needed. I am thankful to my supervisory committee members, Prof. Kelly Hawboldt, and Dr. Yahui Zhang, for their support, mentorship, assistance, and encouragement.

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NOMENCLATURE

AD	Advantages
APB	Acid-producing bacteria
BCSR	Biocatalytic cathodic sulphate reduction theory
BN	Bayesian Network
CMC	Copula-based Monte Carlo
DBN	Dynamic Bayesian network
GHB	Heterotrophic bacteria
HAc	Organic acid
IOB	Iron-oxidizing bacteria
IRB	Iron-reducing bacteria
LBN	Learning-based Bayesian network
MIC	Microbiologically influenced corrosion
MM	Markov Mixture
MMM	Microbiological molecular methods
MOB	Manganese-oxidizing bacteria
NACE	National Association of Corrosion Engineers
NRB	Nitrate Reducing Bacteria
PCR	Polymerase chain reaction
qPCR	Quantitative polymerase chain reaction
SH	Shortages
SOB	Sulfur-oxidizing bacteria
SRA	Sulphate-reducing archaea

SRB	Sulfate-reducing bacteria
THPS	Tetrakis-hydroxymethyl phosphonium
WOS	Web of Science

Chapter 1

Introduction

1.1. Background

The marine environment and offshore sectors are critical challenges for infrastructures, increasing the risk of material degradation. It is exposed to harsh environmental and operating conditions due to the operational, environmental, and external influential factors. The contributing factors might contain the concentration of CO2, pH, biofouling, temperature, pollutants, pressure, velocity, bacteria, carbonate solubility, and salinity. The influential factors induce corrosion of the offshore and marine systems, which further causes integrity and safety concerns. The dynamic interdependencies between the factors and their stochastic behavior in nature support the material degradation of the relevant transportation system in oil and gas industrial sectors (e.g., subsea pipelines). Notably, the two phases of water-oil provide a potential environmental condition contacting the marine and offshore internal face; this then poses microbial growth and CO2 dissolution. The interactions between the microorganisms and influential factors introduce microbiologically-influenced corrosion (MIC) [1].

Commonly, different types of corrosion, including MIC, enface the marine and offshore operating system with integrity challenges. MIC is a stochastic material degradation progression initiated by the metabolic process and microorganisms presence, including bacteria and fungi [2]. Considering MIC metabolic activities and formation, the MIC mechanism produces corrosive substances and makes the failure characteristics of marine and offshore systems complicated. Besides, the external environmental factors and bio-chemical nutrients enhance the formation and mechanism MIC.

In addition, the microorganisms have significant contributions to the deterioration of the subsea systems (e.g., pipeline corrosion) [3,4], reservoir souring [2,5], and cargo tank leakage [6,7]. The newest studies have highlighted that MIC is the cause of over 20 % of worldwide corrosion and the corresponding failures, with the considerable loss [8]. The microbial metabolism complication and growth process make decision-makers in the system face a detailed understanding of the MIC mechanism and its relevant characteristics. Besides, the microorganisms' instability and co-existence on the biofilm contributes to numerous disastrous MIC-based failures in the offshore and marine system [3,9,10]. Specifically, the rupture accident of a natural gas high pressure transportation pipeline near Carlsbad, New Mexico [11] and the transit line failure at Prudhoe Bay [12] are recognized as MIC. The latter one resulted in the loss of over $8 billion, that is while the failure of the gas transporting line claimed 12 deaths with related reputation and consequences loss. This seriously calls the essential research to well-understanding, reliably diagnosing, precisely predicting MIC characteristics and consequences, and adequately managing MIC over time. Having an appropriate MIC knowledge in terms of failure rate would assist in the development of a reliable and robust MIC integrity management approach for the subsea system.

The available model in the state of arts is inadequate to capture interdependencies of the "*physio-chemical parameters*" on MIC rate as well as failure probability estimation. There are a few dynamic-based models to assess the impact of microorganisms and characteristics' dependencies on the rate of MIC of the subsea system. The microorganisms' co-existence impacts the failures of the subsea system have not been considered MIC prediction rate. In addition, the efficiency and applicability of different management actions (e.g., preventive, control, and mitigative) have not been taken into account in the management strategy plan. It is a requirement to improve our understanding and investigate the dynamic and stochastic behavior of MIC in subsea systems to acquire a MIC and integrity management plan reliably.

1.2. Motivation and objectives

MIC poses serious risks of failure in the subsea systems and highlights its significant impact on the whole of system failure and related loss [8,13,14]. MIC can be increased underlying the microorganisms' instability and co-existence on the biofilm. The biofilm is complex structurally and made by the fusion of bacteria cells and extracellular polymeric substances. These complex microbial communities lead to a dynamic system failure impacting the potential subsea systems. Moreover, the complex and stochastic MIC nature includes the interrelationships between physical, chemical factors, and biological, leading MIC modeling to become a challenging task. The existing methodologies assumed the simple mechanistic model for MIC, such as the correlation of the chemical parameters causing the intense MIC occurrences [15]. Moreover, cause and effect connections are realized by controlling the lab scale assessments [16]. Therefore, the dynamic characteristics of microorganisms cause extrapolation to become problematic over time. In addition, the extensive published works in terms of MIC modeling methodologies are according to the worst-scenarios on localized pitting corrosion. Besides, the available MIC modeling frameworks consider only SRB as an influential factor, and some take the balance between sulfate-mass and biofilm. There are also limited methods that have taken the kinetic microorganisms' growth in the mechanistic MIC model. To obtain the time that the system would collapse entirely, the rate of failure probability and pit depth distributions must be investigated systematically.

This research aims to develop a risk-based decision-making model to manage subsea systems impacted by microbial corrosion. The presented decision-making model addresses the complicated interdependencies among the various vital corrosion contributing factors (e.g., steel composition, temperature, carbon content, fluid velocity, CO_2 pressure, and more factors) and the bacteria for the marine and offshore failure system assessment. The research goal is accomplished considering the objectives mentioned below. Figure 1.1 presents the translation of research objectives into a research task.

i. To develop systematic literature on risk-based decision-making models for MIC in offshore pipelines by identifying the existing gaps, needs, and challenges of MIC models and explaining further research opportunities.

ii. To propose a dynamic-based framework to analyze the system reliability of subsea systems with consideration of the non-linear interdependencies among MIC influential and contributing factors.

iii. To develop a probabilistic model to simulate operational subsea pipeline maintenance strategies by studying the time-interval, detection probability, average, and maximum pit depth by identifying the optimum strategy considering MIC multiple defects.

iv. To develop an MIC integrity management framework within the tradeoff between reliability and cost of management practices.

To develop a dynamic framework to assess and evaluate the marine and offshore system's resilience under the influence of microbiological corrosion.

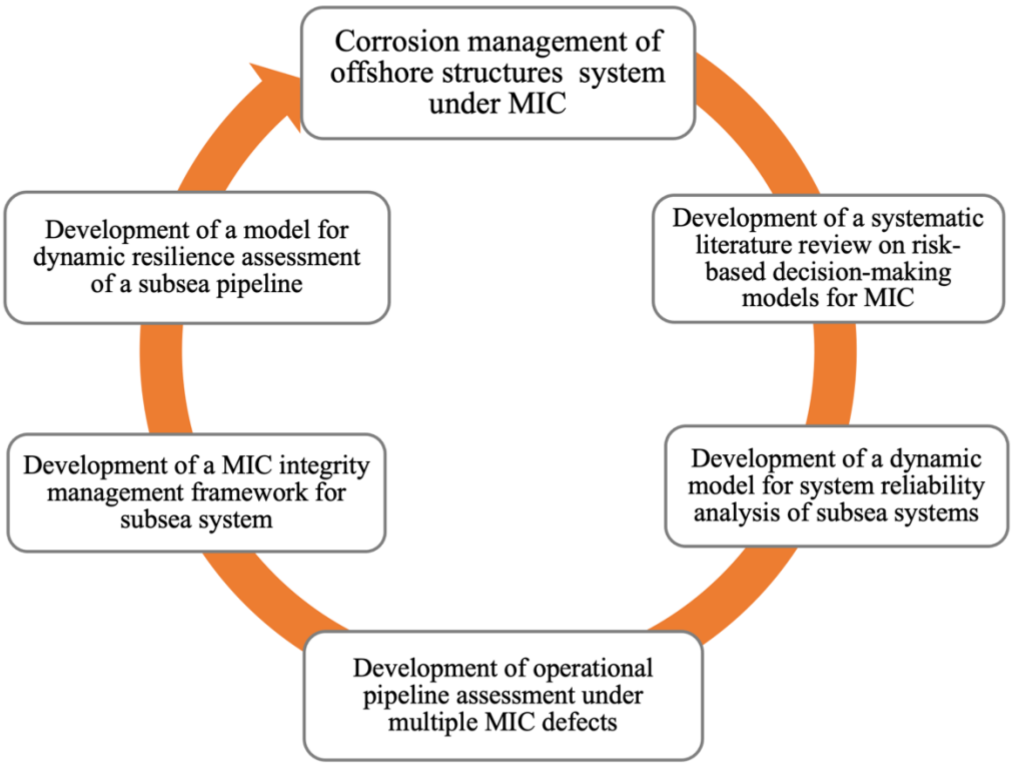


Figure 1.1. The thesis research objectives

1.3. Scope and limitations

This research study is established particularly for subsea operational conditions. The study mainly focuses on the risk-based decision-making models for integrity management of marine and offshore systems suffering from MIC. As mentioned earlier, the MIC degradation process is complex and provides serious concerns in system failure estimation and integrity management. Therefore, robust, reliable, and dynamic MIC management models are required to address the connected complexity, uncertainties, and stochasticity. Besides, it should have enough capabilities to address the safety and reliability of marine and offshore systems. Numerous uncertainties in information, primary data processing MIC contributing factors, and diminishing mechanisms because the availability of sparse data might initiate subjective uncertainty in the introduced approaches. The current research work is not an effort to capture all research gaps, challenges, and needs related to the MIC subsea systems integrity management; however, it is an effort to capture a few of them in subsea systems operations under the influence of microbial corrosion.

1.4. The novelties and contributions

The present doctoral key research's novelties and contributions are in corrosion management of the subsea system suffering from microbial corrosion. The novelties and contributions are highlighted as the following:

- A systematic review attempts to the identification of MIC shortages, requirements, and challenges in risk-based decision-making approaches. The review assessment mainly determines the characteristics, modeling, mechanisms, and management of microbial corrosion. Both theoretical and empirical outcomes are then integrated. The gaps and capabilities of the state of arts are then highlighted, and future research tasks are explained. The novelty and contribution of this research task is presented in chapter 2.

- A new probabilistic model is proposed for the corrosion-based failure rate assessment and failure time of subsea pipelines influenced by microbial corrosion. The proposed model accurately monitors the activities of microorganisms and accordingly develops management strategies. The Continuous Bayesian Network technique with the integration of Hierarchical Bayesian Analysis is utilized to monitor and manage microbial corrosion. Besides, the framework considers both model and data uncertainty and develops a novel MIC mechanistic model to determine pit depth growth. The research task presents a comprehensive knowledge regarding the MIC contributing factors and associated failure probability. The novelty and contribution of this research task is presented in chapter 3.
- A new reliability model is introduced to assess the optimum maintenance of strategy time interval for the marine and offshore process systems impacted by multiple microbial corrosion defects. The presented approach integrated the non-homogeneous Markov processes and Poisson and homogeneous gamma to model the multiple defects generations, the maximum and average pit depth. The introduced methodology reproduces maintenance strategies with consideration of cost, time interval, detection probability, maximum and average pit depth, and classifies the optimum management strategies. The aim of this research task is to help decision-makers to select an optimum maintenance strategy for the subsea system impacted by microbial corrosion. The novelty and contribution of this research task is presented in chapter 4.
- A novel integrity risk management approach is recommended to assess the subsea pipelines' failure behavior. A multi-objective functional methodology involving Dynamic Continuous Bayesian Network modeling to minimize the operational risk associated with the MIC is proposed. The Meta-heuristic algorithm as a Genetic Algorithm is used to obtain

the optimum schedule for performing integrity management actions. The results identify a series of solutions allowing decision-makers to select the optimal combination of integrity management actions with the tradeoff between reliability and cost. The novelty and contribution of this research task is presented in chapter 5.

- A novel "dynamic Bayesian Network-based approach" is proposed to assess the resilience of marine and offshore systems suffering from microbial corrosion over time. The design of the subsea system is based on adequate resilience and performance maintenance considering time dependency and stochastic MIC parameters. The proposed approach helps decision-makers in the resilience consideration of the subsea system during the design and operation period. The promising novelty and contribution of this research task are presented in chapter 6.

1.5. The statement co-authorship

The authorship contributions of Mr. Mohammad Yazdi, Dr. Faisal Khan, Dr. Rouzbeh Abbassi, Dr. Noor Quddus, and Dr. Homero Castaneda-Lopez regarding the thesis [the outlined is structured in Figure 1.2] and present research tasks are explained as the following.

Mohammad Yazdi: Conceptualization, methodology development, idea preparation, MIC integrity management plan development, conducting data analysis, validating the model; writing the original draft of the manuscript for journals submission; editing and reviewing the manuscripts according to the co-authors and journal reviewers' feedback.

Faisal Khan: Idea preparation of research activities, methodology development, MIC integrity management plan development, data analysis supervision; editing and reviewing the manuscripts and thesis.

Rouzbeh Abbassi: Idea preparation of research activities, methodology development, MIC integrity management plan development, data analysis supervision; editing and reviewing the manuscripts and thesis.

Noor Quddus: Assistance in development and data analysis of systematic review work, and reviewing and re-organizing the manuscripts.

Homero Castaneda-Lopez: Assistance in development and data analysis of systematic review paper and reviewing the manuscript.

1.6. The Thesis organization

The present thesis is constructed and written in the format of manuscripts. The five peer-reviewed journal chapters are the primary outcomes of the current thesis work. The organization of the present thesis is depicted in Figure 1.2. The introduction, literature review, and conclusions are presented in Chapters 1, 2, and respectively. Chapters 2 to 6 are prepared according to the peer-reviewed journal's submissions.

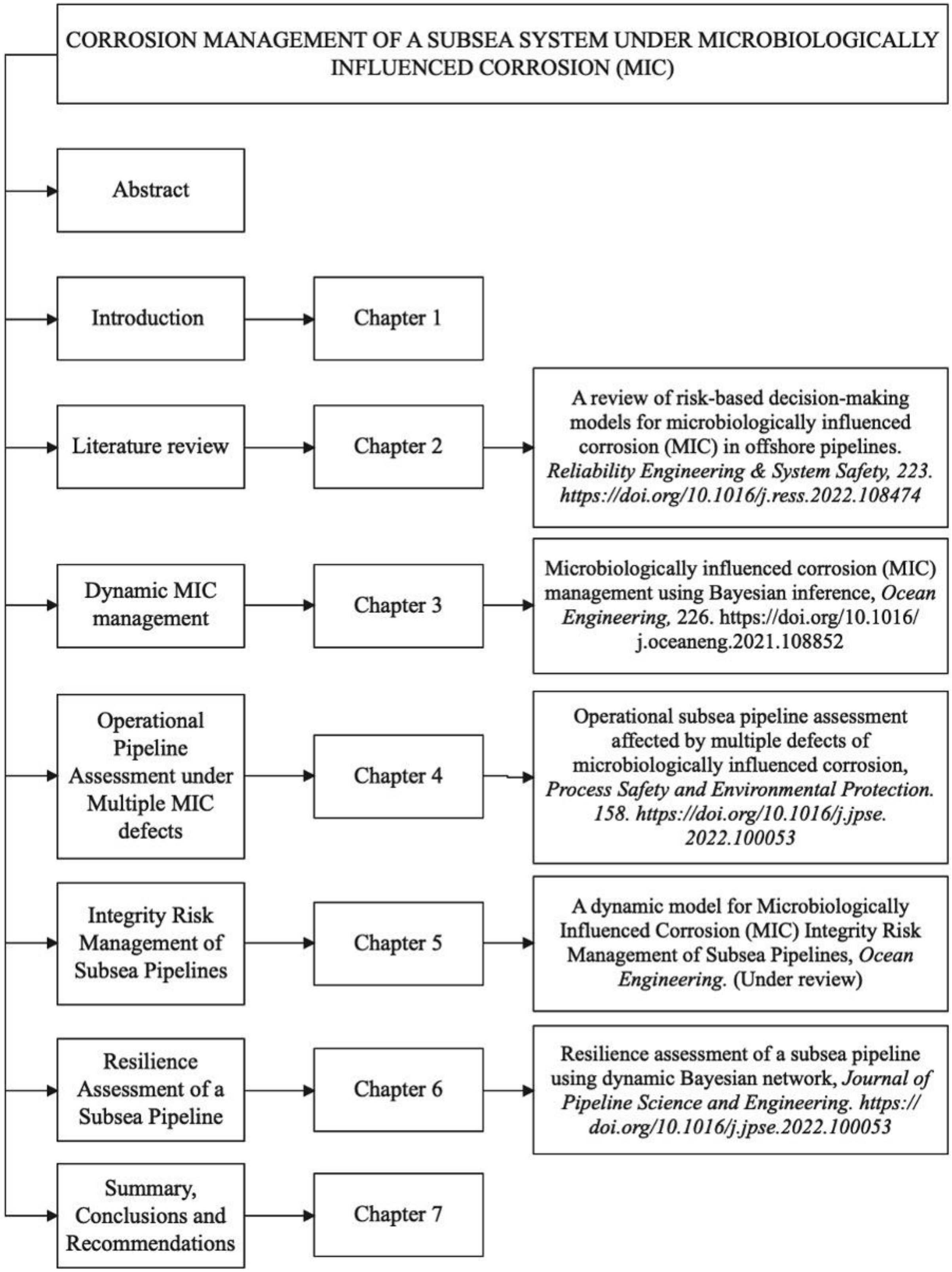


Figure 1.2. The organization of present thesis and the relevant publications

Chapter 2 presents a systematic review related to the research objectives. The chapter contains a state of arts on risk-based decision-making models for microbial corrosion in marine and offshore pipelines. This chapter is published and available online in the journal of *Reliability Engineering & System Safety 2022; 223: 108474.*

Chapter 3 covers a novel dynamic probabilistic approach for MIC management of offshore structures. This chapter is published and available online in the journal of *Ocean Engineering, 2021; 226: 108852*

Chapter 4 introduces an innovative operational offshore structures assessment impacted by multiple microbial corrosion defects. This chapter is published and available online in the journal of *Process Safety and Environmental Protection, 2022; 158: 159-171.*

Chapter 5 presents an integrated dynamic model for MIC Integrity risk management of subsea pipelines by selecting the optimal combination of integrity management actions and the tradeoff between reliability and cost. This chapter is submitted to *Ocean Engineering*

Chapter 6 proposes a probabilistic and dynamic framework to assess and evaluate the resilience of marine and offshore systems in a corrosive environment. The dynamic Bayesian Network and the "two-state Markov chain framework" are integrated to assess the resilience of a subsea pipeline suffering from MIC. This chapter is published and available online in the journal of *Journal of Pipeline Science and Engineering, 2022: 100053*.

References

[1] T.L. Skovhus, J.S. Lee, B.J. Little, Predominant MIC Mechanisms in the Oil and Gas Industry, in: Torben Lund Skovhus ; Dennis Enning ; Jason S. Lee. (Ed.), Microbiol. Influ. Corros. Upstream Oil Gas Ind., 1st ed., CRC Press, Florida, 2017: pp. 75–85.

[2] I.B. Beech, C.C. Gaylarde, Recent Advances in the Study of Biocorrosion - An Overview,

Rev. Microbiol. 30 (1999) 177–190.

[3] R. Eckert, a Field guide for investigating internal corrosion of pipelines, NACE International, Houston, 2003.

[4] M. Taleb-Berrouane, F. Khan, K. Hawboldt, R. Eckert, T.L. Skovhus, Model for microbiologically influenced corrosion potential assessment for the oil and gas industry, Corros. Eng. Sci. Technol. 53 (2018) 378–392. https://doi.org/10.1080/1478422X.2018.1483221.

[5] L.M. Gieg, T.R. Jack, J.M. Foght, Biological souring and mitigation in oil reservoirs, Appl. Microbiol. Biotechnol. 92 (2011) 263–282. https://doi.org/10.1007/s00253-011-3542-6.

[6] K. Alasvand, Z. V Ravishankar, Identification of the traditional and non-traditional sulfate-reducing bacteria associated with corroded ship hull, 3 Biotech. 6 (2016) 1–8. https://doi.org/10.1007/s13205-016-0507-6.

[7] R.T. Huang, B.L. McFarland, R.Z. Hodgman, Microbial Influenced Corrosion in Cargo Oil Tanks of Crude Oil Tankers, in: NACE Int. Corros. Conf., 1997.

[8] B.J. Little, J.S. Lee, Microbiologivally Influenced Corrosion, John Wiley & Sons, Houston, New Jersey, 2007.

[9] J.K. Paik, D.K. Kim, Advanced method for the development of an empirical model to predict time-dependent corrosion wastage, Corros. Sci. 63 (2012) 51–58. https://doi.org/10.1016/j.corsci.2012.05.015.

[10] R.B. Eckert, T.L. Skovhus, Failure Analysis of Microbiologically Influenced Corrosion, 1th ed., CRC Press, 2021. https://doi.org/10.1201/9780429355479.

[11] S.P. Kotu, R.B. Eckert, A framework for conducting analysis of microbiologically influenced corrosion failures, Insp. J. (2019).

[12] A. Bailey, BP:Learning from oil spill lessons, Pet. News. (2006).

[13] S. Adumene, F. Khan, S. Adedigba, Operational safety assessment of offshore pipeline with multiple MIC defects, Comput. Chem. Eng. (2020) 106819. https://doi.org/10.1016/j.compchemeng.2020.106819.

[14] S. Adumene, S. Adedigba, F. Khan, S. Zendehboudi, An integrated dynamic failure assessment model for offshore components under microbiologically influenced corrosion, Ocean Eng. 218 (2020) 108082. https://doi.org/10.1016/j.oceaneng.2020.108082.

[15] R.E. Melchers, Progress in developing realistic corrosion models, Struct. Infrastruct. Eng. 14 (2018) 843–853. https://doi.org/10.1080/15732479.2018.1436570.

[16] T. Gu, Theoretical Modeling of the Possibility of Acid Producing Bacteria Causing Fast Pitting Biocorrosion, J. Microb. Biochem. Technol. 6 (2014) 68–74. https://doi.org/10.4172/1948-5948.1000124.

Chapter 2

A review of risk-based decision-making models for microbiologically influenced corrosion (MIC) in offshore pipelines

Preface

A version of this chapter has been published in the ***Reliability Engineering & System Safety 2022; 223: 108474****. I am the primary author along with the Co-authors, Faisal Khan, Rouzbeh Abbassi, Noor Quddus, Homero Castaneda-Lopez. I developed the conceptual framework for the review of risk-based decision-making models for MIC in offshore pipelines. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' and peer review feedbacks. Co-authors Faisal Khan and Rouzbeh Abbassi provided support in implementing the concept development, reviewing, and revising the manuscript. Co-authors Noor Quddus and Homero Castaneda-Lopez provided assistance in reviewing and correcting the results. The co-authors also contributed to the review and revision of the manuscript.*

Abstract

Microbiologically influenced corrosion (MIC) is one of the critical integrity threats in marine and offshore industrial sectors. Thus, MIC should be considered for effective risk-based decision-making and asset integrity management of systems. The experience with accidents in this domain indicates that many corroded subsea pipelines involve a complex failure mode with MIC implications. Researchers have actively studied the MIC characteristics, mechanisms, modeling, and management since the last decades. However, despite MIC importance and practical

implications for a better understanding of decision-makers, there is a lack of reliable knowledge of risk-based decision-making models for MIC in marine and offshore sectors. The current work aims to present a systematic attempt to identify the gaps, needs, and challenges of MIC in risk-based decision-making models. Therefore, an analysis of the arts in different database core collections is conducted. The analysis is focused on MIC characteristics, mechanisms, modeling, and management. It integrates the empirical and theoretical conclusions, highlighting the capabilities and drawbacks of existing literature and explaining the further research tasks' opportunities.

Keywords: Microbiologically influenced corrosion, MIC, offshore systems, Corrosion Modelling, Pitting, Risk management, Localized corrosion

2.1. Introduction

Offshore structures have faced high corrosion rates because of many operational factors and dynamic environmental circumstances, which raises system safety integrity concerns. The offshore equipment and pipelines are the leading offshore capital assets and have a crucial infrastructure role for oil and gas transportation. However, the offshore assets suffer from microbial influence corrosion (MIC) failure due to metal degradation. The complexity and diversity of the MIC mechanism pose an uncertain and unpredicted failure rate within unacceptable risk levels in offshore systems. Despite extremely varying failure cost estimations, the National Association of Corrosion Engineers (NACE -now AMPP "Association for Materials Protection and Performance") developed a comprehensive study that approximated that the global failure cost of corrosions was 2.5 US trillion in 2013 [1]. In MIC, the material degradation is accelerated with different microorganisms on the metal surface, including bacteria, fungi, and algae [2,3]. The direct and indirect costs due to MIC failures are estimated to be 10 to 20 percent of total corrosion cost [4,5]. However, the unavailability of a public MIC database associated with MIC failure modes, incidents, and accidents would limit the entire understanding of MIC impacts. Several MIC failures that lead to catastrophic accidents have been highlighted in the existing literature, such as an accident in propane tank explosion due to MIC leading to the weld failure, where the approximated loss was almost $180 million (US dollar) because of explosion and fire damages [6]. MIC is also a significant cause of gas pipeline internal corrosion leading to leaks and explosions in the offshore platforms in the Gulf of Mexico [7]. Another significant accident was an oil spill and environmental pollution in Alaska by discharging more than 950 cubic meters of crude oil [8]. Besides direct cost, MIC accidents would be critical when indirect costs result from environmental pollutions [9]—for example, releasing thousands of tons of methane in well casing leakage "the Aliso storage field," causing significant environmental impacts [10].

MIC is created as a result of three fields, including (i) microorganisms, (ii) media (i.e., physical parameters and chemical compositions), and (iii) material characteristics (i.e., metallurgy) [11]. The MIC would occur when microorganisms, media, and material characteristics have acceptable overlap. Thus, it is necessary to mutually understand the mentioned components based on the different MIC investigation views. It should be noted that MIC is a challenge in various materials and grades such as API 5LX70 carbon steel [12], 1010 carbon steel [13], 1018 carbon steel [14], aluminum alloys [15], copper and copper alloys [16], where the operational factors (e.g., low flow and temperature) and stagnation (residence time) period affecting the microbial activities. These statements reaffirm that understanding the MIC requires multi-disciplinary sciences, and investigating its impacts on failures of different materials in various offshore applications is an emergent need.

In order to have insights developing MIC protocols, the relevant MIC-based guidelines are taken into account, such as ASTM E3 "Standard Guide for Preparation of Metallographic Specimens" [17], ASTM A370 "Standard Test Methods and Definitions for Mechanical Testing of Steel Products" [18], ASTM D-93 "Standard Test Methods for Flash Point by Pensky-Martens Closed Cup Tester" [19], ASTM D422-63 "Standard Test Method for Particle-Size Analysis of Soils" [20], NACE SP0775 "Preparation, Installation, Analysis, and Interpretation of Corrosion Coupons in Oilfield Operations" [21], ASTM E1404 "Standard Specification for Laboratory Glass Conical Flasks" [22], and Microbiological NACE TM0194 "Field Monitoring of Bacterial Growth in Oil and Gas Systems" [23]. Despite the numerous published research works on MIC, many gaps still exist, requiring further attempts to deal with MIC problems practically.

For example, Abdulhaqq et al. [24] recently studied a comprehensive investigation on the chemical environment impacting MIC and corresponding model development. In another review, Kannan et al. [25] evaluated the analytical methods used to identify MIC, an aggressive microbiota-facilitated degradation of engineering materials, and discussed their benefits and restrictions. In this regard, the main objective of the present work making differences between related papers is to provide a systematic review of risk-based decision-making models for MIC in offshore sectors by highlighting the shortages and advantages of current approaches and discussing future directions. The specific emphasis in this paper is addressing the following main research questions:

- What research streams have investigated the MIC detection and characterization, MIC modeling, and MIC management in the offshore environment?
- How have the previous investigations and attempts contributed to MIC in the offshore environmental systems, and what needs and gaps remain unaddressed in these studies?

- How should the existing shortages be overcome, and what challenges are decision-makers in MIC approaches facing, which further help decision-makers improve system safety and reliability of offshore systems over time?

The organization of this review work has proceeded as the following. In Section 2, the review methodology is provided. Sections 3, 4, and 5 present the results and discussions. In Section 6, discussion and future work prospects to show the deficiency of current research content and development needs. In Section 7, the conclusion of this review and remarks are explained.

2.2. Review methodology

The reviewing process conducted in this paper has three main steps. In the beginning, the published studies from different primary databases were collected considering the proper keywords such as "MIC" AND "microbiologically influenced corrosion" AND "risk-based" AND "microbiologically induced corrosion". Subsequently, a decision is made about every paper, whether indexed by WOS (Web of Science Core collection) or Scopus. Otherwise, they are excluded. Different databases were searched from January 1980 to the end of August 2021, and the number of paper counts reached 1237. This timeline was selected because most research studies on MIC areas have been released in the last 40 years. Afterward, the related studies' keywords, titles, and abstracts are reviewed. The 428 studies are excluded in the next step considering the title, abstract, and keywords. Then, 297 studies are retrieved by reviewing the full text of the manuscript due to their qualities (particularly based on the index: Science Citation Index, Science Citation Index Expanded, and Social Sciences Citation Index). Finally, all these papers were studied in detail and classified using a systematic review method [26,27], including publication year, application area, sub-application area, and methodology type. Figure 2.1 demonstrates the six main steps of the utilized review methodology in the present study [28].

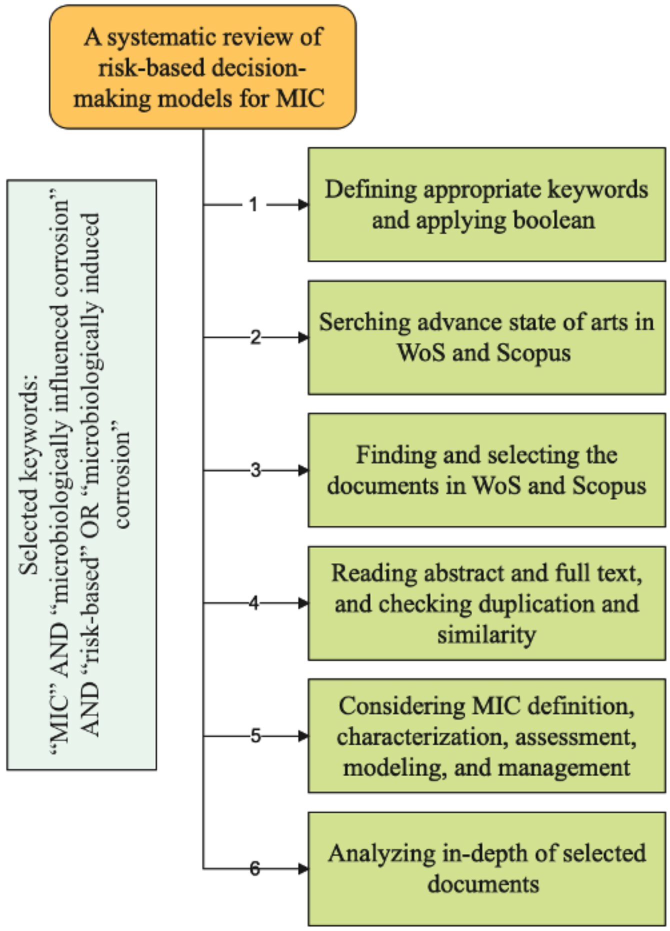


Figure 2.1. The research framework employed for the MIC risk-based decision-making systematic review in the offshore pipelines

2.3. Results and discussion

This section presents a brief review of MIC definiens, and then comprehensive literature in MIC approaches (i.e., MIC detection and characterization, MIC modeling, and MIC management) is discussed. The authors attempted to recognize MIC-based approaches' main drawbacks, needs, and challenges in the offshore structures. In addition, the dominant published works up to this date and directions for future studies are specified.

2.3.1. Definition of MIC

MIC refers to the influence of the microorganisms in the material deterioration mechanism, either metallic or non-metallic, in the presence of water [29]. There are several microbes, which are responsible for MIC occurrence, including sulfate-reducing bacteria (SRB) methanogens, sulfur-oxidizing bacteria (SOB), acid-producing bacteria (APB), iron-oxidizing bacteria (IOB), iron-reducing bacteria (IRB), and manganese-oxidizing bacteria (MOB). Each group of microorganisms might include a multinumber of individual species [30,31]. That is why the MIC would occur naturally with the microbial communities containing several microbes.

MIC is linked with the formation of biofilm on the metal surface. The biofilm is defined as a colony containing different types of bacteria within a “polymeric matrix”, which engages in the degradation process. An individual microorganism could not engage independently [32]. Thus, a biofilm simply plays an essential role as a microorganisms’ habitat. Biofilm creation is the most critical step in MIC formation and metal degradation due to a synergistic relationship among a set of microorganisms. This enables microorganisms for metabolization process turning into influences material degradation. The biofilm is created because of immobilized microbiological cells’ accumulation, which causes the cells to be reproduced on the metal surface, called the biofouling process [33]. During biofilm formation, the exopolymeric substances as extracellular polymers protect the microorganism from the environment [34]. A hypothesis was studied in which the biofilm could increase the chance of microorganisms' life and enhance the transferring conditions and availability of nutrients reaching microorganisms [35]. Besides, exopolymeric substances can also control the interfacial chemistry at the biofilm metal interface, including adhesion, protection, and structure. Therefore, providing a specific condition (e.g., pH and chemical species) would be different from biofilm external environmental conditions. In Figure 2.2, an adaption of biofilm evolution is presented [36].

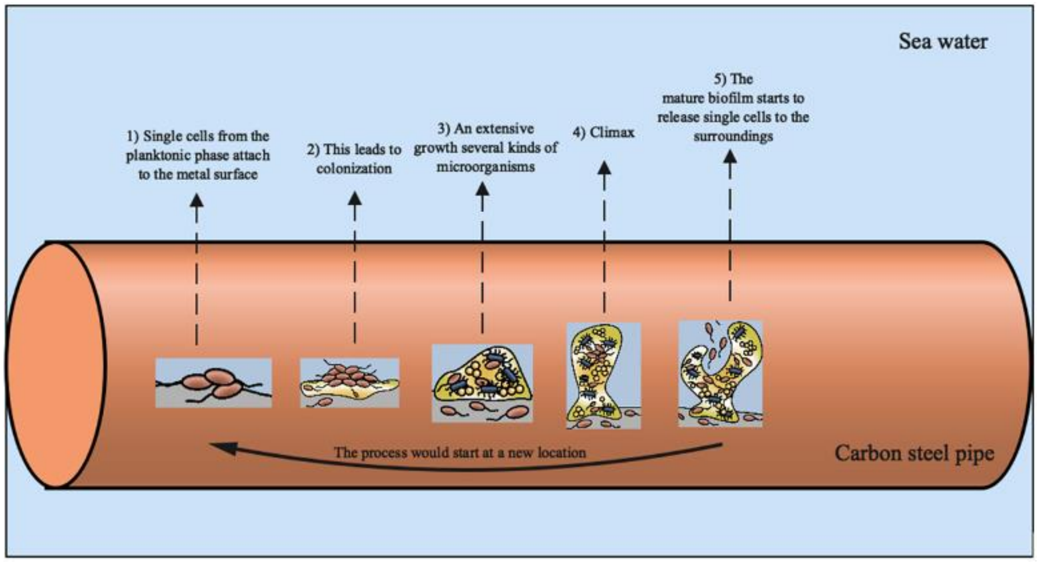


Figure 2.2. The early stage of a biofilm evolution on a metal surface, modified after [37]

The mature biofilm is influenced by various circumstances, such as surface topography, surface wettability, and the presence of the nutrients [24]. In addition, the chemical and physical features of a mature biofilm are heterogeneous. If the environmental conditions include oxygen, this will diffuse to the out layer of biofilm and make it the aerobic area [36]. The rough surfaces would provide more surface zone into the microbiocidal cell adhesion [38]. The surface impact of roughness zone on cell attachment is studied by scholars [39], on a 340L stainless steel. The derived results showed that a significant cell attachment existed in the unwelded surface.

It should be highlighted that the presence of biofilm does not essentially prove the MIC attack, that is, while it is the foremost important observation in the MIC investigation process. The activities of all MIC-based microorganisms are taken place in the biofilm zone. The MIC mechanism is further defined as the activities of microorganisms within a biofilm colony that promotes MIC. It is a vital task to properly understand the mechanism of MIC to deal with MIC investigation (i.e., identifying, characterizing, modeling, and management). In the next Section, the microbial activities and their influence on metal surface degradation have been studied.

2.3.2. MIC mechanisms

The anaerobic microorganisms play an active role in an environment with low or even no oxygen for the evolution of MIC. They are the most referenced problematic microorganisms in oil and gas industrial sectors (e.g., marine and offshore environment) [36]. The most common type of anaerobic microorganism caused by MIC is SRB as an electron acceptor, which receives energy from an organic matter (H2) or even metal (Fe0) under specific environmental circumstances [2]. Figure 2.3 presents a list of common microbiological groups that participated in MIC and includes a limited number of microbial groups, well-known in MIC manner [40].

The metal surface is covered with biofilm; some areas have much denser biofilm, and some are uncovered. Thus, the covered metal with biofilm would have a lower oxygen concentration and play an anodic role. On the opposite side, the covered part with no/less biofilm would reveal a higher oxygen concentration and play a cathodic role. Once the anodic and cathodic sites are settled at the metal surface, the MIC mechanism would have occurred due to differential aeration cells [41]. Furthermore, the microorganisms may create denser metal surface deposits, which can remove the oxygen from the deposit in a short period. This causes the area to be described as an anodic site. Also, the cathodic reaction becomes an oxygen reduction on the surrounding metal surface. In the following, three main MIC mechanisms are explained in detail.

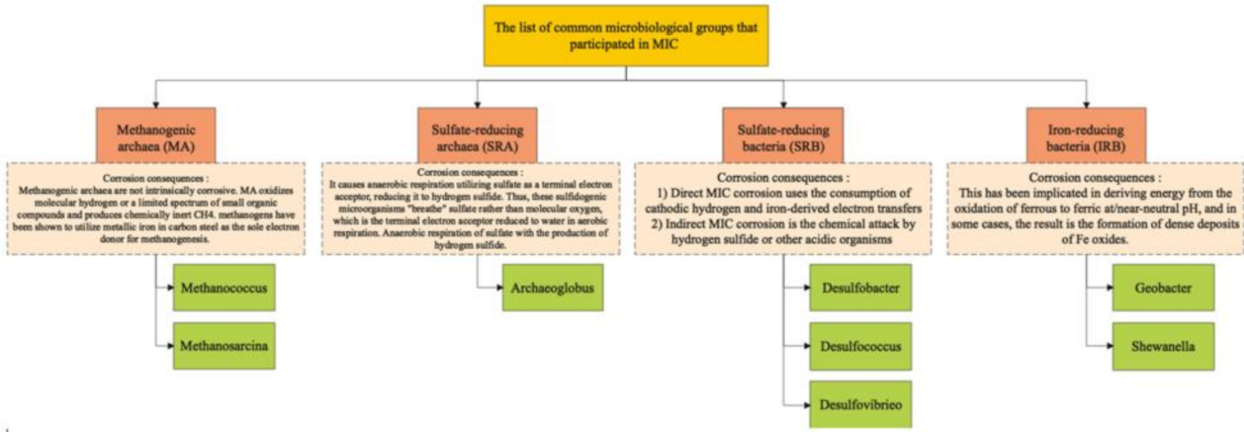


Figure 2.3. Most characteristic microbial groups (Note: the high-resolution of figure is provided in the published version of paper)

2.3.2.1. Microbial activities producing corrosive metabolites

Some microorganisms can attack the surface of metal within metabolic by-products. SRB would react with stainless steel and yield the corrosion products such as FexSy [24]. The deposits could have enough contributions into different aeration cells on the surface of the metal. This, therefore, can induce additional corrosion. In aerobic conditions, the FexSy reactions within oxygen could yield the elemental sulfur (S0), which is highly corrosive [36]. In addition, the acetic acid from APB is a significant metabolic by-product and can directly reduce the electrons from the surface of the metal by producing H+. This may cause a lower pH with the biofilm, making the metal surface susceptible to the MIC [42].

2.3.2.2. Synergy of bacteria in a biofilm consortium accelerating corrosion

The fact is that a microorganisms' metabolic activities can feed another microorganism. The synergy between the microorganism in the biofilm zone is significant for biodiversity. Some microorganisms have conductive structures (e.g., pilis, nanowires) that shuttle electrons to the biofilm zone. Then, these microorganisms could be engaged by those microorganisms inside the biofilm zone. Enning et al. [43] studied the conductive property of microorganisms, in which the

SRB is cultured as an electron donor and the presence of CO2 as a carbon source. The outcome highlighted the metal degradation with aggressive pitting and intimate SRB growth.

Identifying such microorganism that causes degradation is a critical task in understanding MIC mechanisms, and it can provide a vision into MIC occurrence. In recent days, microbiological molecular methods (MMM) such as quantitative polymerase chain reaction (qPCR) and polymerase chain reaction (PCR) analysis are the standard and primary tools to identify the active microorganism in a biofilm zone [44]. As it is not adequately understood, the number of microorganisms and MIC are either correlated or not; therefore, microorganisms can only show the presence of MIC [29]. In addition, the small number of microorganisms can be the cause of MIC occurrence; however, the large amount of the same microorganisms do not necessarily present the severe existence of the MIC process.

Although microorganism identification is an essential step in understanding the MIC mechanism, many attempts have been made to predict the rate of MIC and further MIC modeling. In the next Section, the MIC models have been reviewed.

2.3.3. MIC modeling

The relevant MIC protocols and models have been reviewed in a couple of review works [11,24,25,45,46]. All five published works are recommended to be studied by an interested reader to understand the existing literature's in-depth presentation better. Table 2.1 enlisted the key highlights and drawbacks of current MIC protocols and published reference works. In addition, Table 2.1 enlisted the main outcomes and summarized the reviewed published works.

Table 2.1. The key findings and drawbacks of current MIC protocols and published reference works

Row	References	Key highlights	Drawbacks	Average citations per year*	Total citation**
#1	Little et al. (20200 [11]	Suggesting the proactive, integrated approaches be used for MIC prevention and mitigation.	-Research has not provided tools for detection of MIC in the field. -There are no systematic programs to mitigate and prevent MIC.	10	30
#2	Ibrahim et al. (2018) [24]	Study inform further investigation on the chemical environment impacting MIC and model development.	- There is no MIC identification and characterization developed concepts. - No consideration of identifying more compounds with major contributions, interaction pathways, and their impacts.	3.4	17
#3	Kannan et al. (2018) [25]	- Review evaluates the analytical methods used for detecting MIC. - Challenges are presented by the lack of a comprehensive mechanistic understanding of MIC detection.	There is no application scopes of introduced MIC identification and characterization developed concepts.	3	15
#4	Skovhus et al. (2018) [46]	- MIC can be managed with a three-phase corrosion management approach. - Multidisciplinary work processes should link microbiology and corrosion science.	Combination of system metadata and data from molecular microbiological methods is the key to MIC management.	8.83	53
#5	Marciales et al. (2019) [45]	Most mechanistic MIC models reviewed based their prediction on SRB as the main player.	- No model was found to accurately correlate sessile and planktonic bacteria. - Non biological source of sulphate was taken into consideration in literature.	7.5	30

* This means that the number of Web of Science-based citations for a paper by the end of the year 2021
** This means that the number of Web of Science citation index for a paper by the end of the year 2021

The meta-analysis performed in [25] indicated that the much more reliable MIC modeling approach combined multiple analytical techniques with accurate field observation. As stated in the previous sections, the complex nature of MIC contains the complicated interrelationships between biological, physical, and chemical factors, and it causes MIC modeling to be a challenging task.

The described approaches simplified the MIC mechanistic model; for example, the correlation of chemical factors contributed to severe MIC phenomena [58]. In addition, controlling the lab-scale tests would provide the realization of cause-effect relationships (e.g., MIC biofilm generation (effect) by SRB and APB (cause)) [57]. Thus, extrapolation is a highly challenging task because of the dynamic features of microorganisms over time.

That is why in recent years, the novel developed techniques such as Bayesian Network (BN) [59,60], Fuzzy-based methods [27,61], and neural networks [62,63] with a combination of field data and experts' knowledge are becoming a more effective tool for MIC modeling.

In this regard, Fuzzy-based methodologies provide a development approach according to the predictive models [64]. In a study [65], a risk-based framework based on Fuzzy logic is developed to predict the rate of MIC for oil and gas systems. The Fuzzy logic-based models include the MIC initiation possibility, corrosion kinetics, and the time for required pipelines inspections. In another study [66], authors used a neuro fuzzy-based tool by engaging operational parameters, pipeline characteristics, and microorganisms' concentrations to develop a quantitative MIC risk-based model. Such models are trying to duplicate the cognitive decision-making progression, in which an approach would be provided for uncertain information [67,68]. However, the lack of field data causes the validation of the Fuzzy-based models to be restricted. Thus, the model's reasoning for predicting the MIC would be a difficult task [69].

For Bayesian Network-based studies, Adumene et al. [70] proposed an integrated dynamic failure assessment model for subsea systems under the influence of MIC. In this work, a combination of BN and Markov chain is utilized to predict the system's MIC rate and failure probability. Taleb-Berrouane et al. [44] proposed a network-based framework to examine the essential factors in MIC considering their complex interactions. In another study, Adumene et al. [71] integrated the dynamic Bayesian network (DBN) with loss aggregation tools to estimate the risk of MIC. For example, using DBN, Arzaghi et al. [72] developed a dynamic damage model for fatigue and pitting corrosion of offshore facilities. In another study, Arzaghi et al. [73] developed a risk-based maintenance technique for the subsea pipelines considering fatigue corrosion using BN. Adumene et al. [74] developed a stochastic-based formulation model to estimate MIC rate and obtain the remaining strength and safe operating pressure with multiple MIC defects. A combination of BN and Markov Mixture (MM) was utilized for this purpose. Shekari et al. [75] proposed a framework to predict pit depth growth on equipment under insulation in offshore sectors. The average pit density of multiple defects using the Markov process is obtained. Adumene et al. [76] integrated the BN with Copula-based Monte Carlo (CMC) simulation. The BN considers the dynamic interactions between physio-chemical parameters and microorganisms to estimate the rate of corrosion at the offshore system. In addition, the stochastic MIC factors' dependencies and the corresponding failure modes defining the functionalities' performance are modeled using CMC. Kamil et al. [77] utilized a data-driven approach to engage the available microbiological and operational data as well as learn the data variation. The proposed approach can obtain the correlation between the variables and corresponding characteristics to measure the likelihood of MIC. Thus, the available field and laboratory data are integrated into the Learning-based Bayesian network (LBN) model in this work. The BN-based models have enough capabilities for the uncertainty of knowledge accounting and model uncertainty to make more reliable decision-making [78].

Corrosion behavior is studied in [79] for neural networks-based studies using a neural network as a data mining tool. The neural network learned alloys composition and environmental conditions leading to corrosion rate. Kamrunnahar et al. [80] conducted a back-propagation neural network to train and test the understudy system. Using this approach, the steel corrosion is analyzed, and the experimental error counts as only 5 percent.

The fact is that the MIC modeling task is multidisciplinary demands and needed incorporated mathematical materials engineering to consider the complexity in MIC's model simulation. According to the many efforts that have been done by Wolodko et al. [81], the four tasks have to be combined to provide a robust and reliable model framework, including (i) empirical approaches, (ii) informatics, (iii), scientific modes, and (iv) uncertainty quantification. The mentioned featured model can be extended by integrating with microbiological corrosion methods. This would provide a strong data-driven approach for MIC prediction [25]. Finally, it can be concluded that the models within BN, Fuzzy based, are restricting with standard formulation and integrated solutions [82]. Thus, further high-quality data is required to estimate the accurate MIC rate and failure probabilities.

Up to this point, different types of MIC modeling approaches have been introduced within high contribution to corrosion science. In the following, a couple of recommendations are listed considering the significant shortages of the existing state of arts for MIC modeling [11,25,45,81].

- Such a complicated computational process would enhance the complexity of biological levels as the features of properties' integration and causes that the models would be less reproducible and consistent due to the stochastic nature of MIC,
- Such MIC modeling approaches are required the precise measurement tools at accurate scales in both model development and validation; that is, while such tools are almost unavailable in MIC modeling works,

- Such models should consider the relationships between microorganisms leading MIC and MIC control process; therefore, more attempts are required to consider these connections and multispecies biofilm, and
- Comprehensive investigations are needed for MIC representative communities and an adequate understanding of nutria's chemical and physical parameters.
- Integration of deterministic and mechanistic approaches with stochastic and random nature of the biofilm with the metallic surface could be the next trend

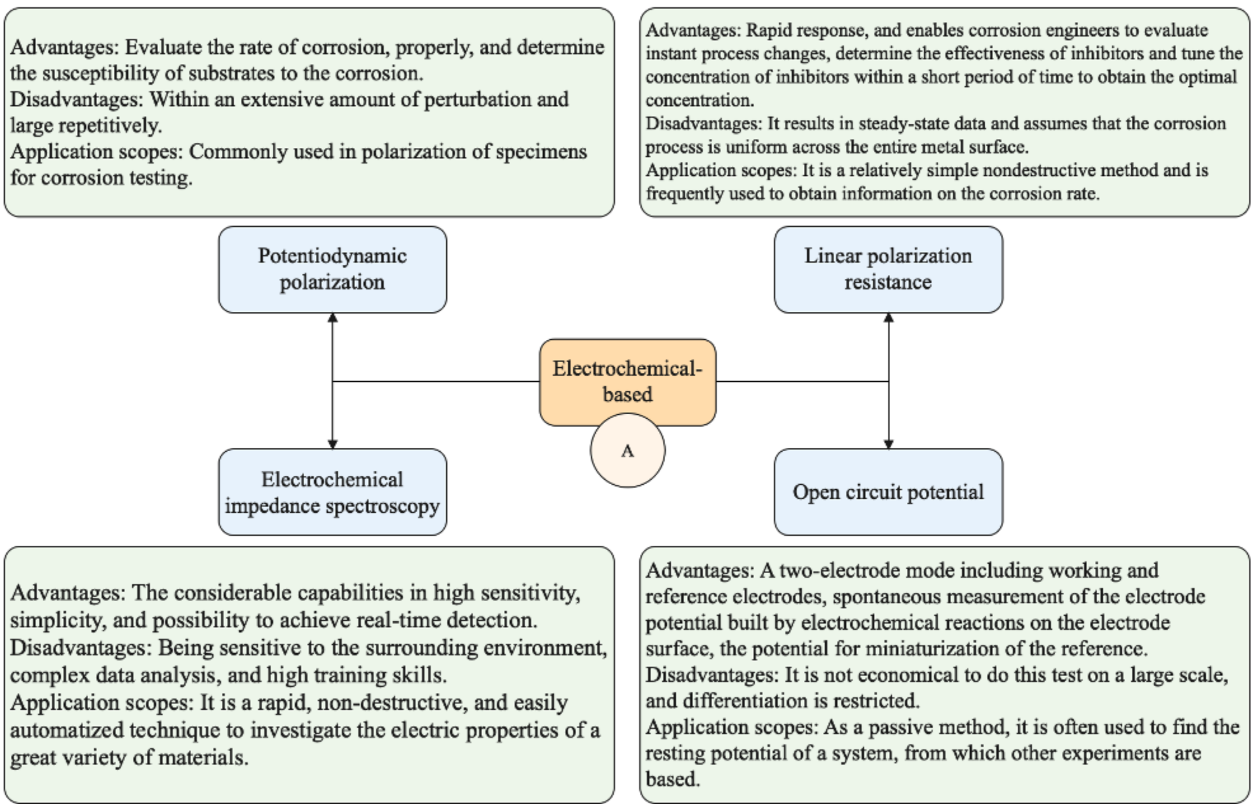
2.4. A review of MIC identification and characterization

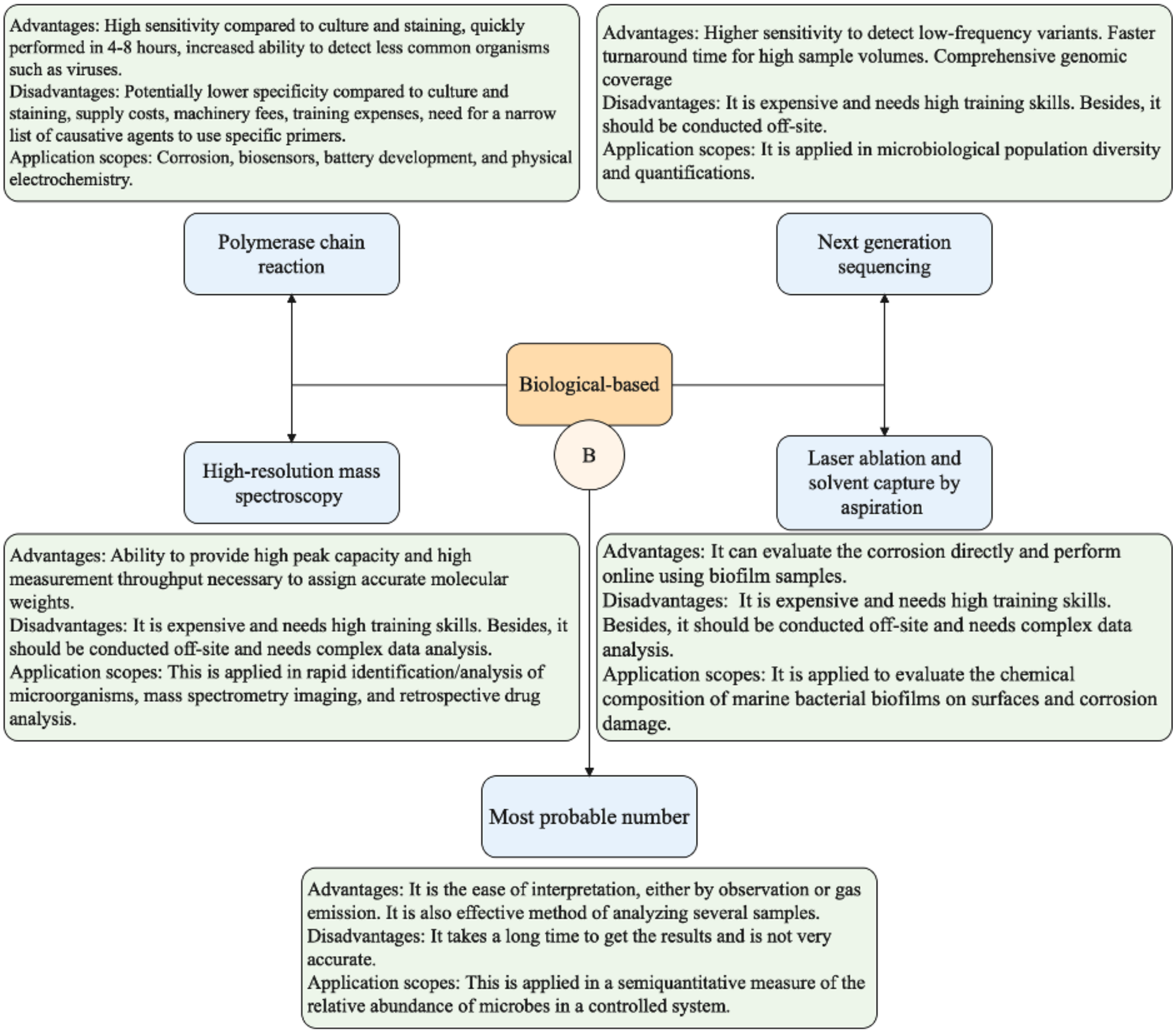
There are two primary ways to detect and identify the MIC in offshore pipelines as online or offline modes [25]. In the online mode, indirect methods such as sampling are included. A couple of systems identify the active indicators of MIC in the biofilm zone according to the based-line comparisons. The settlement impact of microbial activities on the metal surface and continual examining of the surface changes can be conducted. The second mode falls into off-site analysis, including performing pigging, coupons defect site analysis, and samples. The off-site mode can characterize the MIC in different ways, such as the formation of carbon-based compounds, surface resolution of meta, chemical distribution, electrochemical methods, bioactivity (e.g., microorganism), and so on.

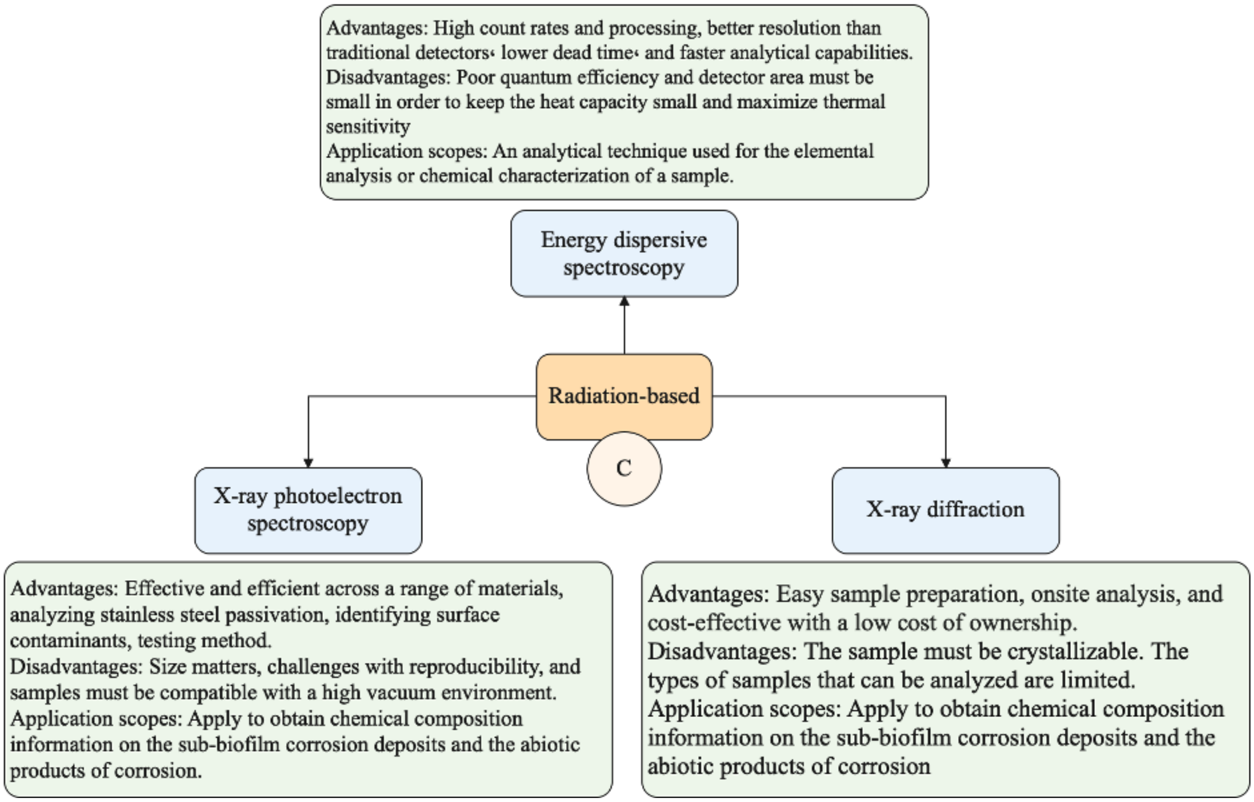
The off-site mode is performed in laboratories near the sampling sites, or the samples are transferred to the centrally located laboratories. A study [83] discussed the sampling procedure accuracy. The oil sample includes an SRB consortium, APB, and common heterotrophic bacteria (GHB) subjected to the 4 stage circumstances, and they were monitored in a week. It is observed that there is a decrease in microbiological concentration when the samples are preserved at four centigrade degrees. Once the samples are stored at different temperatures, including 77°F and

86°F, and cycling in intervals 77°F and 95°F, indicated that the microbiological concentration is increased. This finding is significant because the microorganisms are sensitive to time, temperature, and micro-environmental constitutions.

In Figure 2.4, the four types of MIC identification and characterization techniques developed are depicted. A brief review of identification and characterization techniques has been conducted in the following sub-sections.




Advantages: High sensitivity compared to culture and staining, quickly performed in 4-8 hours, increased ability to detect less common organisms such as viruses.
Disadvantages: Potentially lower specificity compared to culture and staining, supply costs, machinery fees, training expenses, need for a narrow list of causative agents to use specific primers.
Application scopes: Corrosion, biosensors, battery development, and physical electrochemistry.
Advantages: Higher sensitivity to detect low-frequency variants. Faster turnaround time for high sample volumes. Comprehensive genomic coverage
Disadvantages: It is expensive and needs high training skills. Besides, it should be conducted off-site.
Application scopes: It is applied in microbiological population diversity and quantifications.
Polymerase chain reaction
Next generation sequencing
Biological-based
B
High-resolution mass spectroscopy
Laser ablation and solvent capture by aspiration
Advantages: Ability to provide high peak capacity and high measurement throughput necessary to assign accurate molecular weights.
Disadvantages: It is expensive and needs high training skills. Besides, it should be conducted off-site and needs complex data analysis.
Application scopes: This is applied in rapid identification/analysis of microorganisms, mass spectrometry imaging, and retrospective drug analysis.
Advantages: It can evaluate the corrosion directly and perform online using biofilm samples.
Disadvantages: It is expensive and needs high training skills. Besides, it should be conducted off-site and needs complex data analysis.
Application scopes: It is applied to evaluate the chemical composition of marine bacterial biofilms on surfaces and corrosion damage.
Most probable number
Advantages: It is the ease of interpretation, either by observation or gas emission. It is also effective method of analyzing several samples.
Disadvantages: It takes a long time to get the results and is not very accurate.
Application scopes: This is applied in a semiquantitative measure of the relative abundance of microbes in a controlled system.


Advantages: High count rates and processing, better resolution than traditional detectors‹ lower dead time‹ and faster analytical capabilities.
Disadvantages: Poor quantum efficiency and detector area must be small in order to keep the heat capacity small and maximize thermal sensitivity
Application scopes: An analytical technique used for the elemental analysis or chemical characterization of a sample.
Energy dispersive spectroscopy
Radiation-based
C
X-ray photoelectron spectroscopy
X-ray diffraction
Advantages: Effective and efficient across a range of materials, analyzing stainless steel passivation, identifying surface contaminants, testing method.
Disadvantages: Size matters, challenges with reproducibility, and samples must be compatible with a high vacuum environment.
Application scopes: Apply to obtain chemical composition information on the sub-biofilm corrosion deposits and the abiotic products of corrosion.
Advantages: Easy sample preparation, onsite analysis, and cost-effective with a low cost of ownership.
Disadvantages: The sample must be crystallizable. The types of samples that can be analyzed are limited.
Application scopes: Apply to obtain chemical composition information on the sub-biofilm corrosion deposits and the abiotic products of corrosion

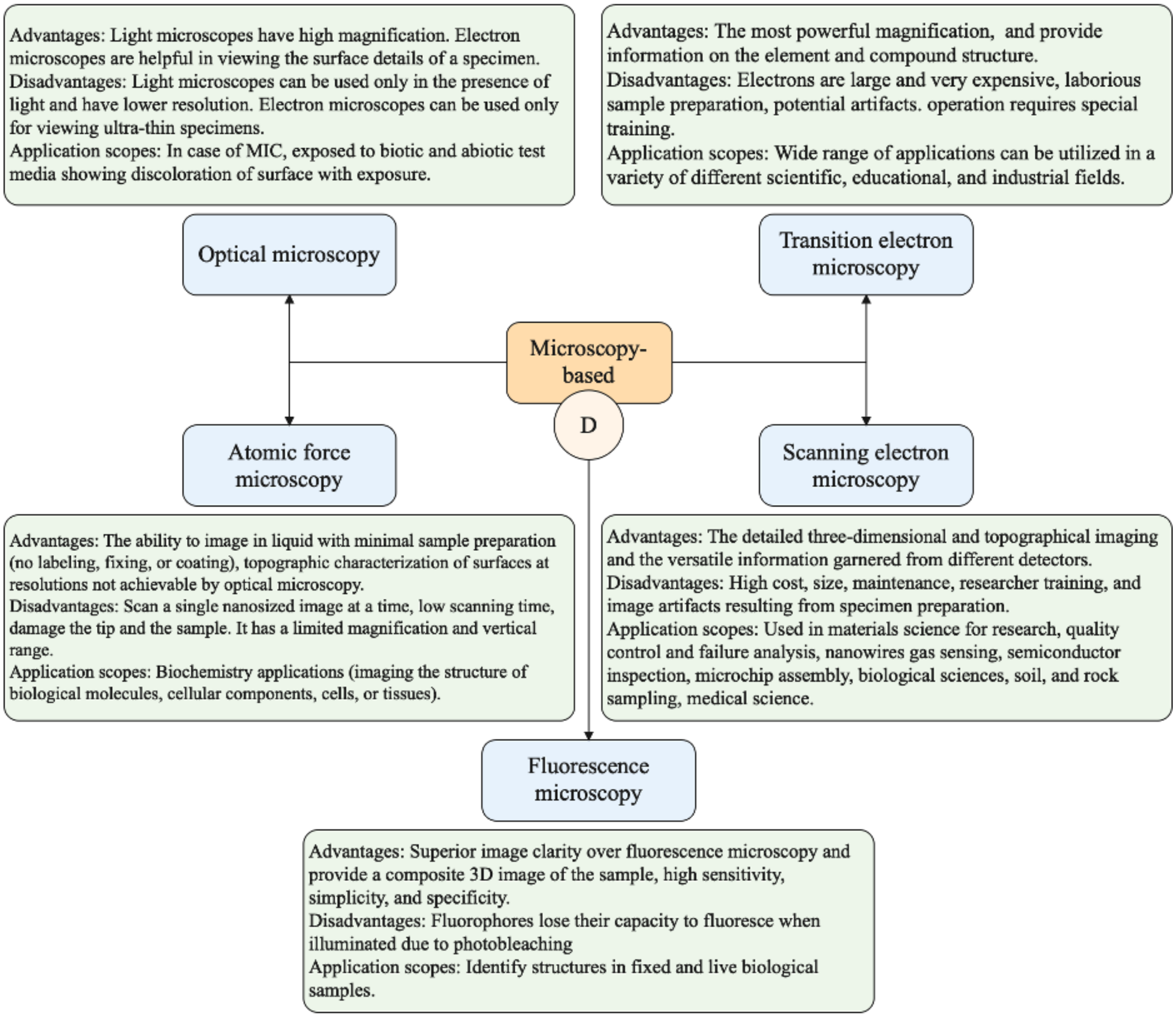


Figure 2.4. A summary of MIC identification and characterization developed concepts (A: Electrochemical-based, B: Biological-based, C: Radiation-based, and D: Microscopy-based)

2.4.1. Radiation-based techniques

In this sub-section, three radiation-based techniques are reviewed in the existing literature. The “X-ray Diffraction and X-ray Photoelectron Spectroscopy” concepts are constructed according to the bio-film zone's abiotic products and chemical composition data. UV radiation tool spectroscopy evaluates the extracellular polymeric substances in highly corrosive conditions

[84,85]. Besides, electrolyte variation impact of amine, ester groups, and carboxyl are examined [86,87]. In another study, X-ray Photoelectron Spectroscopy is utilized to study thin-layer surface composition data [88]. The results highlighted preferential attack concerning the ferrite phase helping in the steel preparation.

X-ray Diffraction has enough capability to provide a valuable understanding of phase variation and compositional in different circumstances. A study investigated the stepwise variation from aerobic into anaerobic environments on the stainless steel under microbiological corrosion [89]. The X-ray Diffraction results for the corrosion specified that in the sterilized coupon, the magnetite exists. It is obtained that the corrosion rate was low; the X-ray Diffraction information can provide a piece of reliable evidence for (i) mechanism and (ii) rate of corrosion.

The Energy Dispersive Spectroscopy is utilized to recognize the coupons deposits underexposure of "Desulfovibrio capillatus" in the separator influenced by severe corrosion [90]. In this study, the Energy Dispersive Spectroscopy indicated the contributed corrosion in steels; API-5XL52 includes S and Fe over forty-five days. Another research highlighted that Energy Dispersive Spectroscopy analysis of the exposed coupon of sterile tap water over 40 weeks without S and Fe. The results indicated a lack of MIC activity [91]. Furthermore, radiation-based techniques have been widely engaged in surface scanning purposes. A study is used for carbon steel exposed to aerobic corrosion to investigate the damages and biofilm formation changes [92]. The results illustrated that increasing biofilm would increase the C, O, and N concentrations, and there would be a decrease in the Cr and Fe concentrations after four weeks of exposure.

X-ray Diffraction obtains information regarding crystallographic evaluation for composition and phases, and X-ray Photoelectron Spectroscopy cares about the thin layer chemical composition on the surface. Besides, the Energy Dispersive Spectroscopy considers the basic composition information. The shortages (SH) and advantages (AD) of the mentioned techniques are as follows X-ray Diffraction (AD: low cost, SH: non-specific data and limited resolution), X-ray Photoelectron Spectroscopy (AD: evaluation of relative composition and elemental analysis, SH: limited spatial coverage and performing offsite), and Energy Dispersive Spectroscopy (AD: comparative compositional examination, and joined through the "electron microscopy" for microbiological perspective, SH: expensive, complex data analysis, limited spatial resolution, and vacuum requirement).

2.4.2. Microscopy-based techniques

The existing literature highlights that microscopy-based techniques are utilized to analyze the surface deposits, fluid samples, biofilms, and coupons. This would provide valuable information to qualify or quantify the variation visualization in metal surfaces (i.e., pits development, grain directions, spatial distribution, microbial colonies). More details can be provided in the study of [25].

A study explained that the three microscopy-based techniques contain "scanning electron microscopy, environmental scanning electron microscopy, and atomic force microscopy", can provide a piece of reliable visual information regarding corrosion [93] as it is discussed in [25], the prominent shortages of scanning electron microscopy are the surface damages and improper biofilm structure. Considering the scanning electron microscopy tools, scanning electron microscopy has the potential to deal with the lack of biological samples [94]. Using the low-energy secondary electrons would help to protect the biofilm integrity, in which the highest number of electrons can cause matching. The biofilm heterogeneity has the complicated spatial distribution of different microorganisms, causing the evaluation process is much more complicated in two-dimensional microscopy. The study investigated the effect of SRB-based microorganisms in the oil field sample of low steel coupons. The scanning electron microscopy technique can recognize the activity of microorganisms between the pitting, sterile, and active culture [95]. The authors concluded that aggressive pitting corrosion in the active culture indicates SRB activity on the surface. In another study, the steel in heat exchangers is studied with "scanning electron microscopy and energy dispersive spectroscopy". The results indicated several organic nutrients on the affected area, sulfide and iron deposits meaning they sing MIC activity [96]. In a similar study, the images from scanning electron microscopy illustrated that biofilm development is efficient.

Moreover, "scanning electron microscopy and energy dispersive spectroscopy" could provide a valuable understanding of surface modification and corrosion site formation [97]. Song et al. [98] have made many attempts to make insights into the corrosion morphology of the pipelines. Their study recommended that the three species of microorganisms, SRB, IOB, and total generated bacteria, are the main causative species.

The "atomic force microscopy" is a non-destructive practice and can explain metal surface variation [99]. Using atomic force microscopy confirmed that heterogeneity biofilm under the microbial steel degradation resulted in mixed culture [100]. A research study conducted by Silva at. Al. [101], The outcome of Aspergillus on the aluminum coupons is examined using "atomic force microscopy". The "atomic force microscopy" made the oxides discrete partials imaged on the metal surface. The results indicated that biofilm has a more excellent interaction zone than the "bulk liquid" than the environment. In another study, the microbial adhesion forces are quantified and found that the greater adhesion forces can be accredited to the growth of the extracellular polymeric substances [102].

Fluorene microscopy ("Confocal laser scanning microscopy") can also be utilized to provide 3-dimensional biofilm images. Fluorene microscopy analyzes the biofilm from samples and illustrates the mechanical properties, including ridges [103]. This was formed because of detrital absorption. The authors concluded that the ridges formed would increase on the metal surface due to microhabitats of differential colonization and additional nutrient resources. Fluorene microscopy technique is utilized on the accelerated corrosion of "duplex stainless" in the study of [104] in the offshore existence "Pseudomonas aeruginosa". It is designated that the pit depth growth path in sterile media and inoculated medial are almost 5 and 12 micrometers. Chen et al. [105] used Fluorene microscopy to compare SRB, and "abiotic sulfide" improved sterile culture. The culture exposed to the "stainless steel 316L", and "Confocal laser scanning microscopy" visualization clearly illustrated that the microorganisms accumulated in the surface clusters. Thus, the localized pitting corrosion was correlated spatially on the coupons' surface.

The microscopic-based techniques are not required to generate the artifact; however, the image of wall surface features might be limited due to inherent shortages of scanning devices [106]. In addition, the non-destructive property of microcopy-based techniques provides an opportunity to visualize the microorganisms and cells by decreasing the images of the artifacts [107]. Besides, using atomic force microscopy characterized the increase of surface roughness and biofilm growth [108]. Research work on the stainless steel with "Geobacter sulfurreducens" microorganisms was discovered ten more times, increasing the defect size within biotic conditions rather than the abiotic condition, highlighting the effect of MIC into the system [109].

The microscopy-based techniques can provide an experimental indication of the existence of microorganisms and general and local corrosion conditions. The advantages (AD) and shortages (SH) of each technique are provided as the following: (i) scanning electron microscopy obtain the information from the magnified micrograph of substrate morphology (AD: quick images, high-resolution, proper for metal and conductive surface, and outstanding reliability, SH: expensive, off-site, bulky equipment, “electron micrography” needs vacuum accumulative, probable harm to the “biological structures”), (ii) atomic force microscopy obtains the information from practical features of the physical contains defect size, friction, shape, cohesiveness, and adhesion forces (AD: sensitive, and quantitative it morphology evaluation, SH: highly skill level, slow performance, limited sampling area, and off-site), (iii) optical microscopy obtains the evaluation of impaired surface (AD: quick, practical infield, and low-cost, SH: limited resolution, and non-specific), (iv) transition electron microscopy obtain the information from the “ultra-high increase, and the resolution of material morphology”, and “crystal structure” (AD: fundamental evolutions, and high-resolution, SH: needs excessive skills, off-site, costly, “sample preparation challenging”, information incomplete due to sampling), and (v) Florence microscopy obtains the information from three-dimension of biofilm and quantification of depth and thickness (AD: restricted sample coupon preparation, and high-resolution, SH: high skill requirements, and off-site).

2.4.3. Electrochemical-based techniques

In this sub-section, the electrochemical-based techniques are reviewed. Electrochemical-based techniques have been widely used in industrial sectors for over 40 years, within fundamental corrosion and thermodynamic mechanisms [110]. Electrochemical-based techniques have been used to understand MIC mechanisms and monitor MIC. However, it is still a challenging topic for scholars and industrial sectors, which provides valuable insights for interpreting field data, corrosion mechanisms, and the dynamic nature of corrosion.

The “Open circuit potential” for the corroded material is the “steady-state potential”, in which the “net current” would be equal to zero. The potential differences amongst the corrosive-medium and standard reference electrodes are commonly used to measure the potential circuit. In addition, the open circuit can be derived with the potentiometric circuit and high impedance voltmeter. The Open circuit potential is widely used in fields and laboratories because of its simplicity in measurement, which would measure the electrochemical performance of materials in the corrosive medium [2].

It is discussed that in the existing literature, microorganisms in the biofilm zone cause a potential circuit with different kinds of metals, including nickel, chromium, gold, stainless steel, etc [111]. The potential circuit signified a positive direction of the potential shift resulting in biofilm formation, leading to oxygen reduction and increasing cathodic reduction rate [112].In the existing state of the arts, much research has been discussed on passive metals like stainless steel during the exposure time with seawater. For example, in the studies [113], it is reported that increasing the voltages to 250-350 in seawater would enhance the microbial activities. A study compared the response of non-carbon steel and low alloy steel to treat the non-treated seawater [114]. After seven-month immersions, the results indicated a small variation amongst the “treated and non-treated seawater”. This means that the higher alloying elements cause a higher circuit potential. In a study, MIC has investigated the “Nickel high nitrogen stainless steel” underlying existence of “Pseudomonas aeruginosa”. It is highlighted that the potential open circuit is more fabulous in the “inoculated medium” comparison of the abiotic controlling [115]. In addition, it is required to be mentioned that the main impact of a potential open circuit is increasing the metrical crevicing probability, initiation, and pitting corrosion propagation. This would be in those material degradations when the potential circuit is near the corrosion potential. In another study, the noises or fluctuations in the open circuit potential measurement have been studied [116]. The noises for the mild steel sample illustrated that these noises follow a stochastic process. It is also concluded that reason if fluctuations were not apparent. Therefore, it is an excellent technique to identify the corrosion mechanism characteristics. The stochastic process correlates with the voltages fluctuations in the corrosion rate and time-based on coupon weight loss. Thus, the two-electrode system is considered the best study system for open circuit potential, in which it has at least a cathode and anode in the system process.

It should be added that “ennoblement” is defined as a “phenomenon exhibited by stainless steel exposed to natural waters. It is characterized by an approximately 400 mV increase in corrosion potential. This increase in corrosion potential can aggravate pitting corrosion” [117], has been observed in various metal types subjected to the different service environmental conditions under MIC attack. However, “it is a difficult task to determine the cause of ennoblement using a potential open circuit over time. Thus, it is challenging to compare the ennoblement data from different site locations since the ennoblement depends on the microbiological population and water chemistry, and the ennoblement is influenced by temperature, rate of flow, and sample size”.

The “electrochemical noise” methods are the “non-destructive and non-interfering” methods, in which they would not vary the steady-state form of the system [118]. This method has enough capability for continual monitoring by ignoring the consideration of external perturbation [119]. The “electrochemical noise” has been widely used to measure and monitor pitting and cracking corrosion. Besides, it can distinguish between localized and uniform corrosion [120].

Generally, the “electrochemical noise” quantities the potential currents’ fluctuations with “spontaneous electrochemical reactions”. The more significant fluctuations and a higher noise level indicate the localized corrosion mechanisms. That is why a uniform corroding metal would be less noisy [121]. A study investigated that noisy electrochemical signals carry the frequency and time domain. The noise signal electrochemical analysis can provide several statistical parameters, including electrochemical noise resistance and localized index [120]. The mentioned parameters are commonly utilized to determine the corrosion rate, and it is discussed that they have some advantages rather than polarization resistance [119]. Men et al. [122] investigated the SRB-based MIC on stainless steel 304 using the back-propagation neural network to identify the passivation pitting induction. The results indicated that the pitting corrosion would increase uniform MIC. A research work [123] highlighted that mathematical analysis could evaluate the localized corrosion mechanisms. The MIC is monitored then by engaging the time instantaneous frequency information on electrochemical noise. It should be worth noticing that frequency domain analysis can be conducted using fast Fourier transformation or maximum entropy methods, in which both can distinguish the corrosion types [25].

The “Potentiodynamic Polarization” technique is a kind of scanning tool which includes the “potential perturbation” far beyond the steady-state corrosion. Potentiodynamic Polarization can be from small voltages into the hundred millivolts in a considerable interval. The Potentiodynamic Polarization can provide a big picture of the given corrosion reactions system, such as transferring charges, controlling diffusion reactions, passivity, pitting, and possible protection. In this regard, the potential would be measured by net charges in the reactions’ rate, and then these are established in the form of corrosion currents. It is appropriate to assess the materials’ susceptibility for localized corrosion in different microbial environments [124]. Anodic polarization curves conducted a study on stainless steel 316 within three environmental conditions (SRB-based, IOB-based, and mixture of both) [125]. The results indicated the stainless steel showed the pitting corrosion in all conditions, and the rate of corrosion was most severe once the environment was the mixture of both IOB and SRB. In addition, the considerable growth in potential current and reduction in the potential passive size is highlighted. Besides, the potential decrease in 316 types of stainless steel means that this is much more prone to localized corrosion attacks.

The “Electrochemical Impedance Spectroscopy” needs a small perturbation to the studied system. The “Electrochemical Impedance Spectroscopy” plays a current alternative method, in which it contains the sinusoidal potential application into the system since measuring the potential current sending [126]. Many works have been conducted applying this method to study material degradation, disbonding, and coating systems [101].

The “Electrochemical Impedance Spectroscopy” method significantly evaluates the “electrochemical reactions” in MIC as the microbiological films adhere to a metal surface in non-conducting and natural environmental conditions. In addition, this method can provide a comprehensive understanding of corrosion mechanisms inducing adsorption, capable controlling, and diffusion [127]. This would be obtained by fitting the results of “Electrochemical Impedance Spectroscopy” into the electrochemical equivalent circuit model, in which the electrochemical parameters would be obtained. This technique also can measure the polarization resistance as it is the inverse of corrosion rate [46].

A study performed by Castaneda et al. [128] reported that biofilm development is moved to the effective mechanism from active transferring charges’ reaction into the restricted diffusion mechanism. In another study, an experimental investigation is performed to obtain the impedance spectra for 316 stainless steel exposing the oil-field produced water in the different periods [129]. In addition, it is correlated with extensive corrosion, indicating the existence of multiple time constants in the “Phase angle plots” (i.e., pitting corrosion happening). Moreover, the growth in the angle phase with the lower occurrences would show a higher thickness value in the formed biofilm [130]. Thus, it is illustrated that the “Electrochemical Impedance Spectroscopy” is a helpful tool in oil-filed for corrosion detection purposes.

It is difficult to obtain the proper model for electrochemical behavior quantification in MIC [131]. Using the external perturbation besides voltage and current density can cause a disturbance to the understudy system as well as a flawed rate of corrosion.

The electrochemical frequency modulation engages the current responses at intermodulation and harmonics of input frequencies within the lowest interference and highest sensitivity from the current density [132]. The capability of “Electrochemical Impedance Spectroscopy” makes it a potential technique for MIC detection and leads to short-term fluctuations in electron chemistry. However, it depends on the speed of fluctuation occurrence, and therefore it might or might not detect the MIC data over different frequencies using “Electrochemical Impedance Spectroscopy” [89]. Thus, it is critical to be careful during data interpretation and use these techniques under steady-state environmental conditions, and it would not be recommended for localized corrosion.

The “Linear Polarization Resistance” is a non-destructive technique typically utilized to obtain the corrosion rate [133,134]. In addition, it is used to monitor the rate of corrosion continuously. In this technique, a small signal perturbation is required regarding the potential corrosion and current density. The corrosion rate is proportional to the polarization resistance near the corrosion potential [111]. Many factors play roles in “Linear Polarization Resistance”, including material density, corrosion rate, Tafel constant, current change, potential change, conversion constant, and equivalent.

It should be added that this technique can provide rapid responses, and the decision-makers can evaluate the instance changes of the system. Moreover, the effectiveness of the injecting inhibitors to the system due to controlling the rate of corrosion can also be determined using “Linear

Polarization Resistance" over time. In a study, the effect of methanogens on the oil pipeline's water corrosion is investigated [134]. The authors evaluated the biocide injecting efficiency and the "Linear Polarization Resistance" technique in this work. The results indicated a strong correlation between the rate of corrosion and methane production in the steel coupon subjected to several biocide injections at different concentrations (e.g., nitrate, NaCl, and tetrakis-hydroxymethyl phosphonium sulfate). The results highlighted an increase in methanogens' production and corrosion rate. Thus, methanogens are the predominant factors in MIC regarding aerobic environmental conditions.

The "Linear Polarization Resistance" would affect the steady-state database, considering the corrosion mechanisms are constant through the surface of the metal. It is worth mentioning that the "polarization curves" are well-known for challenging tasks to be determined. This is because of the stochastic and dynamic features of MIC and biofilm activities on the metal surface as inhomogeneous [135]. The resistance of "duplex stainless steel" under the influence of MIC is investigated. It is discovered that the Tafel slope is changed during the "incubation period". It is regarding biofilm thickness and activities [136]. It could be utilized as an analytical indicator of the high pitting rate.

Finally, the "electrochemical noise" technique obtains the information by distinguishing between uniformed localized corrosion and measuring/monitoring the corresponding rate (AD: providing the differences between abiotic and biotic, non-destructive, and continues, SH: complex data examination, and noises' fluctuation). The "open circuit potential" obtains the "electrochemical behavior" in a corrosive system (AD: low cost and no external perturbation, SH: the difference is controlled, and "ennoblement is non-specific" to the metals). The "linear polarization resistance" obtains the information from monitoring the instantaneous corrosion rate (AD: rapid responses, steady-state data, corrosion rate determination, SH: external perturbation, instantaneous corrosion rate values are unreliable). The "electrochemical impedance spectroscopy" obtains the information from assessing the electrochemical reactions on the surface (AD: mechanistic information and differentiation, SH: complex data analysis and external perturbation). The "potentiodynamic polarization" obtains the information from charges transfers, passivity formation, pitting, and production (AD: corrosion rate determination, and determining the susceptibility of corrosion, SH: significant external perturbation, and repeatability).

2.4.4. Biological analysis-based techniques

The main biological tools have been reviewed in this sub-section, particularly three M methods (molecular microbiological methods). This has been widely utilized in practice, while the conventional methodologies could only capture the one percent of microbes in nature [137]. A couple of new approaches such as "stable isotope probing, functional gene markers, gene hybridization, meta-omics, and whole-genome sequencing" would provide a relief of high-tech analysis and small sample sizes. Moreover, it was made to easily understand metabolic pathways [25]. Well-trained employees, systems feedback, and high-level data analysis are needed to mitigate MIC in the site. There are two types of biological analysis, (i) the metagenomics analysis, in which it could provide a piece of genomic information with the methods, for example, "polymerase chain reaction (PCR) and gene sequencing", and (ii) metabolomic analysis, which engages different methodologies such as "high-performance liquid chromatography", "gas chromatography", and "mass spectroscopy" to recognize and analyze the chemical components in biological environments assessing the metabolome information [138]. Combining (i) and (ii) techniques can deploy the MIC correlated mechanisms with MIC formation chemical reorganization and microbiological communities.

The metabolomic analysis is the biofilm metabolomics contains the microbiological process of the microbiological society in the biofilm zone accessing the chemical components indicating the MIC activities in the metal surface [25]. The high resolution of "mass spectroscopy" requires the differentiae's ability among ions of approximately identical mass and mass determination of an ion within acceptable accuracy, determining the element of composition for an ion [25,45]. The "mass spectroscopy" would be developed using the laser-based technique that leads to practical analysis and efficient transport. The "laser ablation and solvent capture by aspiration" system is the method that material in "laser plumes" would be gathered in a "coarse aerosol" and investigated by "electrospray ionization" in a "high-mass-resolution".

Research conducted by Gutarowska et al. [139], the materials' biodeterioration is assessed, and the samples were utilized to abstract the organic deposits. Furthermore, the "organic residues" were analyzed using "high-performance liquid chromatography". The metabolic activation resulted in "primary and secondary metabolites". It was identified according to the "putative metabolites". A considerable number of merits can be highlighted for this method, such as small information of sample quantity should be obtained with the species interactions. In another study, the "laser ablation and solvent capture by aspiration" method is extended, assessing the corrosion loss at the surface of carbon steel 1018 caused by over 1000 ion-metabolite [140]. This revealed that the biofilm is heterogeneities. In addition, there is a correlation between biofilm metabolome and anaerobic corrosion. It is also recommended that the metabolome spatial correlation might indicate MIC occurrence. In this regard, such studies provided a new MIC perspective focusing on the constituent's activation, meaning that they consider microorganisms instead of sources.

In metagenomic analysis tools, the "polymerase chain reaction"-based have been broadly engaged for the last couple of years, in which this decision-makers to have a better understanding of microbiological mechanism and profile [141,142]. The main shortages of culturing different types of microorganisms in laboratories motivated scholars to use molecular biology methods to examine the presence of different microbiota sample species [143]. Using the "polymerase chain reaction"-based tools have been combined with the methods including the "denaturing gradient gel electrophoresis", in which the gene named 16SrRNA examination are derived once the DNA amplification of uncharacterized microorganisms [144]. It should be highlighted that using these methods is useful in MIC-affected problems since the mixed biofilm species are attached to the metal surface of the system.

The research was conducted by Teng et al. [145] to recognize the microbiological group during biofilm investigation in corroded water network pipelines lines. In this study, the Simpson is utilized to compute the diversity of microorganisms. In the study [146], the "denaturing gradient gel electrophoresis" is established to assess the biofouling corrosion on seawater cooling system. Another improvement is attempted in [147], the combination of DNA optimization technologies is used to enhance the microbiological activities evaluation process. This technique enables decision-makers to quantify the distributions of microorganism populations with 10% accuracy [148].

Moreover, these techniques have been developed for hydraulic fracturing characterization [149], in which there was bacteria proliferation. Subsequently, the 16SrRNA was engaged with clone libraries and pyrosequencing to examine relative microbiota abundance. The chemical analysis illustrated the presence of anaerobic microorganisms and extensive metabolic capabilities. The results indicated the microorganism communities could produce water. Thus, it is required a better understanding of produced water disinfection. In a study conducted by Gonzalez et al. [150], the bacterial communities of corroded oil pipelines recognized multiple SRB-based species (e.g., desulfobacter, desulfococcus desulfonema, and desulfobulbus).

Besides, metagenomic methods are commonly used for collecting data on phylogenetic biofilm diversity [151]. The presence of a hydrogenotrophic and autotrophic methanogen denotes two types of corrosion mechanisms: cathodic depolarization and SRB-based syntrophic actions in the same order. However, these methods do not cover the bacteria species responsible for severe MIC [152]. There is a "polymerase chain reaction" tool to analyze the corrosion deposits of pigging [153]. These methods have been conducted in many different domains, such as gas pipeline [154], Mexico pipeline [155], Alaskan slope infrastructure [156], North Sea area [157], and so on.

2.5. A review of MIC management methods (preventive, control, and mitigative)

In this section, the common MIC management tools are reviewed. In Figure 2.5, the MIC management methods for the vulnerable systems are presented. A description of the management method is provided as the following.

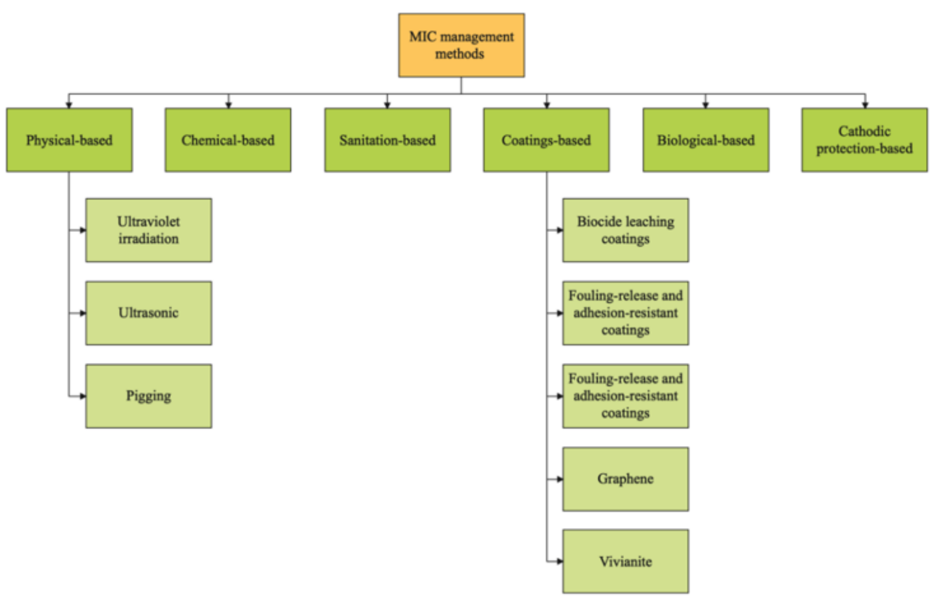


Figure 2.5. The MIC management methods for the vulnerable systems

2.5.1. Physical-based method

The "ultraviolet light" kills the microorganism and can be considered an important alternative for biocides treatments for controlling the MIC mechanism [24]. The critical challenge is that it is difficult to be implemented in practice. The ultraviolet light can only affect the microorganisms, in which they are exposed to the light directly. In case the microorganisms are covered in the production of corrosion, the ultraviolet light cannot affect that; they are properly protected. Furthermore, the internal surface of the pipeline is not suited for ultraviolet light treatments. Besides, the ultraviolet light might inactivate the living cells; however, the cells would not be removed from the surface and would still be in the biofilm zone. Thus, they can play the nutrients roles of the organism, including those prone to the MIC.

The "ultrasonic" or the ultrasound can produce the cavitation bubbles in the fluid, in which once they collapse, they would influence microorganisms detrimental. The ultrasonic treatment is recommended for MIC mitigation purposes [158]. The main concern is that the efficiency of ultrasonic to kill the microorganism in products of corrosion has never been validated. Therefore, it has to be considered that the products of corrosion and MIC-based microorganisms would drastically mitigate the energy of ultrasonic.

The "pigging" as a physical cleaning tool is typically utilized in contrast to the corrosion, without consideration of microbial contributions. In pigging tools, the sponge balls or plugs are inserted into the pipelines to remove the corrosion tuberosities [159]. The challenge of the pigging tool is that it can only be conducted in the specific type of pipelines within the constant diameter and has no impediments throughout the pigging path. Once the pigging process is successfully finished, the metal surface would be a highly anode-active cell. In case of the surface of metal not being passivated, the pigging performing can accelerate the rate of corrosion [11]; moreover, the results of variation of environmental circumstances, the microorganism would react. The thin biofilm zone might be less corrosive than the beginning community [160].

2.5.2. Chemical-based methods

Over the last decades, chemical and corrosion scientists have been attempted to develop biocides, killing the microorganisms as much as possible in many species. The main challenge is that the biocides should be activated on microorganisms of the biofilm zone, in which the cells are more tolerant than planktonic cells [161]. Research suggested using biocide enhancers [162] because the biofilm zone contains more than 98 percent water and does not have a diffusion barrier for such small biocides [163]. However, there is a condition that using biocides could decline the concentration when there is a “reaction diffusion inhibition”. It can also be explained as the microorganism of biofilm transition into the per-sister state or a stress reaction into the biocide exposure [164]. The biocide tolerance would be lost in the case of biofilm cells [165].

One of the main chemical-based treatments is injecting Glutaraldehyde into the oil and gas industrial sectors [166]. The challenge is that Glutaraldehyde can be problematic because of non-toxicity during other treatments such as long-term sanitation. In addition, Glutaraldehyde is corrosive to carbon steel [167], and ionic silver is recommended for microbiological inactivation [168]. Many research tasks highlighted that nanoparticles have significant tolerance in developed biofilms [165]. Another chemical-based treatment is using Tetrakis-hydroxymethyl phosphonium (THPS), which has advantages against SRB; however, there are limited practical application reports in this regard [169].

2.5.3. Sanitation-based methods

In order to eliminate the MIC in the system as much as possible, performing sanitation is vital. Sanitation treats the effect of system microorganisms would reestablish the original properties' performance. In only references [11], authors recommended sanitation against MIC.

The sanitation measures include (i) "physical clean-up", (ii) "mechanical changes", and (iii) using biocides. However, the biocides maybe contain the dispersion agent on more effective outcomes. The sanitation process may cause a disposal problem, which is costly [170].

In the reference book [158], the different levels required for sanitation are explained. The main occlusion remarks are that the replacement absence of corroded metal can be mitigated MIC, considering operational and environmental circumstances [159]. The fact is that sanitation cannot eliminate the further metal damages.

2.5.4. Coating-based methods

The coating-based methods isolate the potential corroding metal surface from an elect, providing some corrosion protection. The coating is one of the main conventional methods to protect the metal surface under the influence of MIC, such as polyimides, epoxy resins, silicones, polyvinyl chlorides. [171]. However, the coating can also be biodegraded or damaged over time [172]. This would then result in the rapid activity off anodic sites for localized pitting corrosion by attracting different microorganisms. In addition, the coating can be justified in order to enhance the surface's coverage and reduce the degradation of metal defects. Besides, this can control microbiological growth by biocide activities and control killing or adhesion resistance [171]. The coating strategies can be performed in a combination or individually. In the following, the main coating-based method has been reviewed.

The “adhesion resistance coating” strategic plan is used to control the MIC according to the properties of the surface, which would prevent bacteria adhesion without killing them. This strategy includes hydrophilic, amphiphilic, biomimetic, hydrophobic, and superhydrophobic [11]. However, biomimetic is designed to minimize the natural occurrence of antifouling metal surfaces. For instance, this strategy is designed to mimic the “antifouling properties of shark skin”, including the overlapping of the nanoscale plate within parallel ridges. The “hydrophilic polymers” based on the interfacial layer could prevent contact between the metal surface and bacteria [171]. The hydrophobic coating-based strategies from a surface by “low surface energy” would remove the bacteria. In addition, the amphiphilic coatings would integrate the hydrophobic element to prevent the microorganism attachment in the metal surface and enhance the antimicrobial coating behavior [173]. It should be highlighted that the adhesion resistance is not just exposed to the microorganisms; it also includes abiotic foulants. The mentioned features adhere to the main properties and encompass their anti-microbiocidal functions.

The “biocide leaching coating” is an agent that contains toxic metal ions or biogenic elements that could be combined with polymers as antifoulants. The efficiency of “biocide leaching coating” is based on the rate of leach prediction. The biocides could leach from polymer, and it can be controlled by polymer degradation. The main challenge is that there are considerable environmental damage sides. Moreover, the biocides have a restricted lifetime due to the release rate and the total amount of activated elements that may be loaded into the coating. There are many biocides leaching coating applications globally, including copper and tin ions, with “a consequence of overt ecotoxicity as well as biomagnification through the food chain” [11].

In the end, the smart-based coating has been developed to protect the metal degradation, such as inhibitors release, to corrosion onset responses [174]. However, there is no practical experience to investigate the biocide release.

The “Vivianite” is a widely established “phosphate-rich” media within different microorganisms, especially in IRB with sulfate reaction on stainless steel [175]. The studies [176,177] recognized the “Vivianite” layer. The results indicated that besides phosphate concentration, “Vivianite” formation is needed, the growth of the microorganisms contact with the metal surface [176]. Three MIC-based reactions are involved in the “dissolution of the thin iron oxide layer” release and the precipitation of “Vivianite”. The authors highlighted that the significant corrosion protection “lasted 4-6 weeks in highly corrosive” media. That is why the conclusion indicated biofilm presence on “Vivianite,” meaning that pitting corrosion occurs. It is recommended that the painting be needed to optimize corrosion protection. Another study presents that the “phosphate-rich layer” is much more protective than the iron oxide based on the abiotic controlling process [175].

The “Graphene” is typically recommended with considerable advantages rather than conventional coating strategies for MIC p/revention purposes [178]. The “Graphene” is thicker than carbon in terms of atoms, and it is bounded in “hexagonal honeycomb lattice”. The main features to describe the “Graphene” are (i) light material, (ii) thin and strong compound, (iii) adequate conductivity for electricity and temperature compared to the existing compounds. In addition, the “Graphene” is avoided for the major defects in the mentioned study work. It is a deliciated coating strategy and would be damaged easily. In a study [179], it is highlighted that resistance oxidation of “Graphene” was less than when there is long-term exposure with air. It is found that there is a low performance of “Graphene” for coating irregularities. Thus, the anodic sites would be developed in highly cathodic “Graphene” coating. Thus, research [180] recommended that the multilayer of

"Graphene" would be better for coating strategy. The main challenge is that using the "Graphene" in abiotic substances would restrict the practical advantages of coating, especially in long-term exposure. The "Graphene" is performed using thermalizes to protect the metal surface from corrosion and erosion. The fact is that the failure mechanism is caused by the delimitation of the thermal spray coating, which begins at heterogeneous defects [181]. In the study [182], the "Graphene"-based coating is designed to reduce the mild stainless steel porosity. The results indicated that such coating strategies could reduce the numbers of sessile and planktonic SRB. Moreover, there was no localized corrosion on the metal surface with coated stainless steel; however, the general form of corrosion was observed.

Finally, the "Contact-killing and conductive coating" includes the positively charged compound immobilization with the polymer matrix. The mechanism is that the positive charges interact with the negative ones as bacterial cells; therefore, it disrupts cell walls [168]. Besides, the positive charges can be added to the polymers such as chitosan, "quaternary ammonium salts", conductive polymers, etc.

The conductive polymers have been widely utilized as an anti-corrosion coating strategy for different metals, copper, aluminum, and stainless steel [168]. The mixture of the oxide layer can protect the metals against corrosion [183]. It also has anti-fouling features, in which positive charges nitrogen can interact with negative charges bacterial cells, which causes material degradation.

In this regard, the coated metal surface plays the anode role, and the un-coated surface of metal contacting with seawater plays the cathode role [184]. It should be noted that, in case of a weak current between the two anodes and cathode, the seawater would be electrolyzed. A study concluded that the polyaniline with the special features is conducted in the absence of applied current density. In addition, the polyaniline conduction could vary the hydrophobicity of the coated metal surface responding to the electric signal changes. Besides, this could produce anti-fouling in case of adding other types of anti-fouling agents in the metal coating. The different types of anti-fouling incorporated with coating strategy plans are described in the study of [171], such as the immobilization of steel surface with “quaternary ammonium salts” provided the information regarding biocide leaching contact would kill the combination of microorganisms. The coated metal surface indicated that there are sufficient advantages without coating.

Furthermore, the combination of adhesion resistance killing may be utilized for anti-bacterial coating purposes. However, the significant challenge is that contact killing strategic plans are available in the limited range of candidate compounds [185]. Thus, decision-makers need to determine the efficiency and effectiveness of the contact killing plans, considering operational parameters and the interface between all parameters. The point is that, in case of working, the metal surface coating is restricted, and the inactivated cells would remain on the main coating. Long-term exposure is required to examine the challenges mentioned earlier.

2.5.5. Biological-based methods

The main idea of using biological-based methodologies is to inhibit the MIC microorganisms' activities by engaging non-MIC-supported microorganisms. The fact is that the observation highlighted that not all microorganisms would enhance the rate of corrosion [11]. Besides, the term “MIC” supports that some bacteria in some media could be inhibited [164]. The biological methods can convert the products of reactive corrosion into stable biogenic minerals such as siderite and vivianite [186]. However, there is no evidence to show that the inhabitation methods using microorganisms would be performed in practical applications [187].

For example, the different approaches, “extracellular polymeric substances” against MIC, “quorum sensing inhibitors”, or “strategy to transferring into the non-corrosive species,” might be working in the laboratory, it most probably cannot be applied in the work field [188]. In addition, the “quorum sensing inhibitors” method requires a large number of materials. It should be considered that there would be tolerance in corroding site directions, and the cost of such treatments methods is so much.

In practice, nitrate injection is the most common way to crush reservoir souring. The nitrate-reducing bacteria (NRB) would suppress the SRB-caused MIC. Due to the fact that the NEB could outcompete the SRB since the energy of nitrate reduction is much more than sulfate reduction. Moreover, the activity NRB would restrict the production of H2S and increase the redox potential. Thus, it can be considered a proper alternative for biocide performance [189]. The mentioned studies reported that the mentioned biological method was successful and could mitigate MIC over time.

In addition, the biological manipulation needs enough nitrate levels, which depend on water volume and environmental conditions [190]. The NRB includes a range of microorganisms, and some of them can increase the corrosion rate [191]. Besides, some SRB microorganisms can utilize nitrate-causing MIC [192]. In the studies [193], it is reported that the rate of corrosion is increased after nitrate mediated souring control process.

2.5.6. Cathodic protection-based methods

The cathodic protection-based methods to control MIC SRB-based have been widely studied in the literature. The cathodic protection is a control tool that can be conducted in the system with coating integration or independence to protect the marine and offshore pipelines. The cathodic protection mechanism limits the structure of metal corrosion by changing the metal as an electrochemical cell. This can be performed in two ways: (i) impressing the current density with an external current source or (ii) using a more active material as an anode. In fact, in the ideal cathodic protection, a potential is needed to reduce the level of corrosion for an exposed structure to a corrosive environment [194].

The Calcareous deposits are poor electrons' conductors and do not have the potential supporting oxygen reduction. It can contribute to the efficiency of cathodic protection; however, it may lead to a small diameter of pipeline blockages. A study reported that the micro-fouling-organism would be grown on the sacrificial anode; however, it cannot prevent anodes from the stainless-steel structure effectively [195].

Generally, the alkaline generated from cathodic protection polarization could slow bacterial proliferation and activities [196]. That is why there are studies against it. In the study [197], it is highlighted that cathodic protection polarization, the SRB-based counts on coupons are two times bigger than coupons with no cathodic protection. It is recommended that the SRB engage the cathodes as electron donors for the metabolism process [198]. It concluded that cathodic protection polarization could feed the MIC-based microorganism on the metal surface within electrons' energy underlying the anaerobic environmental circumstances [131]. Another study discussed that the cathodic protection under an anaerobic environment could activate the microorganism on cathodes [199]. An attempt has been made to control the oxygen reduction activity of microorganisms to control the cathodic protection system considering the microbial fuel cell [200].

The SRB can induce additional pressure on the cathodic protection system by generating the H2S and dissociating sulfite (S2-) and bisulfite (HS-). In addition, the insoluble ferrous sulfides can move the cathodic protection potential circuit into much more negative amounts. Subsequently, in the case of sulfide presentation, the common standards suggested that the cathodic protection potential circuit has less negative values than normal references, such as “DNV RP B401”. The environmental circumstances play an important role in the cathodic protection-based method's effectiveness. In the study [201], it is noticed that cathodic protection polarization potential requires much more negative values to prevent SRB-based corrosion.

The strong electrical fields and high pH value due to the cathodic protection polarization circuit can disbond coatings. This means that the protective coating would be delaminated from protected features because of hydroxyl ions formations over the protected metal surface [202]. Fatehi et al. studied that the SRB causes severe corrosion compared to abiotic control [203]. Many microorganisms growing cathodic surface protected indicated that when cathodic protection is intermittent, the corrosion would be aggressive [204]. Thus, the SRB might be assassinated with the coating cathodic disbondment in a couple of metals.

The cathodic protection has negative side effects as producing a hydrogen atom. The hydrogen atom is small and can easily diffuse within the steel structure. In addition, the hydrogen may cause hydrogen blistering. Moreover, the negative potential to protect the MIC would enhance the number of hydrogen atoms. Therefore, the risk of hydrogen embrittlement is high. For example, in the study [205], the hydrogen atoms in the steel structure within cathodic protection in seawater under the influence of SRB are investigated. It is reported that the SRB would enhance the rate of the hydrogen atom with ferrite pearlite. In this regard, SRB causes hydrogen steel deterioration at the cathodic potential circuit. In another research, the hydrogen blistering in steel seawater the influence of SRB at a potential range of cathodic protection is studied [206]. The hydrogen concentrations absorbed by steel were greater than cathodic protection. It is concluded that the increased sulfide based on SRB on the metal surface would be enhanced by hydrogen atom sorption.

To recapitulate, chemical treatments, pigging, and sanitation mitigates the MIC. The biological methods can mitigate the MIC; however, they are not practical. It is needed to understand the MIC mechanism much more effectively. The only option to limit microbial growth is restricting the nutrients. The coatings management actions are designed to protect the pipeline for long-term exposure. However, the cost of coatings is high and would be lost because of biofilm formation over time.

Moreover, the cathodic protection cannot effectively protect the pipeline from biofilm formation and cannot prevent the MIC. Once the potential circuit is much more negative than standard practice, it can prevent MIC. However, the cost of such operations would be extremely high.

2.6. Discussion and future work prospects

MIC has been significantly evolved in recent years. However, by reviewing risk-based decision-making models for MIC in offshore pipelines, it can be found that there are still further attempts required to be taken into account to enhance MIC knowledge and reduce the critical gaps:

- It is a challenging task to provide a risk-based decision-making model of MIC as it might have several potential effects, such as pitting corrosion,
- It is challenging to assess and manage MIC and requires a well-understanding of microbiological circumstances and corrosion. Integrating the outcomes of published works indicated that the nature of MIC is dynamic and difficult to be predicted, including microbiological activities and chemical environments,

- It is a challenging task to provide an MIC management plan by preventing, controlling, and mitigating MIC contributing factors, including microorganisms, metal-fluid interactions, chemical, and environmental conditions,
- It is still challenging to understand MIC due to the varieties of affected areas starting from produced water, tanks, flowlines, and reaching other sections. Thus, it calls further and deeply assessing oil, solid, aqueous phases to define a comprehensive picture of MIC, and
- It is challenging to provide a MIC risk-based decision-making model because of data scarcity, potential uncertainty of MIC contributing factors, and potential correlation among microbiological activities and chemical environments.

Keeping in mind that developing a MIC risk-based decision-making model is multidisciplinary and stochastic. Thus, it is siloed between four main subject areas as (i) material and MIC products, (ii) chemical environment, (iii) physical and operational conditions, and (iv) microbiology, as depicted in Figure 2.6 [3].

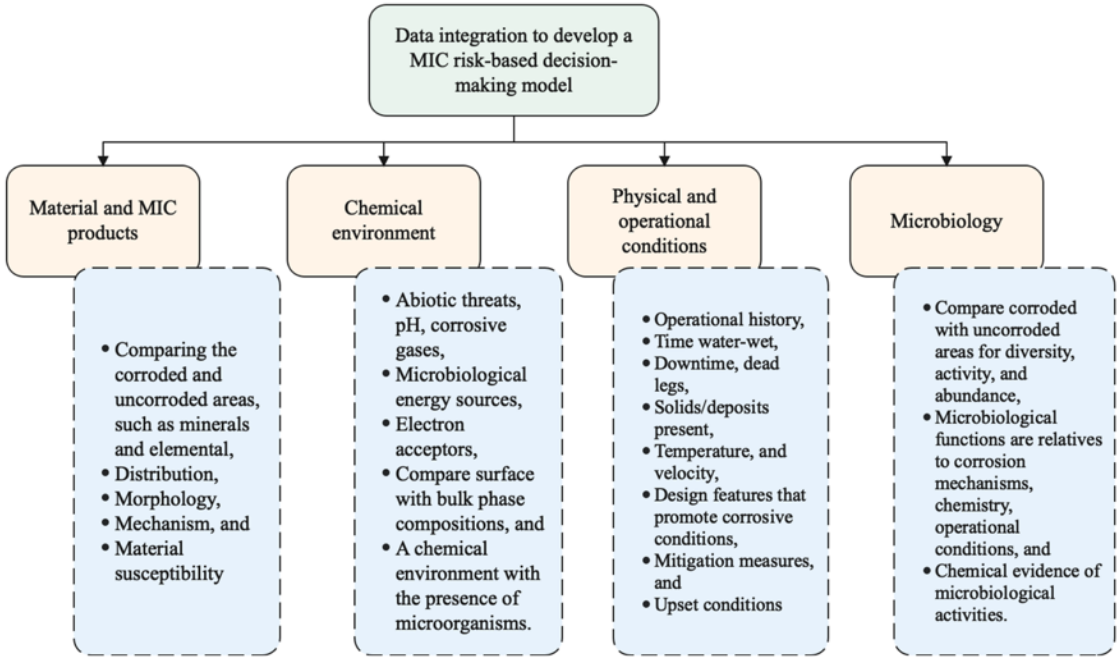


Figure 2.6. The schematic representation of data integration developing a MIC risk-based decision-making model

The presented schematic representation of data integration developing a MIC risk-based decision-making model can be further elaborated by addressing a series of questions considering the sample, data collection, assessments, and analysis. Some examples of questions are provided as the following but not limited to:

- Material and MIC products: "Are there corrosion products present that can only be produced by microbial activity? How does the corrosion morphology relate to the chemical, microbiological and physical conditions present? Are both general corrosion and pitting corrosion observed? Is the damage observed characteristic for this alloy in this environment? Does the metallurgy of the component conform with the standards to which it was manufactured?"
- Chemical environment: "What types of microbial nutrients are present? How does the composition change over time or during upsets or maintenance? How does the chemical environment compare with the microbial functional groups or types of detected

microorganisms? Are there bioproducts of microbial activity present? Does the environment support their growth?"

- Physical and operational conditions: "When did the corrosion occur relative to changes in the operational history of the asset? How long was the component exposed to water? How do temperature and velocity contribute to the corrosive conditions? Are there design features that contribute to the corrosive environment? What mitigation measures have been used, and how have they been applied? How were they monitored?", and
- Microbiology: "How do the numbers, types, or activities of microorganisms at the corroded location differ from areas where there is no corrosion or from the bulk phase? Which microorganisms could thrive under the chemical and physical conditions that are present? Which would not?".

The future work prospects fall in the use of mechanistic, empirical MIC, probabilistic, and other models together, in which the potential risk-based decision-making models will integrate data from a MIC investigation. As much as decision-makers could provide precise and accurate responses to the questions mentioned earlier and more, the model will be reliable to a great extent. In addition, an effective and efficient risk-based decision-making model can be derived if and only if the MIC mechanism was correctly identified at the first stage, following that the model would be developed.

2.7. Conclusions

This literature review provides a different observation regarding MIC characteristics, detection, modeling, and management in the existing literature. In the following, the main findings are highlighted:

- The presence of microorganisms in the pipeline does not necessarily mean that there would be any evidence of MIC activities,

- Most of the studies suffer from using off-site facilities, and they are restricted to rapid assessment due to the high cost of simulation environmental conditions,
- The microbiological evaluation-based method (e.g., metabolomic and metagenomic) is the most robust tool for MIC determination,
- The significant point to detect MIC in a short period is the characterizing the diversity of microorganisms on suspectable field sites,
- The data mining on the microbiological data set may provide a valuable understanding for the most remarkable possible proliferation of MIC impacts,
- The probabilistic and fuzzy-based methods can enhance the system's capabilities to assess MIC treatments. Thus, an intelligent system can provide a much more realistic timeline for decision-makers and operators to obtain the level of risk,
- Utilizing such qPCR techniques to derive the total numbers of a single gene (16S rRNA), bacteria, and archaea is the critical performing indicator of consistent reporting in the system,
- Engaging the nano-material tools can provide insights for robust detection sensors, such as smart pigs and miniaturized kits,
- Reducing the cost of MIC management can only be applied in case using multi-disciplinary approaches between chemical, corrosion, and safety engineering,
- There is a requirement for research tasks to obtain the solutions for MIC in dynamic environmental circumstances.

It should be highlighted that the impact of such research works in the MIC field can reduce the MIC-based accidents and follow the costs. Thus, it can provide a reliable and low-cost solution.

Exploring the available investigations and findings into the MIC-risk-based models could deal with difficulties and provide the research opportunities for future research tasks.

Acknowledgments

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References

[1] Koch G., Varney J., Thompson N., Moghissi O., Gould M., Payer J. International Measures of Prevention, Application and Economics of Corrosion Technologies Study. Houston, TX: 2016.

[2] Skovhus TL, Enning D, Lee JS. Microbiologically Influenced Corrosion in the Upstream Oil and Gas Industry. Taylor & Francis; 2017.

[3] Eckert RB, Skovhus TL. Failure Analysis of Microbiologically Influenced Corrosion. 1th ed. CRC Press; 2021. https://doi.org/10.1201/9780429355479.

[4] Bhandari J, Khan F, Abbassi R, Garaniya V, Ojeda R. Modelling of pitting corrosion in marine and offshore steel structures - A technical review. J Loss Prev Process Ind 2015;37:39–62. https://doi.org/10.1016/j.jlp.2015.06.008.

[5] Foorginezhad S, Mohseni-Dargah M, Firoozirad K, Aryai V, Razmjou A, Abbassi R, et al. Recent Advances in Sensing and Assessment of Corrosion in Sewage Pipelines. Process Saf Environ Prot 2021;147:192–213. https://doi.org/10.1016/j.psep.2020.09.009.

[6] Chang JI, Lin C-C. A study of storage tank accidents. J Loss Prev Process Ind 2006;19:51–9. https://doi.org/https://doi.org/10.1016/j.jlp.2005.05.015.

[7] Abdullah A, Yahaya N, Md Noor N, Mohd Rasol R. Microbial Corrosion of API 5L X-70 Carbon Steel by ATCC 7757 and Consortium of Sulfate-Reducing Bacteria. J Chem 2014;2014:130345. https://doi.org/10.1155/2014/130345.

[8] ISO 31000: Risk Management. Int Stand Organ 2009.

[9] Taleb-Berrouane M, Khan F, Hawboldt K. Corrosion risk assessment using adaptive bow-tie (ABT) analysis. Reliab Eng Syst Saf 2021;214:107731. https://doi.org/https://doi.org/10.1016/j.ress.2021.107731.

[10] Conley S, Franco G, Faloona I, Blake DR, Peischl J, Ryerson TB. Methane emissions from the 2015 Aliso Canyon blowout in Los Angeles, CA. Science (80-) 2016;351:1317 LP – 1320. https://doi.org/10.1126/science.aaf2348.

[11] Little BJ, Blackwood DJ, Hinks J, Lauro FM, Marsili E, Okamoto A, et al. Microbially influenced corrosion—Any progress? Corros Sci 2020;170:108641. https://doi.org/https://doi.org/10.1016/j.corsci.2020.108641.

[12] Liu T, Cheng YF. The influence of cathodic protection potential on the biofilm formation and corrosion behaviour of an X70 steel pipeline in sulfate reducing bacteria media. J Alloys Compd 2017;729:180–8. https://doi.org/https://doi.org/10.1016/j.jallcom.2017.09.181.

[13] Wang H, Ju L-K, Castaneda H, Cheng G, Zhang Newby B. Corrosion of carbon steel C1010 in the presence of iron oxidizing bacteria Acidithiobacillus ferrooxidans. Corros Sci 2014;89:250–7. https://doi.org/https://doi.org/10.1016/j.corsci.2014.09.005.

[14] Jia R, Tan JL, Jin P, Blackwood DJ, Xu D, Gu T. Effects of biogenic H2S on the microbiologically influenced corrosion of C1018 carbon steel by sulfate reducing Desulfovibrio vulgaris biofilm. Corros Sci 2018;130:1–11. https://doi.org/https://doi.org/10.1016/j.corsci.2017.10.023.

[15] Rosales BM, Iannuzzi M. Aluminium AA2024 T351 aeronautical alloy: Part 1. Microbial influenced corrosion analysis. Mater Sci Eng A 2008;472:15–25. https://doi.org/https://doi.org/10.1016/j.msea.2007.06.079.

[16] Liu H, Xu D, Yang K, Liu H, Cheng YF. Corrosion of antibacterial Cu-bearing 316L stainless steels in the presence of sulfate reducing bacteria. Corros Sci 2018;132:46–55. https://doi.org/https://doi.org/10.1016/j.corsci.2017.12.006.

[17] ASTM E3-2017. Standard guide for preparation of metallographic specimens. West Conshohocken: 2017. https://doi.org/10.1520/E0003-11R17.

[18] ASTM A370. Standard test methods and definitions for mechanical testing of steel products. West Conshohocken: 2020. https://doi.org/10.1520/ A0370-20.

[19] ASTM D-93. Standard test methods for flash point by Pensky- Martens closed cup tester. West Conshohocken: 2020. https://doi.org/2020. 10.1520/ D0093-20.

[20] ASTM D422-63-Standard test method for particle-size analysis of soils. West Conshohocken: 2007.

[21] SP0775-Preparation, installation, analysis, and interpretation of corrosion coupons in oilfield operations. Houston, TX: 2018.

[22] ASTM E1404. Standard specification for laboratory glass conical flasks. West Conshohocken: 2019.

[23] TM0194-Field monitoring of bacterial growth in oil and gas systems. Houston, TX: 2014.

[24] Ibrahim A, Hawboldt K, Bottaro C, Khan F, Ibrahim A, Hawboldt K, et al. Review and analysis of microbiologically influenced corrosion : the chemical environment in oil and gas facilities environment in oil and gas facilities. Corros Eng Sci Technol 2018;2782. https://doi.org/10.1080/1478422X.2018.1511326.

[25] Kannan P, Su SS, Mannan MS, Castaneda H, Vaddiraju S. A Review of Characterization and Quantification Tools for Microbiologically Influenced Corrosion in the Oil and Gas Industry: Current and Future Trends. Ind Eng Chem Res 2018;57:13895–922. https://doi.org/10.1021/acs.iecr.8b02211.

[26] Govindan K, Jepsen MB. ELECTRE: A comprehensive literature review on methodologies and applications. Eur J Oper Res 2016;250:1–29. https://doi.org/https://doi.org/10.1016/j.ejor.2015.07.019.

[27] Li H, Guo J-Y, Yazdi M, Nedjati A, Adesina KA. Supportive emergency decision-making model towards sustainable development with fuzzy expert system. Neural Comput Appl 2021;33:15619–15637. https://doi.org/10.1007/s00521-021-06183-4.

[28] Yazdi M. A review paper to examine the validity of Bayesian network to build rational consensus in subjective probabilistic failure analysis. Int J Syst Assur Eng Manag 2019;10:1–18. https://doi.org/10.1007/s13198-018-00757-7.

[29] Little BJ, Lee JS. Microbiologically influenced corrosion: an update. Int Mater Rev 2014;59:384–93. https://doi.org/10.1179/1743280414Y.0000000035.

[30] Eckert RB, Skovhus TL. Advances in the application of molecular microbiological methods in the oil and gas industry and links to microbiologically influenced corrosion. Int Biodeterior Biodegrad 2018;126:169–76. https://doi.org/10.1016/j.ibiod.2016.11.019.

[31] Yazdi M, Khan F, Abbassi R. Operational subsea pipeline assessment affected by multiple defects of microbiologically influenced corrosion. Process Saf Environ Prot 2021;158:159–71. https://doi.org/10.1016/j.psep.2021.11.032.

[32] Beech IB, Sunner JA, Arciola CR, Cristiani P. Microbially-Influenced Corrosion: Damage to Prostheses, Delight for Bacteria. Int J Artif Organs 2006;29:443–52. https://doi.org/10.1177/039139880602900415.

[33] Lewandowski Z, Beyenal H. Mechanisms of Microbially Influenced Corrosion BT - Marine and Industrial Biofouling. In: Flemming H-C, Murthy PS, Venkatesan R, Cooksey K, editors., Berlin, Heidelberg: Springer Berlin Heidelberg; 2009, p. 35–64. https://doi.org/10.1007/978-3-540-69796-1_3.

[34] Beech IB, Sunner J. Biocorrosion: towards understanding interactions between biofilms and metals. Curr Opin Biotechnol 2004;15:181–6. https://doi.org/https://doi.org/10.1016/j.copbio.2004.05.001.

[35] Lewandowski Z. Structure and Function of Bacterial Biofilms 1998.

[36] Skovhus TL, Lee JS, Little BJ. Predominant MIC Mechanisms in the Oil and Gas Industry. In: Torben Lund Skovhus ; Dennis Enning ; Jason S. Lee., editor. Microbiol. Influ. Corros. Upstream Oil Gas Ind. 1st ed., Florida: CRC Press; 2017, p. 75–85.

[37] Hall-Stoodley L, Costerton JW, Stoodley P. Bacterial biofilms: from the Natural environment to infectious diseases. Nat Rev Microbiol 2004;2:95–108. https://doi.org/10.1038/nrmicro821.

[38] Korber DR, Choi A, Wolfaardt GM, Ingham SC, Caldwell DE. Substratum topography influences susceptibility of Salmonella enteritidis biofilms to trisodium phosphate. Appl Environ Microbiol 1997;63:3352–8. https://doi.org/10.1128/aem.63.9.3352-3358.1997.

[39] Sreekumari KR, Nandakumar K, Kikuchi Y. Bacterial attachment to stainless steel welds: Significance of substratum microstructure. Biofouling 2001;17:303–16. https://doi.org/10.1080/08927010109378490.

[40] Javaherdashti R. Microbiologically Influenced Corrosion. 2nd Editio. Springer International Publishing Switzerland; 2017.

[41] Salgar-Chaparro SJ, Lepkova K, Pojtanabuntoeng T, Darwin A, Machuca LL. Nutrient level determines biofilm characteristics and subsequent impact on microbial corrosion and biocide effectiveness. Appl Environ Microbiol 2020;86:1–23. https://doi.org/10.1128/AEM.02885-19.

[42] Gu T, Xu D. Demystifying Mic Mechanisms 2010.

[43] Dennis E, Julia G. Corrosion of Iron by Sulfate-Reducing Bacteria: New Views of an Old Problem. Appl Environ Microbiol 2014;80:1226–36. https://doi.org/10.1128/AEM.02848-13.

[44] Thomsen US, Meng RLC, Larsen J. Monitoring and Risk Assessment of Microbiologically Influenced Corrosion in Offshore Pipelines 2016.

[45] Marciales A, Peralta Y, Haile T, Crosby T, Wolodko J. Mechanistic microbiologically influenced corrosion modeling — A review. Corros Sci 2019;146:99–111. https://doi.org/10.1016/j.corsci.2018.10.004.

[46] Skovhus TL, Andersen ES, Hillier E, Gl DN V. Management of Microbiologically Influenced Corrosion in Risk-Based Inspection Analysis. Int. Oilf. Corros. Conf. Exhib., 2018, p. 9–10.

[47] Peng C-G, Suen S-Y, Park JK. Modeling of Anaerobic Corrosion Influenced by Sulfate-Reducing Bacteria. Water Environ Res 1994;66:707–15.

[48] Al-Darbi MM, Agha K. Modeling and Simulation of the Pitting Microbiologically Influenced Corrosion in Different Industrial Systems 2005.

[49] Al-Darbi MM, Agha K, Islam MR. Comprehensive Modelling of the Pitting Biocorrosion of Steel. Can J Chem Eng 2005;83:872–81. https://doi.org/https://doi.org/10.1002/cjce.5450830509.

[50] Melchers RE, Wells T. Models for the anaerobic phases of marine immersion corrosion. Corros Sci 2006;48:1791–811. https://doi.org/https://doi.org/10.1016/j.corsci.2005.05.039.

[51] Maxwell S. Predicting Microbially Influenced Corrosion in Seawater Injection Systems 2006. https://doi.org/10.2118/100519-MS.

[52] Gu T, Zhao K, Nesic S. A new mechanistic model for MIC based on a biocatalytic cathodic sulfate reduction theory. Corrosion 2009:1–12.

[53] Sørensen KB, Thomsen US, Juhler S, Larsen J. Cost Efficient MIC Management System based on Molecular Microbiological Methods. NACE Int. Conf. expo, 2012.

[54] Larsen J, Sørense KB, Juhler S, Pedersen DS. The Application of Molecular Microbiological Methods for early Warning of MIC in Pipelines 2013.

[55] Gu T. Theoretical Modeling of the Possibility of Acid Producing Bacteria Causing Fast Pitting Biocorrosion. J Microb Biochem Technol 2014;6:68–74. https://doi.org/10.4172/1948-5948.1000124.

[56] Haile T, Teevens P, Zhu Z. Sulphate-reducing bacteria growth kinetics'-based microbiologically influenced corrosion predictive model. J Pipeline Eng 2105;14:259–67.

[57] Xu D, Li Y, Gu T. Mechanistic modeling of biocorrosion caused by biofilms of sulfate reducing bacteria and acid producing bacteria. Bioelectrochemistry 2016;110:52–8. https://doi.org/https://doi.org/10.1016/j.bioelechem.2016.03.003.

[58] Melchers RE. Progress in developing realistic corrosion models. Struct Infrastruct Eng 2018;14:843–53. https://doi.org/10.1080/15732479.2018.1436570.

[59] Byun J-E, Song J. Generalized matrix-based Bayesian network for multi-state systems. Reliab Eng Syst Saf 2021;211:107468. https://doi.org/https://doi.org/10.1016/j.ress.2021.107468.

[60] Zhang X, Mahadevan S. Bayesian network modeling of accident investigation reports for aviation safety assessment. Reliab Eng Syst Saf 2021;209:107371. https://doi.org/https://doi.org/10.1016/j.ress.2020.107371.

[61] Jiang G-J, Chen H-X, Sun H-H, Yazdi M, Nedjati A, Adesina KA. An improved multi-criteria emergency decision-making method in environmental disasters. Soft Comput 2021. https://doi.org/10.1007/s00500-021-05826-x.

[62] Nagulapati VM, Lee H, Jung D, Brigljevic B, Choi Y, Lim H. Capacity estimation of batteries: Influence of training dataset size and diversity on data driven prognostic models. Reliab Eng Syst Saf 2021;216:108048. https://doi.org/https://doi.org/10.1016/j.ress.2021.108048.

[63] Dehghani NL, Zamanian S, Shafieezadeh A. Adaptive network reliability analysis: Methodology and applications to power grid. Reliab Eng Syst Saf 2021;216:107973. https://doi.org/https://doi.org/10.1016/j.ress.2021.107973.

[64] Javaherdashti R. (Mathematical) Modelling of MIC by Fuzzy Logic BT - Microbiologically Influenced Corrosion: An Engineering Insight. In: Javaherdashti R, editor., Cham: Springer International Publishing; 2017, p. 185–99. https://doi.org/10.1007/978-3-319-44306-5_10.

[65] Singh M, Pokhrel M. A Fuzzy logic-possibilistic methodology for risk-based inspection (RBI) planning of oil and gas piping subjected to microbiologically influenced corrosion (MIC). Int J Press Vessel Pip 2018;159:45–54. https://doi.org/10.1016/j.ijpvp.2017.11.005.

[66] Urquidi-Macdonald M, Tewari A, Ayala F. A Neuro-Fuzzy Knowledge-Based Model for the Risk Assessment of Microbiologically Influenced Corrosion in Crude Oil Pipelines. Corrosion 2014;70:1157–66.

[67] Yazdi M, Kabir S, Walker M. Uncertainty handling in fault tree based risk assessment: State of the art and future perspectives. Process Saf Environ Prot 2019;131:89–104. https://doi.org/10.1016/j.psep.2019.09.003.

[68] Yazdi M, Nedjati A, Abbassi R. Fuzzy dynamic risk-based maintenance investment optimization for offshore process facilities. J Loss Prev Process Ind 2019:194–207. https://doi.org/10.1016/j.jlp.2018.11.014.

[69] Skovhus TL, Eckert RB, Rodrigues E. Management and control of microbiologically influenced corrosion (MIC) in the oil and gas industry—Overview and a North Sea case study. J Biotechnol 2017;256:31–45. https://doi.org/10.1016/j.jbiotec.2017.07.003.

[70] Adumene S, Adedigba S, Khan F, Zendehboudi S. An integrated dynamic failure assessment model for offshore components under microbiologically influenced corrosion. Ocean Eng 2020;218:108082. https://doi.org/10.1016/j.oceaneng.2020.108082.

[71] Adumene S, Khan F, Adedigba S, Zendehboudi S, Shiri H. Dynamic risk analysis of marine and offshore systems suffering microbial induced stochastic degradation. Reliab Eng Syst Saf 2020;207:107388. https://doi.org/10.1016/j.ress.2020.107388.

[72] Arzaghi E, Abbassi R, Garaniya V, Binns J, Chin C, Khakzad N, et al. Developing a dynamic model for pitting and corrosion-fatigue damage of subsea pipelines. Ocean Eng 2018;150:391–6. https://doi.org/10.1016/j.oceaneng.2017.12.014.

[73] Arzaghi E, Abaei MM, Abbassi R, Garaniya V, Chin C, Khan F. Risk-based maintenance planning of subsea pipelines through fatigue crack growth monitoring. Eng Fail Anal 2017;79:928–39. https://doi.org/10.1016/j.engfailanal.2017.06.003.

[74] Adumene S, Khan F, Adedigba S. Operational safety assessment of offshore pipeline with multiple MIC defects. Comput Chem Eng 2020:106819. https://doi.org/10.1016/j.compchemeng.2020.106819.

[75] Shekari E, Khan F, Ahmed S. Probabilistic modeling of pitting corrosion in insulated components operating in offshore facilities. ASCE-ASME J Risk Uncertain Eng Syst Part B Mech Eng 2017;3:1–11. https://doi.org/10.1115/1.4034603.

[76] Adumene S, Khan F, Adedigba S, Zendehboudi S. Offshore system safety and reliability considering microbial influenced multiple failure modes and their interdependencies. Reliab Eng Syst Saf 2021:107862. https://doi.org/https://doi.org/10.1016/j.ress.2021.107862.

[77] Kamil MZ, Taleb-Berrouane M, Khan F, Amyotte P. Data-Driven Operational Failure Likelihood Model for Microbiologically Influenced Corrosion. Process Saf Environ Prot 2021. https://doi.org/https://doi.org/10.1016/j.psep.2021.07.040.

[78] Yazdi M, Khan F, Abbassi R, Rusli R. Improved DEMATEL methodology for effective safety management decision-making. Saf Sci 2020;127:104705. https://doi.org/https://doi.org/10.1016/j.ssci.2020.104705.

[79] Kamrunnahar M, Urquidi-Macdonald M. Prediction of corrosion behavior using neural network as a data mining tool. Corros Sci 2010;52:669–77. https://doi.org/https://doi.org/10.1016/j.corsci.2009.10.024.

[80] Parthiban T, Ravi R, Parthiban GT, Srinivasan S, Ramakrishnan KR, Raghavan M. Neural network analysis for corrosion of steel in concrete. Corros Sci 2005;47:1625–42. https://doi.org/https://doi.org/10.1016/j.corsci.2004.08.011.

[81] Wolodko J, Haile T, Khan F, Taylor C, Eckert R, Hashemi SJ, et al. Modeling of Microbiologically Influenced Corrosion (MIC) in the Oil and Gas Industry - Past, Present and Future 2018.

[82] Villa V, Paltrinieri N, Khan F, Cozzani V. Towards dynamic risk analysis: A review of the risk assessment approach and its limitations in the chemical process industry. Saf Sci 2016;89:77–93. https://doi.org/10.1016/j.ssci.2016.06.002.

[83] Kilbane J. Effect of Sample Storage Conditions on Oilfield Microbiological Samples 2014.

[84] Kagarise C, Vera JR, Eckert RB. The Importance of Deposit Characterization in Mitigating UDC and MIC in Dead Legs 2017.

[85] Burns MG. The Tales That Rust Can Tell: The Use of Corrosion Product Analyses In Corrosion Failure Investigations 2016. https://doi.org/10.2118/179927-MS.

[86] Sharma M, Liu H, Chen S, Cheng F, Voordouw G, Gieg L. Effect of selected biocides on microbiologically influenced corrosion caused by Desulfovibrio ferrophilus IS5. Sci Rep 2018;8:16620. https://doi.org/10.1038/s41598-018-34789-7.

[87] Harimawan A, Devianto H, Kurniawan IC, Utomo JC. Influence of incubation temperature on biofilm formation and corrosion of carbon steel by Serratia marcescens. AIP Conf Proc 2017;1805:60005. https://doi.org/10.1063/1.4974441.

[88] Huttunen-Saarivirta E, Honkanen M, Lepistö T, Kuokkala V-T, Koivisto L, Berg C-G. Microbiologically influenced corrosion (MIC) in stainless steel heat exchanger. Appl Surf Sci 2012;258:6512–26. https://doi.org/https://doi.org/10.1016/j.apsusc.2012.03.068.

[89] El Hajj H, Abdelouas A, El Mendili Y, Karakurt G, Grambow B, Martin C. Corrosion of carbon steel under sequential aerobic–anaerobic environmental conditions. Corros Sci 2013;76:432–40. https://doi.org/https://doi.org/10.1016/j.corsci.2013.07.017.

[90] Miranda E, Bethencourt M, Botana FJ, Cano MJ, Sánchez-Amaya JM, Corzo A, et al. Biocorrosion of carbon steel alloys by an hydrogenotrophic sulfate-reducing bacterium Desulfovibrio capillatus isolated from a Mexican oil field separator. Corros Sci 2006;48:2417–31. https://doi.org/https://doi.org/10.1016/j.corsci.2005.09.005.

[91] Ilhan-Sungur E, Çotuk A. Microbial corrosion of galvanized steel in a simulated recirculating cooling tower system. Corros Sci 2010;52:161–71. https://doi.org/https://doi.org/10.1016/j.corsci.2009.08.049.

[92] Yuan SJ, Pehkonen SO. Microbiologically influenced corrosion of 304 stainless steel by aerobic Pseudomonas NCIMB 2021 bacteria: AFM and XPS study. Colloids Surfaces B Biointerfaces 2007;59:87–99. https://doi.org/https://doi.org/10.1016/j.colsurfb.2007.04.020.

[93] Beech IB. Corrosion of technical materials in the presence of biofilms—current understanding and state-of-the art methods of study. Int Biodeterior Biodegradation 2004;53:177–83. https://doi.org/https://doi.org/10.1016/S0964-8305(03)00092-1.

[94] Surman SB, Walker JT, Goddard DT, Morton LHG, Keevil CW, Weaver W, et al. Comparison of microscope techniques for the examination of biofilms. J Microbiol Methods 1996;25:57–70. https://doi.org/https://doi.org/10.1016/0167-7012(95)00085-2.

[95] Cetin D, Aksu ML. Corrosion behavior of low-alloy steel in the presence of Desulfotomaculum sp. Corros Sci 2009;51:1584–8. https://doi.org/https://doi.org/10.1016/j.corsci.2009.04.001.

[96] Bairamov AK, Ahmed T, Al-Sonidah MN, Liang J, Bradley R. Excessive Rate of MIC on 316 SS in Seawater 2002.

[97] Romero M, de Rincon O, Zoilabet D, Araujo J, Perez O. Hydrogen Permeation Study with Palladium in a Sulfate-Reducing Culture 2001.

[98] Song X, Yang Y, Yu D, Lan G, Wang Z, Mou X. Studies on the impact of fluid flow on the microbial corrosion behavior of product oil pipelines. J Pet Sci Eng 2016;146:803–12. https://doi.org/https://doi.org/10.1016/j.petrol.2016.07.035.

[99] Parthipan P, Elumalai P, Ting YP, Rahman PKSM, Rajasekar A. Characterization of hydrocarbon degrading bacteria isolated from Indian crude oil reservoir and their influence on biocorrosion of carbon steel API 5LX. Int Biodeterior Biodegradation 2018;129:67–80. https://doi.org/https://doi.org/10.1016/j.ibiod.2018.01.006.

[100] Steele A, Goddard DT, Beech IB. An atomic force microscopy study of the biodeterioration of stainless steel in the presence of bacterial biofilms. Int Biodeterior Biodegradation 1994;34:35–46. https://doi.org/https://doi.org/10.1016/0964-8305(94)90018-3.

[101] Silva AMA, Santiago TM, Alves CR, Guedes MIF, Freire JAK, Vieira RHSF, et al. An evaluation of the corrosion behavior of aluminum surfaces in presence of fungi using atomic force microscopy and other tests. Anti-Corrosion Methods Mater 2007;54:289–93. https://doi.org/10.1108/00035590710822134.

[102] Fang HHP, Chan K-Y, Xu L-C. Quantification of bacterial adhesion forces using atomic force microscopy (AFM). J Microbiol Methods 2000;40:89–97. https://doi.org/https://doi.org/10.1016/S0167-7012(99)00137-2.

[103] Neu TR, Lawrence JR. Development and structure of microbial biofilms in river water studied by confocal laser scanning microscopy. FEMS Microbiol Ecol 1997;24:11–25. https://doi.org/10.1111/j.1574-6941.1997.tb00419.x.

[104] Xu D, Xia J, Zhou E, Zhang D, Li H, Yang C, et al. Accelerated corrosion of 2205 duplex stainless steel caused by marine aerobic Pseudomonas aeruginosa biofilm. Bioelectrochemistry 2017;113:1–8. https://doi.org/https://doi.org/10.1016/j.bioelechem.2016.08.001.

[105] Chen S, Frank Cheng Y, Voordouw G. A comparative study of corrosion of 316L stainless steel in biotic and abiotic sulfide environments. Int Biodeterior Biodegradation 2017;120:91–6. https://doi.org/https://doi.org/10.1016/j.ibiod.2017.02.014.

[106] Xu L-C, Chan K-Y, Fang HHP. Application of atomic force microscopy in the study of microbiologically influenced corrosion. Mater Charact 2002;48:195–203. https://doi.org/https://doi.org/10.1016/S1044-5803(02)00239-5.

[107] Zhu R, Tan DT, Shuai D. Research highlights: applications of atomic force microscopy in natural and engineered water systems. Environ Sci Water Res Technol 2016;2:415–20. https://doi.org/10.1039/C6EW90012G.

[108] Dong ZH, Shi W, Ruan HM, Zhang GA. Heterogeneous corrosion of mild steel under SRB-biofilm characterised by electrochemical mapping technique. Corros Sci 2011;53:2978–87. https://doi.org/https://doi.org/10.1016/j.corsci.2011.05.041.

[109] Mehanna M, Basseguy R, Delia M-L, Gubner R, Sathirachinda N, Bergel A. Geobacter species enhances pit depth on 304L stainless steel in a medium lacking with electron donor. Electrochem Commun 2009;11:1476–81. https://doi.org/https://doi.org/10.1016/j.elecom.2009.05.035.

[110] Pourbaix M. Applications of electrochemistry in corrosion science and in practice. Corros Sci 1974;14:25–82. https://doi.org/https://doi.org/10.1016/S0010-938X(74)80006-5.

[111] Li H, Zhou E, Zhang D, Xu D, Xia J, Yang C, et al. Microbiologically Influenced Corrosion of 2707 Hyper-Duplex Stainless Steel by Marine Pseudomonas aeruginosa Biofilm. Sci Rep 2016;6:20190. https://doi.org/10.1038/srep20190.

[112] Wang B, Liang Y, Yang C, Sang Z. ok m Onl ad in e b e V y er th si is on fil O e i n s I ly . m Onl ad in e b e V y er th si is on fil O e i n 2016;9:121–36.

[113] Debuy S, Pecastaings S, Bergel A, Erable B. Oxygen-reducing biocathodes designed with pure cultures of microbial strains isolated from seawater biofilms. Int Biodeterior Biodegradation 2015;103:16–22. https://doi.org/https://doi.org/10.1016/j.ibiod.2015.03.028.

[114] Malard E, Kervadec D, Gil O, Lefevre Y, Malard S. Interactions between steels and sulphide-producing bacteria—Corrosion of carbon steels and low-alloy steels in natural seawater. Electrochim Acta 2008;54:8–13. https://doi.org/https://doi.org/10.1016/j.electacta.2008.05.075.

[115] Conlette OC, Emmanuel NE, Chijoke OG. Methanogen Population of an Oil Production Skimmer Pit and the Effects of Environmental Factors and Substrate Availability on Methanogenesis and Corrosion Rates. Microb Ecol 2016;72:175–84. https://doi.org/10.1007/s00248-016-0764-2.

[116] Searson PC, Dawson JL. Analysis of Electrochemical Noise Generated by Corroding Electrodes under Open-Circuit Conditions. J Electrochem Soc 1988;135:1908–15. https://doi.org/10.1149/1.2096177.

[117] Little BJ, Hinks J, Blackwood DJ. Microbially influenced corrosion: Towards an interdisciplinary perspective on mechanisms. Int Biodeterior Biodegradation 2020;154:105062. https://doi.org/https://doi.org/10.1016/j.ibiod.2020.105062.

[118] Homborg AM, Cottis RA, Mol JMC. An integrated approach in the time, frequency and time-frequency domain for the identification of corrosion using electrochemical noise. Electrochim Acta 2016;222:627–40. https://doi.org/https://doi.org/10.1016/j.electacta.2016.11.018.

[119] Xia D-H, Song S, Behnamian Y, Hu W, Cheng YF, Luo J-L, et al. Review—Electrochemical Noise Applied in Corrosion Science: Theoretical and Mathematical Models towards Quantitative Analysis. J Electrochem Soc 2020;167:81507. https://doi.org/10.1149/1945-7111/ab8de3.

[120] Padilla-Viveros A, Garcia-Ochoa E, Alazard D. Comparative electrochemical noise study of the corrosion process of carbon steel by the sulfate-reducing bacterium Desulfovibrio alaskensis under nutritionally rich and oligotrophic culture conditions. Electrochim Acta 2006;51:3841–7. https://doi.org/https://doi.org/10.1016/j.electacta.2005.11.001.

[121] Mansfeld F. The use of electrochemical techniques for the investigation and monitoring of microbiologically influenced corrosion and its inhibition – a review. Mater Corros 2003;54:489–502. https://doi.org/https://doi.org/10.1002/maco.200390111.

[122] Men H, Zhang J, Zhang L. Intelligent recognition for microbiologically influenced corrosion based on Hilbert-huang transform and BP neural network. J Comput 2012;7:2283–91. https://doi.org/10.4304/jcp.7.9.2283-2291.

[123] Homborg AM, Leon Morales CF, Tinga T, de Wit JHW, Mol JMC. Detection of microbiologically influenced corrosion by electrochemical noise transients. Electrochim Acta 2014;136:223–32. https://doi.org/https://doi.org/10.1016/j.electacta.2014.05.102.

[124] Batmanghelich F, Li L, Seo Y. Influence of multispecies biofilms of Pseudomonas aeruginosa and Desulfovibrio vulgaris on the corrosion of cast iron. Corros Sci 2017;121:94–104. https://doi.org/https://doi.org/10.1016/j.corsci.2017.03.008.

[125] Xu C, Zhang Y, Cheng G, Zhu W. Localized corrosion behavior of 316L stainless steel in the presence of sulfate-reducing and iron-oxidizing bacteria. Mater Sci Eng A 2007;443:235–41. https://doi.org/https://doi.org/10.1016/j.msea.2006.08.110.

[126] Shukla PK, Mintz TS, Dasgupta B, Fisher J. Using Local Electrochemical Impedance Spectroscopy to Detect Coating Defects On Buried Pipelines 2012.

[127] Liu H, Fu C, Gu T, Zhang G, Lv Y, Wang H, et al. Corrosion behavior of carbon steel in the presence of sulfate reducing bacteria and iron oxidizing bacteria cultured in oilfield produced water. Corros Sci 2015;100:484–95. https://doi.org/https://doi.org/10.1016/j.corsci.2015.08.023.

[128] Castaneda H, Benetton XD. SRB-biofilm influence in active corrosion sites formed at the steel-electrolyte interface when exposed to artificial seawater conditions. Corros Sci 2008;50:1169–83. https://doi.org/https://doi.org/10.1016/j.corsci.2007.11.032.

[129] Lahme S, Mand J, Longwell J, Smith R, Enning D. Severe corrosion of carbon steel in oil field produced water can be linked to methanogenic archaea containing a special type of [NiFe] hydrogenase. BioRxiv 2020:2020.07.23.219014. https://doi.org/10.1101/2020.07.23.219014.

[130] Chabowski K, Junka AF, Piasecki T, Nowak D, Nitsch K, Smutnicka D, et al. Impedance Sensors Made in PCB and LTCC Technologies for Monitoring Growth and Degradation of Pseudomonal Biofilm. Metrol Meas Syst DOI - 101515/Mms-2017-0032 2017;24:369–380–369–380.

[131] Jansen S, van Burgel M, Gerritse J, Büchler M. Cathodic Protection and MIC - Effects of Local Electrochemistry 2017.

[132] Obot IB, Onyeachu IB. Electrochemical frequency modulation (EFM) technique: Theory and recent practical applications in corrosion research. J Mol Liq 2018;249:83–96. https://doi.org/https://doi.org/10.1016/j.molliq.2017.11.006.

[133] Rajala P, Huttunen-Saarivirta E, Bomberg M, Carpén L. Corrosion of Stainless Steels AISI 304 and AISI 316 Induced by Sulfate Reducing Bacteria in Anoxic Groundwater 2017.

[134] Birketveit øystein, Stipanicev M. Insight in Sidestream Corrosion Field-testing from the North Sea: Experiences, Benefits and Pitfalls 2016.

[135] Beese P, Venzlaff H, Srinivasan J, Garrelfs J, Stratmann M, Mayrhofer KJJ. Monitoring of anaerobic microbially influenced corrosion via electrochemical frequency modulation. Electrochim Acta 2013;105:239–47. https://doi.org/https://doi.org/10.1016/j.electacta.2013.04.144.

[136] Motoda S, Suzuki Y, Shinohara T, Tsujikawa S. The effect of marine fouling on the ennoblement of electrode potential for stainless steels. Corros Sci 1990;31:515–20. https://doi.org/https://doi.org/10.1016/0010-938X(90)90155-X.

[137] Eckert RB, Skovhus TL. Advances in the application of molecular microbiological methods in the oil and gas industry and links to microbiologically influenced corrosion. Int Biodeterior Biodegradation 2018;126:169–76. https://doi.org/https://doi.org/10.1016/j.ibiod.2016.11.019.

[138] Liang R, Aktas DF, Aydin E, Bonifay V, Sunner J, Suflita JM. Anaerobic Biodegradation of Alternative Fuels and Associated Biocorrosion of Carbon Steel in Marine Environments. Environ Sci Technol 2016;50:4844–53. https://doi.org/10.1021/acs.est.5b06388.

[139] Gutarowska B, Celikkol-Aydin S, Bonifay V, Otlewska A, Aydin E, Oldham AL, et al. Metabolomic and high-throughput sequencing analysis—modern approach for the assessment of biodeterioration of materials from historic buildings . Front Microbiol 2015;6:979.

[140] Brauer JI, Makama Z, Bonifay V, Aydin E, Kaufman ED, Beech IB, et al. Mass spectrometric metabolomic imaging of biofilms on corroding steel surfaces using laser ablation and solvent capture by aspiration. Biointerphases 2015;10:19003. https://doi.org/10.1116/1.4906744.

[141] Noah F, A. JJ, Rytas V, B. JR. Assessment of Soil Microbial Community Structure by Use of Taxon-Specific Quantitative PCR Assays. Appl Environ Microbiol 2005;71:4117–20. https://doi.org/10.1128/AEM.71.7.4117-4120.2005.

[142] Klein D. Quantification using real-time PCR technology: applications and limitations. Trends Mol Med 2002;8:257–60. https://doi.org/https://doi.org/10.1016/S1471-4914(02)02355-9.

[143] Bartling C, Kucharzyk KH, Mullins L, Minard-Smith A, Busch-Harris J. Interpreting Omic Data for Microbially Influenced Corrosion: Lessons from a Case Study Involving a Seawater Injection System 2017.

[144] Muyzer G, de Waal EC, Uitterlinden AG. Profiling of complex microbial populations by denaturing gradient gel electrophoresis analysis of polymerase chain reaction-amplified genes coding for 16S rRNA. Appl Environ Microbiol 1993;59:695–700. https://doi.org/10.1128/aem.59.3.695-700.1993.

[145] Teng F, Guan YT, Zhu WP. Effect of biofilm on cast iron pipe corrosion in drinking water distribution system: Corrosion scales characterization and microbial community structure investigation. Corros Sci 2008;50:2816–23. https://doi.org/https://doi.org/10.1016/j.corsci.2008.07.008.

[146] Carvalho ML, Doma J, Sztyler M, Beech I, Cristiani P. The study of marine corrosion of copper alloys in chlorinated condenser cooling circuits: The role of microbiological components. Bioelectrochemistry 2014;97:2–6. https://doi.org/https://doi.org/10.1016/j.bioelechem.2013.12.005.

[147] Al-Moniee MA, Zhu X, Tang L, Juhler S, Nuwaiser FI, Sanders PF, et al. Optimization of DNA Staining Technology for Development of Autonomous Microbe Sensor for Injection Seawater Systems. J Sens Technol 2016;06:27–45.

[148] Zhu XY, Modi H, Ayala A, Kilbane II JJ. Technical Note: Rapid Detection and Quantification of Microbes Related to Microbiologically Influenced Corrosion Using Quantitative Polymerase Chain Reaction. Corrosion 2006;62:950–5. https://doi.org/10.5006/1.3278233.

[149] Murali Mohan A, Hartsock A, Bibby KJ, Hammack RW, Vidic RD, Gregory KB. Microbial Community Changes in Hydraulic Fracturing Fluids and Produced Water from Shale Gas Extraction. Environ Sci Technol 2013;47:13141–50. https://doi.org/10.1021/es402928b.

[150] Neria-González I, Wang ET, Ramírez F, Romero JM, Hernández-Rodríguez C. Characterization of bacterial community associated to biofilms of corroded oil pipelines from the southeast of Mexico. Anaerobe 2006;12:122–33. https://doi.org/10.1016/j.anaerobe.2006.02.001.

[151] Schmeisser C, Krohn-Molt I, Streit WR. Metagenome Analyses of Multispecies Microbial Biofilms: First Steps Toward Understanding Diverse Microbial Systems on Surfaces BT - Functional Metagenomics: Tools and Applications. In: Charles TC, Liles MR, Sessitsch A, editors., Cham: Springer International Publishing; 2017, p. 201–15. https://doi.org/10.1007/978-3-319-61510-3_12.

[152] Sven L, Jaspreet M, John L, Ramsey S, Dennis E, M. SAJ. Severe Corrosion of Carbon Steel in Oil Field Produced Water Can Be Linked to Methanogenic Archaea Containing a Special Type of [NiFe] Hydrogenase. Appl Environ Microbiol 2021;87:e01819-20. https://doi.org/10.1128/AEM.01819-20.

[153] Zhu X, Kilbane II J, Ayala A, Modi H. Application of Quantitative, Real-Time PCR in Monitoring Microbiologically Influenced Corrosion (MIC) in Gas Pipelines 2005.

[154] Jan-Roblero J, Romero JM, Amaya M, Le Borgne S. Phylogenetic characterization of a corrosive consortium isolated from a sour gas pipeline. Appl Microbiol Biotechnol 2004;64:862–7. https://doi.org/10.1007/s00253-004-1613-7.

[155] Jan-Roblero J, Posadas A, Zavala Díaz de la Serna J, García R, Hernández-Rodríguez C. Phylogenetic characterization of bacterial consortia obtained of corroding gas pipelines in Mexico. World J Microbiol Biotechnol 2008;24:1775–84. https://doi.org/10.1007/s11274-008-9674-x.

[156] Duncan KE, Gieg LM, Parisi VA, Tanner RS, Tringe SG, Bristow J, et al. Biocorrosive Thermophilic Microbial Communities in Alaskan North Slope Oil Facilities. Environ Sci Technol 2009;43:7977–84. https://doi.org/10.1021/es9013932.

[157] Dahle H, Garshol F, Madsen M, Birkeland N-K. Microbial community structure analysis of produced water from a high-temperature North Sea oil-field. Antonie Van Leeuwenhoek 2008;93:37–49. https://doi.org/10.1007/s10482-007-9177-z.

[158] Javaherdashti R. Technical Mitigation of Corrosion: Corrosion Management, 2017, p. 9–15. https://doi.org/10.1007/978-3-319-44306-5_2.

[159] Cristiani P. 15 - Risk assessment of biocorrosion in condensers, pipework and other cooling system components. In: Liengen T, Féron D, Basséguy R, Beech IBBT-UB, editors., Oxford: Woodhead Publishing; 2014, p. 357–84. https://doi.org/https://doi.org/10.1533/9781782421252.3.357.

[160] Vigneron A, Head IM, Tsesmetzis N. Damage to offshore production facilities by corrosive microbial biofilms. Appl Microbiol Biotechnol 2018;102:2525–33. https://doi.org/10.1007/s00253-018-8808-9.

[161] Flemming H-C, Wingender J, Szewzyk U, Steinberg P, Rice SA, Kjelleberg S. Biofilms: an emergent form of bacterial life. Nat Rev Microbiol 2016;14:563–75. https://doi.org/10.1038/nrmicro.2016.94.

[162] Jia R, Unsal T, Xu D, Lekbach Y, Gu T. Microbiologically influenced corrosion and current mitigation strategies: A state of the art review. Int Biodeterior Biodegradation 2019;137:42–58. https://doi.org/https://doi.org/10.1016/j.ibiod.2018.11.007.

[163] S. SP, Mahmoud G, Matthew P, Marvin W, Pranab M. Antimicrobial Tolerance in Biofilms. Microbiol Spectr 2015;3:3.3.07. https://doi.org/10.1128/microbiolspec.MB-0010-2014.

[164] Kim J-S, Chowdhury N, Yamasaki R, Wood TK. Viable but non-culturable and persistence describe the same bacterial stress state. Environ Microbiol 2018;20:2038–48. https://doi.org/https://doi.org/10.1111/1462-2920.14075.

[165] Königs AM, Flemming H-C, Wingender J. Nanosilver induces a non-culturable but metabolically active state in Pseudomonas aeruginosa . Front Microbiol 2015;6:395.

[166] Yazdi M, Khan F, Abbassi R. Microbiologically influenced corrosion (MIC) management using Bayesian inference. Ocean Eng 2021. https://doi.org/10.1016/j.oceaneng.2021.108852.

[167] Eid MM, Duncan KE, Tanner RS. A semi-continuous system for monitoring microbially influenced corrosion. J Microbiol Methods 2018;150:55–60. https://doi.org/https://doi.org/10.1016/j.mimet.2018.05.018.

[168] Guo J, Yuan S, Jiang W, Lv L, Liang B, Pehkonen SO. Polymers for Combating Biocorrosion . Front Mater 2018;5:10.

[169] Ocando L, Urribarrí A, Urdaneta E, de Romero MF, González D, Fuenmayor H. Evaluation of Sulfate-Reducing Bacteria Biofilms in the Presence of Biocides 2013.

[170] Loto CA. Microbiological corrosion: mechanism, control and impact—a review. Int J Adv Manuf Technol 2017;92:4241–52. https://doi.org/10.1007/s00170-017-0494-8.

[171] Abdolahi A, Hamzah E, Ibrahim Z, Hashim S. Application of Environmentally-Friendly Coatings Toward Inhibiting the Microbially Influenced Corrosion (MIC) of Steel: A Review. Polym Rev 2014;54:702–45. https://doi.org/10.1080/15583724.2014.946188.

[172] Bhola R, Bhola SM, Mishra B, Olson DL. Microbiologically influenced corrosion and its mitigation: (A review). Mater Sci Res India 2010;7:407–12. https://doi.org/10.13005/msri/070210.

[173] Mahalakshmi P V, Vanithakumari SC, Gopal J, Mudali UK, Raj B. Enhancing corrosion and biofouling resistance through superhydrophobic surface modification. Curr Sci 2011;101:1328–36.

[174] Nazeer AA, Madkour M. Potential use of smart coatings for corrosion protection of metals and alloys: A review. J Mol Liq 2018;253:11–22. https://doi.org/https://doi.org/10.1016/j.molliq.2018.01.027.

[175] Cote C, Rosas O, Basseguy R. Geobacter sulfurreducens: An iron reducing bacterium that can protect carbon steel against corrosion? Corros Sci 2015;94:104–13. https://doi.org/https://doi.org/10.1016/j.corsci.2015.01.044.

[176] Volkland H, Harms H, Knopf K, Wanner O, Zehnder AJB. Corrosion inhibition of mild steel by bacteria. Biofouling 2000;15:287–97. https://doi.org/10.1080/08927010009386319.

[177] Lee S, Yoshikawa H, Matsui T. Biomineralization of Vivianite on Carbon Steel Surface Attacked by the Iron Reducing Bacteria. MRS Online Proc Libr 2010;1265:601. https://doi.org/10.1557/PROC-1265-AA06-01.

[178] Krishnamurthy A, Gadhamshetty V, Mukherjee R, Natarajan B, Eksik O, Ali Shojaee S, et al. Superiority of Graphene over Polymer Coatings for Prevention of Microbially Induced Corrosion. Sci Rep 2015;5:13858. https://doi.org/10.1038/srep13858.

[179] Schriver M, Regan W, Gannett WJ, Zaniewski AM, Crommie MF, Zettl A. Graphene as a Long-Term Metal Oxidation Barrier: Worse Than Nothing. ACS Nano 2013;7:5763–8. https://doi.org/10.1021/nn4014356.

[180] Tiwari A, Singh Raman RK. Long-Term Corrosion Protection of a Cupro-Nickel Alloy Due to Graphene Coating. Coatings 2017;7. https://doi.org/10.3390/coatings7120210.

[181] Zhang P, Xu D, Li Y, Yang K, Gu T. Electron mediators accelerate the microbiologically influenced corrosion of 304 stainless steel by the Desulfovibrio vulgaris biofilm.

Bioelectrochemistry 2015;101:14–21. https://doi.org/https://doi.org/10.1016/j.bioelechem.2014.06.010.

[182] Zhang LM, Yan MC, Zhang SD, Zhu LY, Umoh AJ, Ma AL, et al. Significantly enhanced resistance to SRB corrosion via Fe-based amorphous coating designed with high dose corrosion-resistant and antibacterial elements. Corros Sci 2020;164:108305. https://doi.org/https://doi.org/10.1016/j.corsci.2019.108305.

[183] Baldissera AF, De Miranda KL, Bressy C, Martin C, Margaillan A, Ferreira CA. Using conducting polymers as active agents for marine antifouling paints. Mater Res 2015;18:1129–39. https://doi.org/10.1590/1516-1439.261414.

[184] Li Y, Ning C. Latest research progress of marine microbiological corrosion and bio-fouling, and new approaches of marine anti-corrosion and anti-fouling. Bioact Mater 2019;4:189–95. https://doi.org/https://doi.org/10.1016/j.bioactmat.2019.04.003.

[185] Klibanov AM. Permanently microbicidal materials coatings. J Mater Chem 2007;17:2479–82. https://doi.org/10.1039/B702079A.

[186] M. KW, Thomas J, Migun S, Mathilde M, W. DK, Kaushik V, et al. Remedial Treatment of Corroded Iron Objects by Environmental Aeromonas Isolates. Appl Environ Microbiol 2021;85:e02042-18. https://doi.org/10.1128/AEM.02042-18.

[187] Alasvand Zarasvand K, Rai VR. Microorganisms: Induction and inhibition of corrosion in metals. Int Biodeterior Biodegradation 2014;87:66–74. https://doi.org/https://doi.org/10.1016/j.ibiod.2013.10.023.

[188] Grooters M, Harneit K, Wöllbrink M, Sand W, Stadler R, Fürbeth W. Novel Steel Corrosion Protection by Microbial Extracellular Polymeric Substances (EPS) – Biofilm-Induced Corrosion Inhibition. Adv Mater Res 2007;20–21:375–8. https://doi.org/10.4028/www.scientific.net/AMR.20-21.375.

[189] Kip N, van Veen JA. The dual role of microbes in corrosion. ISME J 2015;9:542–51. https://doi.org/10.1038/ismej.2014.169.

[190] Agrawal A, Park H soo, Nathoo S, Gieg LM, Jack TR, Miner K, et al. Toluene Depletion in Produced Oil Contributes to Souring Control in a Field Subjected to Nitrate Injection. Environ Sci Technol 2012;46:1285–92. https://doi.org/10.1021/es203748b.

[191] Jia R, Yang D, Xu J, Xu D, Gu T. Microbiologically influenced corrosion of C1018 carbon steel by nitrate reducing Pseudomonas aeruginosa biofilm under organic carbon starvation. Corros Sci 2017;127:1–9. https://doi.org/https://doi.org/10.1016/j.corsci.2017.08.007.

[192] Kebbouche-Gana S, Gana ML. Biocorrosion of carbon steel by a nitrate-utilizing consortium of sulfate-reducing bacteria obtained from an Algerian oil field. Ann Microbiol 2012;62:203–10. https://doi.org/10.1007/s13213-011-0247-0.

[193] Drønen K, Roalkvam I, Beeder J, Torsvik T, Steen IH, Skauge A, et al. Modeling of Heavy Nitrate Corrosion in Anaerobe Aquifer Injection Water Biofilm: A Case Study in a Flow Rig. Environ Sci Technol 2014;48:8627–35. https://doi.org/10.1021/es500839u.

[194] Schwenk W. 2 - Fundamentals and Concepts of Corrosion and Electrochemical Corrosion Protection. In: von Baeckmann W, Bohnes H, Franke G, Funk D, Gey C, Gräfen H, et al., editors., Burlington: Gulf Professional Publishing; 1997, p. 27–78. https://doi.org/https://doi.org/10.1016/B978-088415056-5/50009-5.

[195] Blackwood DJ, Lim CS, Teo SLM. Influence of fouling on the efficiency of sacrificial anodes in providing cathodic protection in Southeast Asian tropical seawater. Biofouling 2010;26:779–85. https://doi.org/10.1080/08927014.2010.515305.

[196] Barlo TJ, Berry WE. An assessment of the present criteria for cathodic protection of buried steel pipelines. United States: NACE; 1984.

[197] Olivares GZ-, Mejia GM, Caloca GG, Esquivel RG, Lopez IG, Ulloa-Ochoa CM, et al. Sulfate Reducing Bacteria Influence on the Cathodic Protection of Pipelines That Transport Hydrocarbons. Corros 2003 2003.

[198] Guan F, Zhai X, Duan J, Zhang M, Hou B. Influence of Sulfate-Reducing Bacteria on the Corrosion Behavior of High Strength Steel EQ70 under Cathodic Polarization. PLoS One 2016;11:e0162315.

[199] Erable B, Féron D, Bergel A. Microbial Catalysis of the Oxygen Reduction Reaction for Microbial Fuel Cells: A Review. ChemSusChem 2012;5:975–87. https://doi.org/https://doi.org/10.1002/cssc.201100836.

[200] Orfei LH, Simison S, Busalmen JP. Stainless Steels Can Be Cathodically Protected Using Energy Stored at the Marine Sediment/Seawater Interface. Environ Sci Technol 2006;40:6473–8. https://doi.org/10.1021/es060912m.

[201] Angst U, Büchler M, Martin B, Schöneich H-G, Haynes G, Leeds S, et al. Cathodic protection of soil buried steel pipelines – a critical discussion of protection criteria and threshold values. Mater Corros 2016;67:1135–42. https://doi.org/https://doi.org/10.1002/maco.201608862.

[202] Zamanzadeh M, Bayer GT, Chikkam AK. Cathodic Protection, Coatings That Shield Cathodic Protection, Stress Corrosion Cracking and Corrosion Assessment in Aging Coated Pipe Lines and Buried Utility Structures. Corros 2018 2018.

[203] Fatehi A, Eslami A, Golozar MA, Raeissi K, Ashari R. Cathodic Protection Under a Simulated Coating Disbondment: Effect of Sulfate-Reducing Bacteria. Corrosion 2019;75:417–23. https://doi.org/10.5006/2709.

[204] Guezennec JG. Cathodic protection and microbially induced corrosion. Int Biodeterior Biodegradation 1994;34:275–88. https://doi.org/https://doi.org/10.1016/0964-8305(94)90088-4.

[205] Lunarska E, Birn J, Domżalicki P. Hydrogen uptake by structural steels at cathodic protection in sea water inoculated with sulfate reducing bacteria. Mater Corros 2007;58:13–9. https://doi.org/https://doi.org/10.1002/maco.200603980.

[206] Robinson MJ, Kilgallon PJ. Hydrogen Embrittlement of Cathodically Protected High-Strength, Low-Alloy Steels Exposed to Sulfate-Reducing Bacteria. Corrosion 1994;50:626–35. https://doi.org/10.5006/1.3293536.

Chapter 3

Microbiologically influenced corrosion (MIC) management using Bayesian inference

Preface

A version of this chapter has been published in the ***Ocean Engineering, 2021; 226: 108852****. I am the primary author along with the Co-authors, Faisal Khan, and Rouzbeh Abbassi. I developed the conceptual framework for the model and carried out the literature review. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' and peer review feedbacks. Co-author Faisal Khan helped in the concept development and testing the model, reviewing, and revising the manuscript. Co-author Rouzbeh Abbassi provided support in implementing the concept and testing the model. The co-authors also contributed to the review and revision of the manuscript.*

Abstract

Microbiologically influenced corrosion (MIC) is a complex phenomenon that occurs when a microbial community is involved in the degradation of an asset (e.g., pipelines). It is widely recognized as a significant cause of hazardous hydrocarbon release and subsequently, fires, explosions, and economic and environmental impacts. This paper presents a new MIC management methodology. The proposed methodology assists in accurately monitoring MIC activity and accordingly develop strategies to manage it. The MIC monitoring and management activities are achieved using Continuous Bayesian Network (CBN) technique with Hierarchical

Bayesian Analysis (HBA). The integration of HBA and CBN helps overcome the Bayesian network's discrete value limitations (BN) and source-to-source uncertainty for each node in the network. The methodology can provide the accurate value of parameters, such as failure probability and MIC occurrence rate. The application of the methodology is demonstrated on a subsea pipeline. The study provides a better understanding of the influencing factors of MIC rate and failure probability. This assists in developing effective MIC management strategies.

Keywords: Safety management, Subsea pipeline**,** Uncertainty**,** Pipeline**,** Markov Chain Monte Carlo method, Bayesian analysis

3.1. Introduction

Microbiologically influenced corrosion (MIC), also known as biocorrosion, is a significant threat to asset integrity in most industries especially in oil and gas industrial sectors [1–3]. Because of their activities based on metabolites MIC is caused by microbial biofilms, where their activities reflect in reservoir souring and asset deterioration [4,5]. As industrial assets age, MIC becomes a common risk factor leading to an accident (e.g., fluid flooding, leakage, rupture, *etc*). Besides, MIC has been extensively reported as annually causing the loss of billions of dollars in the US [6]. MIC has been attributed to approximately 10% of corrosion cases in the UK [7], the largest, Prudhoe Bay's oil spill occurred due to MIC in 2006 [5], and Alaskan pipeline leakage was caused by microbial activities.

Staying with the aforementioned introduction, performing MIC management is therefore vital, whereby operators can use quantitative, semi-quantitative, and qualitative models to support decision making to manage corrosion. MIC management, underlying the idea of corrosion management approaches, should employ the key factors of recently introduced corrosion management systems (CMS) [8] to make sure that all required MIC preventives, control and mitigative actions are performed in a sustainable, well-established, and effective manner [9,10]. Three main steps need to be considered in any corrosion management approach: (i) understanding the MIC threat mechanism and how it affects the assets, (ii) recognizing and performing an appropriate management practice, and (iii) monitoring the management practices to examine whether the practices are effective or need further modifications [10,11]. These steps are taken into account based on CMS procedures on a daily, weekly, monthly, and annual basis. Thus, corrosion management in general, and MIC specifically, can be viewed as a supporting program, in which management practice is presented and facilitated. It should be highlighted that MIC management in an ongoing and continuous process since MIC is known as an asset integrity threat, which further increases the operational risk. Therefore, MIC management has to follow the ISO 31000 [12] framework on risk management.

There are a considerable number of corrosion management programs based on the reliability/availability of assets proposed by both the academic and industrial sectors over the past few decades. These management programs are typically categorized into different classes, namely: (i) calculating the failure probability of asset (pipeline) over a period (before and after launching in-line inspection and cleaning tools), (ii) repairing the defect if required, (iii) optimizing the periodic schedule of in-line inspection tools to determine the defects and corresponding sizes of the defects, (iv) manipulating operational parameters, (v) using chemical compounds (e.g., inhibitors and biocides), (vi) applying coating and cathodic protection, and combination of the classes [13–20].

The pit depth growth models play an important role in proposing a corrosion management practice, to approximate the failure probability of the pipeline as a function of time, predicting the remaining strength of the pipeline, as well as examining the defect's location and determining the efficiency of each management practice. This is why utilizing the data collected from pipeline history over time is essential for the industry to develop a pit depth growth model in a much more realistic way. In literature, pit depth growth models can be developed by using conservative and non-conservative techniques. The latter may lead to critical defects being overlooked by the management practice and increase the occurrence of serious consequences. On the other hand, the conservative pit depth growth models will increase the uncertainty of management practice [21]. Developing a mechanistic model for pit depth growth models is an intrinsically complex process as it may include two types of variables, namely temporal and spatial. The temporal variables are defined as the pit depth growth path of a defect that varies over time, while the spatial variables are defined as the pit depth growth path of more than one defect. However, all variables may be correlated. The probabilistic pit depth growth model is widely used in the literature as random variables and stochastic-based models. It simply means that the pit depth growth is considered to follow a linear or power-law function of time [14,16,17,19,22,23]. As an example, the growth of a corrosion defect is characterized by utilizing the Markov process and a gamma distribution with a shape and scale parameter as time-variant and time-invariant, respectively [24–26]. A gamma process is employed to characterize corrosion growth of the multiple defect [27]. A non-homogenous Markov process is used for pit growth according to the experimental data for Aluminum [27]. A non-homogenous Markov process is also used by [28,29] to characterize the pitting corrosion, in which Weibull distribution is assumed for corrosion initiation time. A power-law function of time is considered to model the parameters in transition probability. In another study, the time-dependent transition intensities were examined by collecting the pipeline defect information with in-line inspection tools [30]. However, there are significant challenges associated with modeling the pit growth by adopting Markov process-based models: (i) selecting a transition probability function and the sufficient numbers of damage state, (ii) using data from in-line inspection tools introduces the uncertainties as well as errors, and (iii) facing the spatial correlation between the defects.

This is why the Bayesian-based methodologies are robust and powerful tools, utilizing data for pit depth growth modeling. As an example, hierarchical Bayesian methodology and dynamic Bayesian networks, by incorporating new data, have been used to analyze the deterioration mechanistic model of corrosion and updating the parameters in the model [31–34]. The hierarchical Bayesian analysis (HBA) is utilized to model the pit growth in the pipeline [21]. Researchers used a non-homogenous gamma process to derive the probability distribution for the parameters within multiple defects. In another study, Al-Amin et al. [35] developed a pit depth growth model for a specific defect using HBA based on the data obtained from the in-line inspection tools. A hierarchical Bayesian framework was developed by Qin et al. [36] to model defect generation and growth of metal deterioration in oil and gas steel pipelines. Pesinis and Tee [37] proposed a framework to estimate corrosion-based failure probabilities of underground natural gas pipelines and corrosion growth defects by using a hierarchical Bayesian model. A hierarchical Bayesian model based on a non-homogeneous gamma process is proposed considering the operational conditions of a pipeline over a period of time [38]. Zhang and Wang [32] used a Bayesian network (BN) to construct a knowledge-based model by analyzing the failure probability and leakage size of corrosion for an underground gas pipeline.

However, in all aforementioned studies, there is a lack of comprehensive pit depth growth modelling considering both model and data uncertainties, which further helps on-site operators to make decisions by proposing a management practice. Therefore, to deal with the lack of previous studies, CBN along with HBA can be used. CBN which can be considered as an extension of typical BN [39] is a powerful tool and can handle model uncertainty using adaptive models. In addition, CBN, by utilizing continuous nodes, can better reflect those variables that change continuously in nature. CBN and its extensions have been broadly used such as, but not limited to the field of safety, reliability, and risk management [40–44]. HBA is also a robust technique to deal with different sources of information known as data uncertainty. In safety, reliability, and risk management domains, the existing data is generally inadequate to conduct analysis, especially modeling the pit depth growth, where improper modeling causes pipeline failure. Thus, to obtain acceptable results to support decision making, HBA utilizes and then aggregates a wide range of information. In addition, in recent years, the availability of Markov Chain Monte Carlo (MCMC) using a sampling application can help decision-makers to fully track performing HBA [45–48].

The contribution of this study is threefold. The first contribution is in providing CBN along with HBA in one methodology framework for MIC management. Thus, the proposed framework takes into account both model and data uncertainty. Second is in developing a new mechanistic model for pit depth growth under the influence of MIC, and third is using the Bayesian-based model over a period of time to propose the optimum and best management practices.

The organization of the paper is presented as follows. In Sections 2 and 3, the preliminaries of CBN and HBA are explained, respectively. In Section 4, a framework is proposed to manage MIC considering both types of model and data uncertainties. In Section 5, a corroded pipeline is studied as a case study to demonstrate the application of the developed methodology. In the final section a conclusion, challenges of the current study, and direction for upcoming research are provided.

3.1.1. Continuous Bayesian Network

The BN has enough capacity to analyze the behavior of each node over time given new data, making it one of the most powerful and robust tools. Common BN-based approaches have been widely used in different engineering domains such as, but not limited to [49–56]. BN-based approaches can employ different types of input data (objective or subjective) to estimate the probability centered event by reducing the model uncertainty with consideration of interdependency between all the participating nodes. However, the common BN-based models ignore the preciseness and modeling flexibility since the discrete nodes are used in the models. In other words, the common BN-based approaches consider the continuous nature of causal factors in the network as discrete variables. Therefore, these types of estimations provides uncertainty during the analysis process [57–63]. In real-world applications, there are often variables that continuously change over time and therefore cannot be modeled using common BN-based models with discrete variables. Such is the case for MIC.

To deal with the abovementioned drawbacks, the common BN-based approaches can be further developed as a CBN considering the continuous causal factors. In CBN, the nodes of the models can be represented as a combination of discrete and continuous variables. To see how CBN can be constructed from a common BN-based model, Guozheng et al [39] proposed a framework to convert BN into the CBN. According to this study, two significant changes are required so that the parental nodes can quantitatively signify the child nodes. First of all, all nodes with a continuous nature in BN-based modes must be defined by employing measurable variables. Next, the child nodes' value in CBN needs to be represented as a function of the parental nodes' value. This simply means that the conditional probability tables (CPTs) in the common BN-based models are transferred into the conditional probability distributions or mathematical functions that represent the relationships between the value of the child and parental nodes.

In CBN, the computation of posterior distribution becomes much more complex and therefore the analytical methods or Monto Carlo simulations cannot compute the posterior distributions. Markov Chain Monto Carlo (MCMC) is a robust tool and has high level capacity to compute the complicated posterior distribution with high dimensions. To elaborate, MCMC has two main parts (i) Monto Carlo, and (ii) Markov Chain. Monto Carlo refers to a method that relies on the generation of random numbers and Markov Chain refers to a sequence of numbers in which each number depends on the previous number in the sequence. However, Monto Carlo simulations fail to sample from the complicated distribution which has different types of dependent variables. To handle this issue, Markov Chain is used to assist Monto Carlo, and therefore MCMC is utilized. To obtain more details about MCMC and its algorithms one can refer to [64].

3.1.2. Hierarchical Bayesian Analysis

Simply put, Bayesian analysis is one of the main elements of the Bayesian methods that deal with the unknown parameters of a mechanistic process as random variables instead of using deterministic values. The Bayesian analysis makes use of prior knowledge about the mechanistic process' parameters which may be derived from expert opinion, past experience, and information from previous research studies. Subsequently, the prior knowledge is adjusted based on the newly observed data to update the opinions about the parameters of a mechanistic model. Furthermore, the updated belief can then be considered as the prior distribution for updating in the future as the new data becomes obtainable. Thus, by repeating this process, the data uncertainty about the parameters of the mechanistic model is reduced. Hierarchical Bayesian Analysis (HBA) [65] is a unique case of the Bayesian methods, in which the prior distribution is disjointed into the conditional distribution sequentially [66]. HBA is a powerful tool for making statistical inferences about the parameters of the mechanistic model in which there are complicated interactions between the parameters. In addition, HBA is principally appropriate for population, where the model's parameters described as a sample in the population are measured to be associated with the parameters for another sample from the same population [35,67].

Let it be assumed that there is a population of n random variable, $\mathcal{Y}_i(1 = 1,2,3, \ldots, n)$ which can describe similar mechanistic processes. Consider that there is a set of unknown parameters where θ_i denotes the probability distribution of a random variable $\mathcal{Y}_i$. The prior distribution $p(\theta_i|\omega)$ can be assigned to θ_i, in which $p(\theta_i|\omega)$ signifies the PDF of θ_i and is conditioned on the known parameters ω, and are considered to be common to the population of $\mathcal{Y}_i$. Moreover, let it be us assumed that y_i denotes a set of observed data for $\mathcal{Y}_i$. The updated opinion of θ_i can be obtained using Bayes' theorem [68] by combining the prior distribution and the observed data in the following Equation:

$$p(\theta_i|y_i) = \frac{L(y_i|\theta_i) \times p(\theta_i|\omega)}{p(y_i)} \tag{3.1}$$

$L(y_i|\theta_i)$ is the known likelihood function is based on the information provided by the data, which is conditional on θ_i. Besides, the entity $p(\theta_i|\omega)$ is called the posterior distribution, which reflects the combination information of prior information and obtained new data. The quantity $p(y_i)$ is the normalizing constant which confirms that the left-hand side of Equation 3.1 is a probability distribution. The $p(\theta_i|y_i)$ integrates to be unity and is known as the marginal likelihood, which can further be determined by integrating the numerator on the right-hand side of Equation 3.1, regarded as θ_i.Therefore, the following Equation can be derived:

$$p(y_i) = \int L(y_i|\theta_i) \times p(\theta_i|\omega) d\theta_i \tag{3.2}$$

Keeping the normalization constant in mind, using proportionality symbol ($\propto$), Equation 3.1 can be rewritten as:

$$p(\theta_i|y_i) \propto L(y_i|\theta_i) \times p(\theta_i|\omega) \tag{3.3}$$

The abovementioned explanations are based on standard Bayesian formulations, where it is assigned a prior distribution into the parameter θ_i by controlling the distribution $\mathcal{Y}_i$. However, the standard Bayesian formulations can be further developed by considering that the parameter ω which controls the distribution of θ_i is a random variable as well, by assigning the prior distribution, $p(\omega|\psi)$, into the ω. According to this extension, the $p(\omega|\psi)$ is named as hyper-prior and ψ in named as hyper-parameter [65,66]. In addition, the hyper-parameter can be known and can present the prior belief about ψ. In practice, ω can also be treated as random variables and proceed to the next level of hierarchy. As can be seen from Figure 3.1 (modified after [65]), the simple graphical structure of a common HBN of extended Bayesian model is provided. Therefore, the extended Bayesian model can be summarized as follows:

i. Likelihood of data: $L(y_i|\theta_i)$,

ii. First stage of prior: $p(\theta_i|\omega)$,

iii. Second stage of prior: $p(\omega|\psi)$,

iv. Posterior distribution of θ_i: $p(\theta_i|y_i) \propto L(y_i|\theta_i)p(\theta_i|\omega)$,

v. Posterior distribution of ω: $p(\omega|\theta_i) \propto L(\theta_1, \theta_2, \dots, \theta_n|\omega)p(\omega|\psi)$.

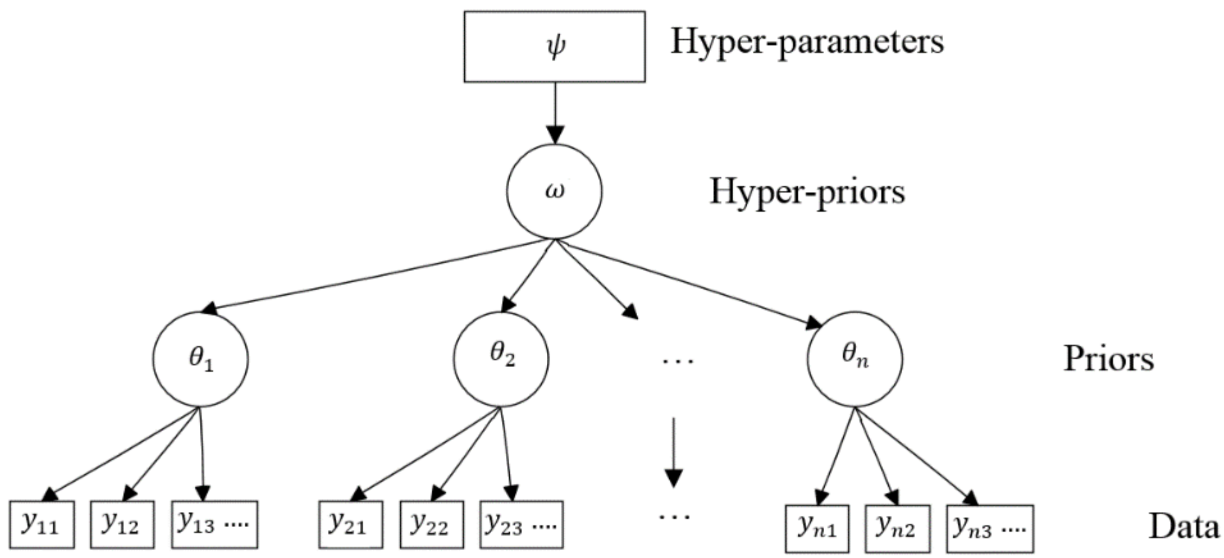


Figure 3.1. The simple graphical structure of a common hierarchical Bayesian Network (square and circle nodes represent the deterministic and stochastic component)

In such cases, HBA can be defined in four levels, due to the fact that level one is based on inspection data, i.e., the defect depths described by inspections which are connected to measurement uncertainties, level two highlights the auxiliary variables, including the actual depths at the times of inspections and increments of the actual depths between two consecutive inspections, level two also makes the likelihood function for the measured depth mathematically tractable and facilitates the Bayesian updating, in level three the parameters for level two are provided (e.g., the parameters in gamma distributions), and finally in level four hyperparameters assist in finding out the parameters in level three. It should be added that based on the type of decision-making problem, the level can be increased or shortened. By studying the literature and with the support of decision-makers such as, but not limited to [35,46,69–71], and to the best of the authors' understanding, some of the merits of HBA compared to other statistical models can be highlighted as following:

(i) HBA enables one to deal with the source to source uncertainties by utilizing the hierarchical prior assignment. Thus, the feature of HBA makes a robust estimation of the parameters, in which the posterior results are based on the average from different possible prior options [66].

(ii) HBA using the conditional hierarchical priors can better describe the spatiotemporally (space-time) correlated data [72].

(iii) The computations of the Bayesian model are commonly simplified by the hierarchical structure within posterior distribution simplification. This results from priors' decomposition. Thus, different sampling algorithms can be employed to update the parameters [65,66,72].

(iv) In HBA, a specific group or singular parameter can derive information from the equivalent of the parameters[73]. Thus, the level of singular inference can be obtained as precisely as possible and shows its merits when the observed data and sample size are small. To characterize the pit depth for a single MIC defect of a subsea pipeline, HBA using inferences is practically advantageous, since the information that is linked to give defect is commonly limited.

The mean, standard deviation, and other probabilistic characteristics of random variables, which are entered in HBA can be determined by integrating and combining the posterior distribution. However, there is a lack of close form solutions to obtain the posterior distribution when the Bayesian Network has high dimensions and is complex. Therefore, similar to the CBN mentioned in Preliminary 2, the difficulties can be handled using MCMC techniques. In the MCMC methods, a Markov chain is initially constructed to consider the start values of the parameters, and subsequently converges to the posterior distribution which is actual target density. It should be added that the sample is dependent on the start value; therefore, the influence of the start value needs to be reduced by ignoring the first part of the sample. This period is referred to as the burning-in period. The burning-in period is the time it takes the chains to be stabilized, which means therefore that there is not up and down drifting over time by ignoring the sample in the burning-in period. Afterward, the sample can be used for Bayesian inference of the parameters. There are some important algorithms that are commonly utilized to perform an MCMC, such as, but not limited to "Metropolis random walk Hastings", "Slice sampling", and "Gibbs's sampling". To get more details about MCMC methods and corresponding algorithms, one can refer to the following references [65,66,72,73].

3.2. Methodology

It is important to predict the rate of MIC as well as pit depth growth in the early stage of subsea pipeline development to provide appropriate management practice(s), which can prevent, mitigate, and control the occurrence of pipeline failure caused by MIC. However, MIC management is a challenging task for decision-makers due to a lack of information in probabilistic risk analysis. The rate of MIC and pit depth growth can be estimated by utilizing modeling techniques such as Bayesian network. Such Bayesian network modeling techniques have a number of shortfalls which result from some degree of uncertainty. As can be seen from Figure 3.2, the proposed six step methodology enables consideration of both types of data and model uncertainties by modeling CBN and HBA. In the proposed methodology, CBN and HBA can deal with the model and data uncertainties, respectively.

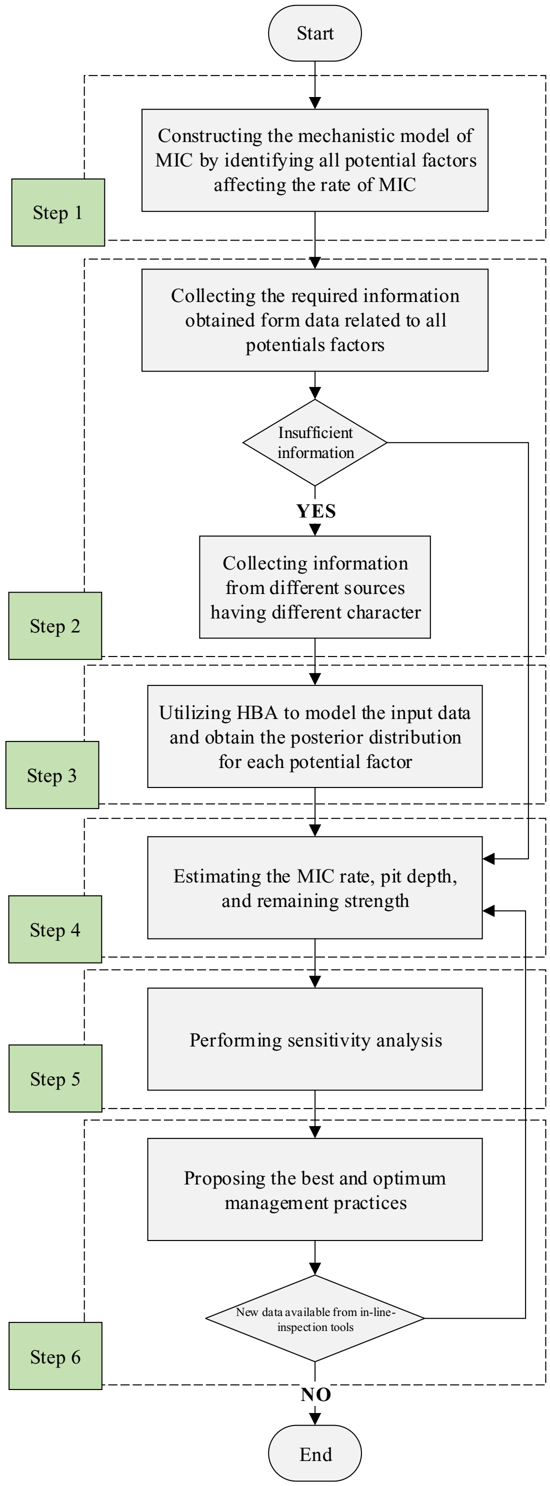


Figure 3.2. The developed methodology framework

Step 1: Constructing the mechanistic model of MIC

In this step, mechanistic modelling of individual pit initiation influenced by MIC is developed. The mechanistic model considers the type of corrosion, which in our case is MIC, chemical, material type, alloy composition, mechanic characteristics of the system (e.g. subsea, onshore), and effective environmental and operational conditions. This can further lead, but is not limited. to the rate of corrosion, material strength properties, depth and width of the pits, and remaining age of the pipeline. Once all potential factors impacting on the MIC are identified, the BN tool is further developed to consider the relationship between different parameters in the MIC mechanistic model.

Step 2: Collecting all the required information

The related data for each node in developed. BN are obtained from different sources including different industrial sectors, operational conditions, various regions, or subjective opinions from experts in the field. Because the nodes in BN can be defined by combination of both discrete and continuous variables, CBN is therefore used instead of BN.

Collecting data is the key step in any kind of statistical inference. Data can be defined as an observation value in a stochastic domain which may have different sources of uncertainty. However, assessing, evaluating, manipulating, and organizing any form of data is referred as information. Knowledge, in its general form, is assembled from the information. The inference is referred to as the process of obtaining a conclusion according to what is known for us [45].

In addition, once all required data/information is collected, they are further processed into the intervals to approximate their probabilities for identified ranges. Therefore, the predicted probabilities can be used as input data for the CBN model. The CBN, similarly to the BN, can deal with model uncertainty.

Step 3: Utilizing Hierarchical Bayesian Analysis to deal with data uncertainty

As mentioned in Preliminary 3, HBA is used to derive the probability of each node in CBN. After collecting the relevant data for each node from different sources, the likelihood function of continuous nodes is specified for each data set according to the type of aggregated data. As an example, if the number of observed variables is collected in a specific period, the Poisson likelihood function can be used to model the data set [45]. Thereafter, the hierarchical model can be structured as the following:

$x_i \sim \text{Poisson}\ (\lambda_i, t_i)$ as likelihood function,

$\lambda_i \sim \text{gamma}\ (\alpha, \beta)$ as the first state of prior,

$\alpha \sim \text{gamma}\ (0.0001, 0.0001)$ diffusive hyperprior,

$\beta \sim \text{gamma}\ (0.0001, 0.0001)$ diffusive hyperprior.

According to this point, HBA provides a posterior distribution for the parameter of interest, which is probability. In addition, probability reflects the mean and reliable intervals. The mean value signifies the most fitting value for the interested parameter. The obtained distribution denotes source to source uncertainties in the interested parameter, and therefore can be used as a prior information distribution when new information becomes available. Thus, HBA correctly deals with data uncertainty.

Step 4: Estimating the rate of MIC and pit depth growth

Once all the probabilities of each node to be used in the developed CBN are obtained, the pit depth growth can be estimated. Firstly, the probability of parental nodes in CBN will be used as a prior belief to estimate the probability of pit depth growth. Secondly, the probability of each node will be updated, given new information through the probability propagation or reasoning process. Moreover, CBN enables the setting of evidence in the network at any stage. Hence, the posterior distribution estimated by HBA is considered as an informative prior distribution. Thereafter, the obtained informative prior distribution is used to update the probability of the nodes. Using probability reasoning processes, the CBN is then updated the model completely.

To compute the pit depth growth over time, it is assumed that the actual depth of an MIC defect follows a power-law path. It is further assumed that the parameters of power-law growth are constant by time and quantified for each specific defect [45]. Therefore, it is also considered that the pit depth growths of different defects are spatially independent. According to the power-law path model, the pit depth growth of the defect i at time j can be estimated in the following equation [21,35]:

$$da_{ij} = a_i (t_j - t_{0i})^{b_i} + \eta_{ij} \tag{3.4}$$

where the parameter a_i ($a_i > 0$) is an indication of pit depth growth for defect i in one year from the initiation time of defect, the parameter t_j is the proceed time (elapse time in a year) from installation date until time j as the reorganization of a defect, the parameter t_{0i} represents the MIC initiation time (the proceed time from installation date to the time when defect i starts to grow), in practice $t_{0i} > t_j$, the parameter b_i ($b_i > 0$) denotes the MIC rate of growth path, in which $b_i =$

$0, b_i > 0$, and $b_i < 1$ representthe linear, acceleration, and deceleration pit depth growth path, respectively, η_{ij} denotes the model error of the pit depth growth connected with defect i at time j.

In practice, there is no date for the specific defect until the first launch of an in-line inspection tool. Thus, HBA, using prior distribution are considered for the parameters. The truncated normal distribution is allocated for the prior distribution of the parameter a_i, due to the fact that it should be positive. In addition, selecting a normal distribution provides better computational stability as well as enhancing the efficiency of the model. The parameter b_i is approximated with respect to the mechanistic model of MIC. The prior distribution of the parameter t_{0i} is assumed to be uniformly distributed in interval zero and t_1, since t_1 is the elapsed time from installation until the reorganization of a defect using observation, inspection tools, *etc*. The parameter η_{ij} as the model error for the defect i at time j is considered to be normal distribution having a value of mean equal to zero, which means that the power-law model is considered to be on average unbiased for each defect. Therefore, the prior distribution of three parameters a_i, t_{0i}, and η_{ij} $(i = 1,2,3, \ldots m; j = 1,2,3, \ldots n)$ are represented as the following Equations:

$$a_i \sim N(\mu_a, \sigma_a^2) \tag{3.5a}$$

$$t_{oi} \sim U(0, t_1) \tag{3.5b}$$

$$\eta_{ij} \sim N_i(\mu_a, \sigma_{\eta i}^2) \tag{3.5c}$$

in which all above-mentioned distributions are identically distributed and independent. $N(x, y)$ represents the normal distribution with mean and variance of x and y, respectively. $U(lx, uy)$ denotes a uniform distribution having a lower and upper bound of lx and uy, respectively. The parameter η_{ij} is considered to be independent and identically distributed for a given defect i in a different time slice. In addition, the parameter η_{ij} is considered to be independent at a given time the parameter η_{ij} for different defects.

The prior distribution of parameter of b_i is obtained from the MIC mechanistic model using CBN. The prior distribution parameters for a_i and η_{ij} are assigned another level of prior, named hyper-prior as they deal with the random variables. To treat the random variables, the normal and inverse-gamma distributions are considered for mean μ_a, and standard deviation σ_a^2 and $\sigma_{\eta i}^2$ as prior distributions, respectively. The normal and inverse-gamma distributions are well-known conjugate priors of a normal distribution and using conjugate priors further provides posterior distributions without numerical integration [14]. Keeping the above mentioned explanations, the hyper-priors can be defined as the following:

$$\mu_a \sim N(A, B) \tag{3.6a}$$

$$\sigma_a^2 \sim IG(C, D) \tag{3.6b}$$

$$\sigma_{\eta i}^2 \sim IG(E, F) \tag{3.6c}$$

where $IG(x, y)$ denotes the probability density function of inverse gamma distribution with shape and scale factors x, and y, respectively. The parameters A, B, C, D, E, and F are named as hyper-priors of the model and are considered to be known using non-informative distribution. In addition, as mentioned earlier, the $\mu_{\eta i}$ is assumed to be zero.

The fully hierarchical Bayesian model for pit depth growth is established in Figure 3.3 with respect to the aforementioned hyper-priors.

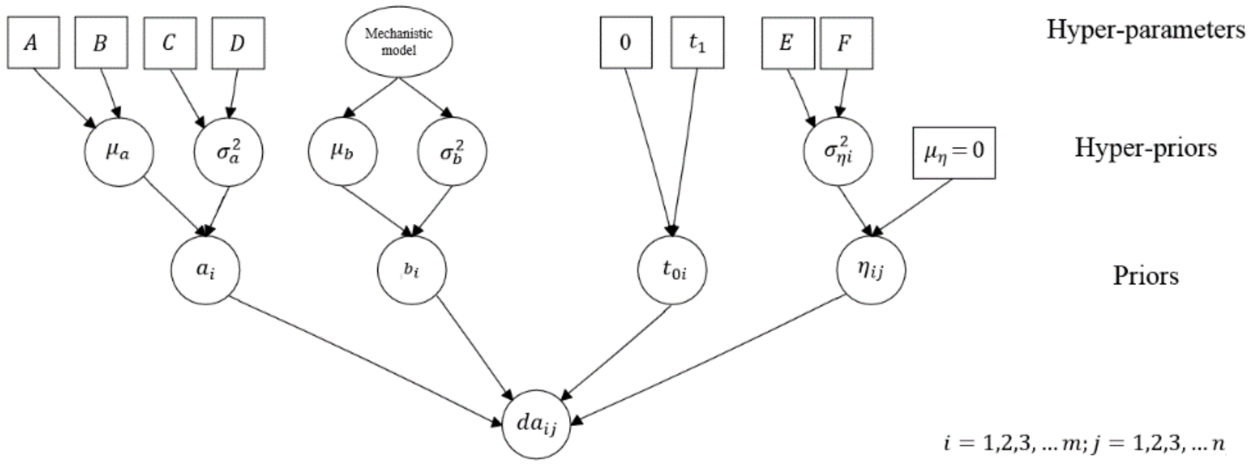


Figure 3.3. The schematic representation of a fully hierarchical Bayesian model for pit depth growth (rectangular nodes and circle nodes represent the constant and stochastic (uncertain) components of the model, respectively and arcs show the relationships between the nodes which can be deterministic or stochastic)

Step 5: Performing sensitivity analysis

The sensitivity analysis is carried out to study how the output uncertainty of the pit depth growth model can be separated into the different sources of input uncertainties [74]. In addition, sensitivity analysis helps to validate the model by using different methods such as, but not limited to, the conditional variances-first path, conditional variances second path, higher-order sensitivity indices, total effects, *etc*. To obtain more details, one can refer to [75].

MIC case is a highly complex process, and as a result, relationships between inputs and outputs in the model are not easy to follow. Therefore, sensitivity analysis helps decision-makers to see how changing, or a combination of, input parameters impacts the output. According to this point, in this study, a sensitivity analysis is performed to provide valuable information for the next step to propose the best and optimum management practice.

Step 6: Proposing the best and optimum management practice

Once sensitivity analysis is performed from the previous step, the behavior vitiation of each root parameter with the pit depth growth path will be obtained over a period of time. In addition, as mentioned earlier, applying each management program with respect to its corresponding characteristics, has an identified effect on the pit depth growth path. By comparing all possible management programs including each practice as well as a combination of them, we can select the optimum management practices in each time slice.

3.3. Application to a case study

The proposed methodology is applied to an APL 5L grade X42 subsea hydrocarbon transition pipeline which is highly suspect of internal MIC and is required to be in operational condition for at least 40 years. The pipeline carries co-mingled fluids from a different number of subsea resources.

According to the first step of the developed methodology, the mechanistic model of maximum pit depth growth influence by MIC appears in Figure 3.4. The mechanistic model of MIC is drawn with consideration to (i) environmental conditions, including salinity, CO_2 partial pressure, pH, O_2, temperature, water cut, and Sulphides, (ii) operational conditions including fluid velocity and pressure, (iii) material conditions including steel composition and Carbon content, (iv) biofilm, and (v) exposure duration.

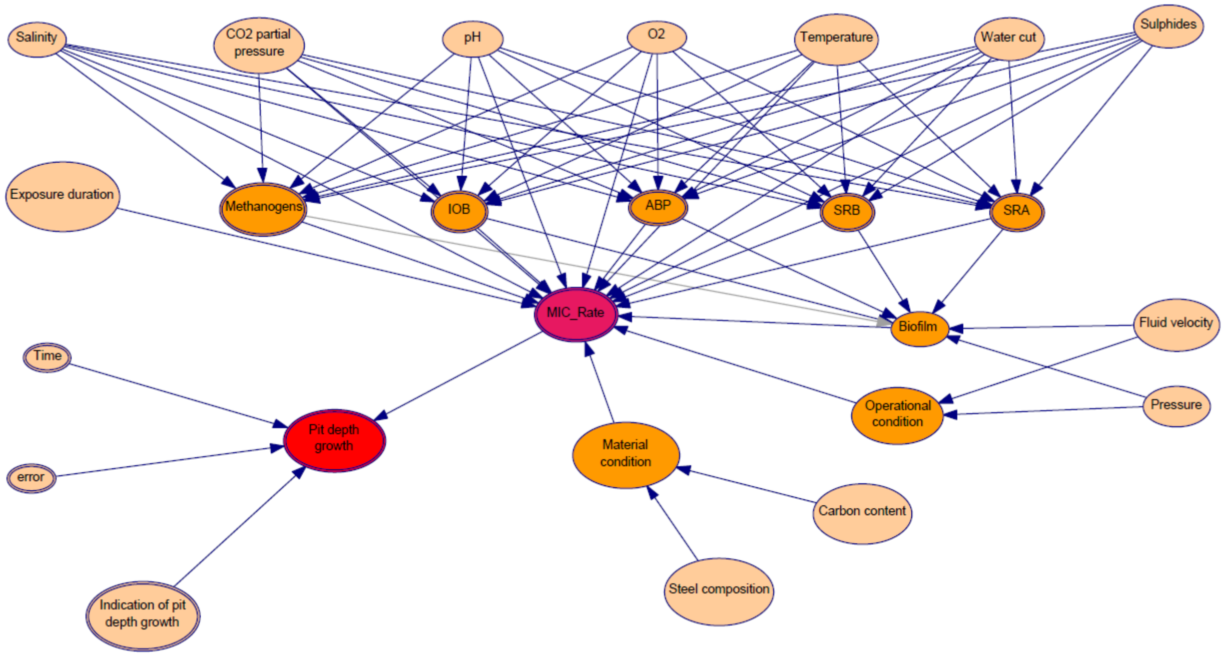


Figure 3.4. The influence diagram of the mechanistic model of maximum pit depth growth influence by MIC (SRB (sulfate-reducing bacteria), SRA (sulfate-reducing Archaea), and IOB (iron-oxidizing bacteria)

In the second step, the pipeline operational data and information, according to the operational environment, are provided in Table 3.1 based on the combination of discrete and continuous variables. The provided data is based on literature [19,33,34,52,57,59,76–79] and mean value of continuous variables are based on operational and chemical analysis from SeaRose FPSO. It is assumed that the pipeline contains multiple defects throughout. The non-informative distributions (i.e., distributions with small means and very large variances) are allocated as hyper-priors to the pit depth growth factors a_i , t_{oi} , and η_{ij} . To obtain pit depth growth, Bayesian updating software such as OpenBugs (www.openbugs.net) using MCMC methods is utilized by 1000000 iterations within interval 2 tinning, in which the estimated parameters of the growth models were then used to estimate the depth of a defect. Table 3.2 provides a chemical analysis of produced water showing the total number of microorganisms using the qPCR (quantitative Polymerase Chain Reaction) method, different types of microorganisms percentage as well as sulfate reduction rate (SRR), which further means that the defect in the pipeline is influenced by MIC. In addition, the sulfate reduction rate is used in the mechanistic model of MIC.

Table 3.1. The pipeline operational parameters' data range

Variables	Descriptions
pH	Distribution: 3.2-7.86
Temperature (degree)	Distribution: 0-50
Flow rate (m^3/s)	Distribution: 0.01-1.116
Exposure time (yrs)	Distribution: 2.5- 3.5
Salinity	Discrete: Present/Absent
Steel composition	Discrete: Present/Absent
Carbon content	Discrete: Present/Absent
Pressure	Discrete: High/Moderate/Low
O_2	Discrete: High/Moderate/Low
Sulfate ion (ppm)	Distribution: 0.01-32000
CO_2 partial pressure:	Discrete: High/Moderate/Low
Water cut	Discrete: High/Moderate/Low
Biofilm	Discrete: High/Moderate/Low thickness

Table 3.2. Characteristic of microorganisms affecting the MIC (Chemical analysis was performed from produce water after separator (PW-Terra Nova SC003, F2-P (2019)

Category	Name of organism	Value %
SRB	Desulfacinum	0
	Desulfobulbaceae	0

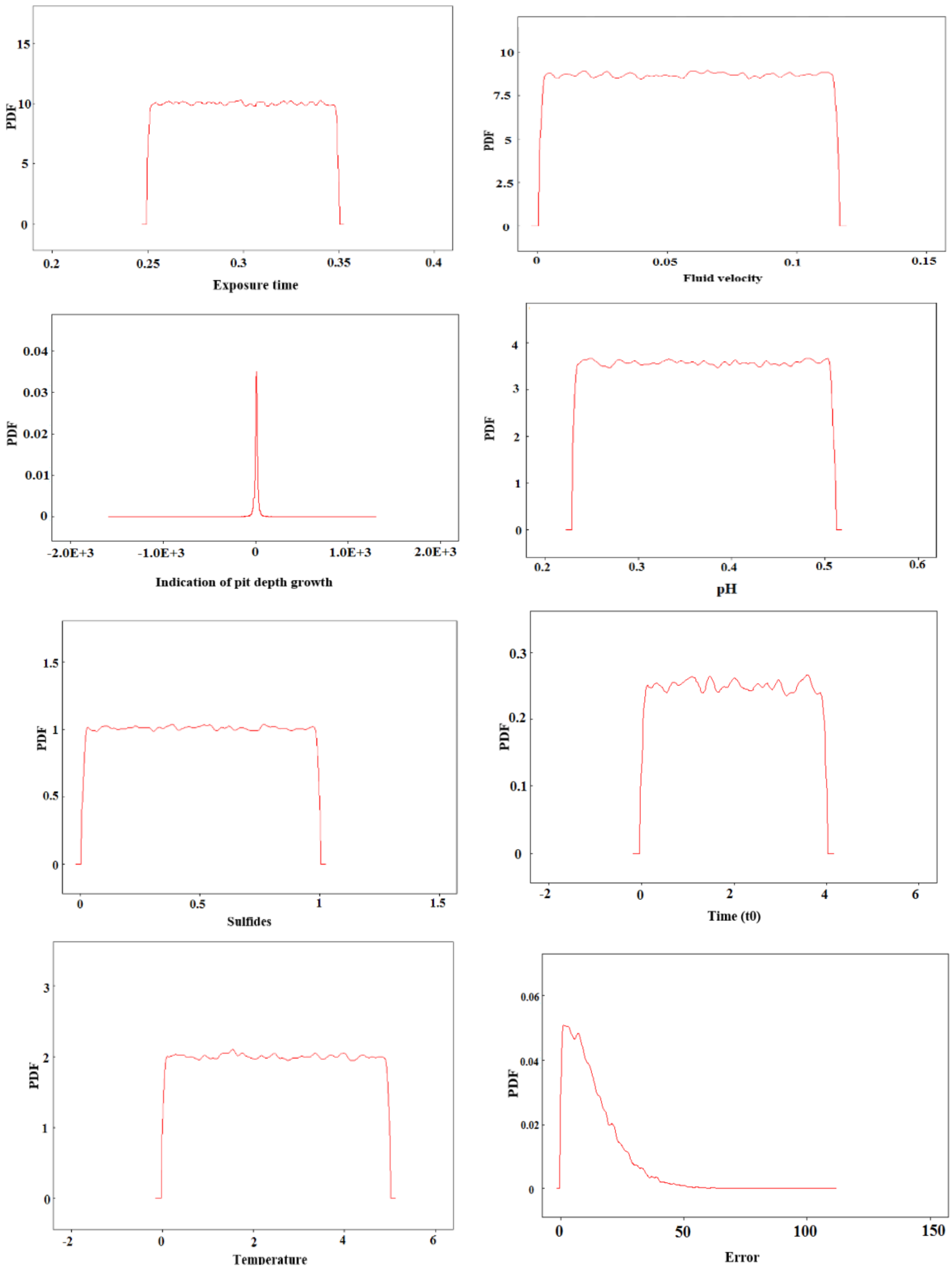
	Desulfonauticus	0
	Desulfomicrobium	0
	Desulfoplanes	0
	Desulfovibrio	8.72
	Desulfuromonas	0
	Desulfuromonadaceae	0
	Dethiosulfatibacter	10.14
	Dethiosulfovibrio	0
	Fusibacter	0
	Marinitoga	0
	Sulfurospirillum	0
SRA	Archaeoglobus	38.36
	Caminicella	0
	Kosmotoga	0
	Petrotogaceae	0
	Thermacetogenium	0
	Thermoanaerobacter	1.35
	Thermoanaerobacteraceae	0
	Thermococcus	9.9
	Thermosipho	3.6
Methanogen	Methanosarcinaceae	0
	Methanothermococcus	0
	Methanolobus	0
	Methermicoccus	4.79 %
IOB	Unknown	-
ABP	Unknown	-

Sum		76.86 %
qPCR	3.19E+06 (16S copies/mL sample)	
SRR in situ		0.52
SRB (sulfate-reducing bacteria), SRA (sulfate-reducing Archaea), IOB (iron-oxidizing bacteria), and ABP (Acid-producing bacteria), qPCR (quantitative Polymerase Chain Reaction), SRR (sulfate reduction rate)		

To propose a management practice in this study, a pit within a maximum pit depth is considered for evaluation.

In the third step, testing data are provided from Table 3.1 with HBA as described in Section 3 (Preliminary of Hierarchical Bayesian Analysis) which provides a probability distribution (i.e. a predictive posterior distribution for each node in CBN) as shown in Figure 3.5. The mean value of the distributions represents an adequate value of each node. After obtaining the Description and probability value of all nodes in CBN, it will then be used as prior belief in CBN to estimate the rate of MIC and further pit depth growth as shown in Figure 3.6. As it can be seen from Figure 3.6, the node "pit depth growth" is constructed based on an equation, representing that time-varying characteristics of pit depth growth considered in the BN prediction mode. In addition, it should be highlighted that parameters such as pit indication of pit depth growth using gamma distribution represent the randomness in the BN model.

In the fourth step, the probability of pit depth growth gained from the previous analysis can further be utilized to estimate the probability of pit depth growth over a period, considering that only t_j and t_{0i} are varied by time. Figure 3.7 depicts the approximation of pit depth growth over a period showing mean, median, and 10 percent error.


PDF
Exposure time
Fluid velocity
Indication of pit depth growth
pH
Sulfides
Time (t0)
Temperature
Error

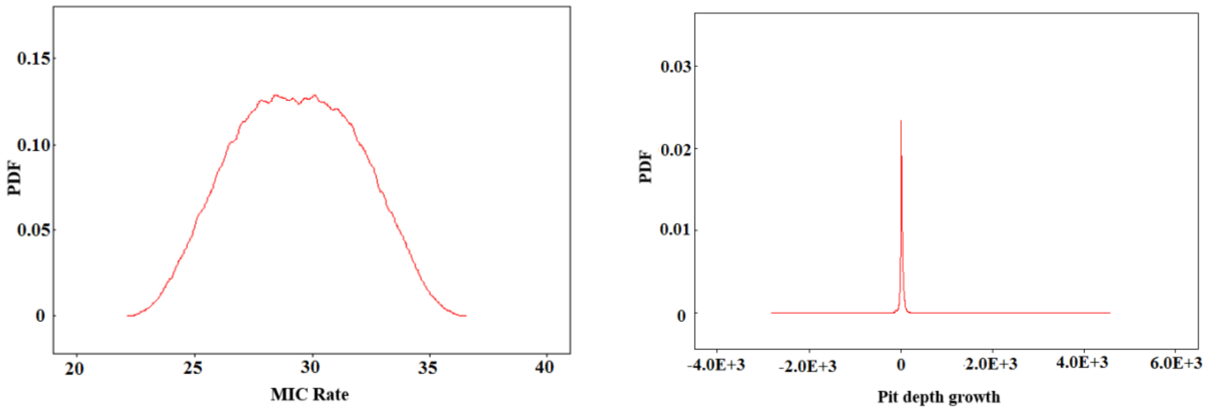


Figure 3.5. Posterior predictive distribution for each root node

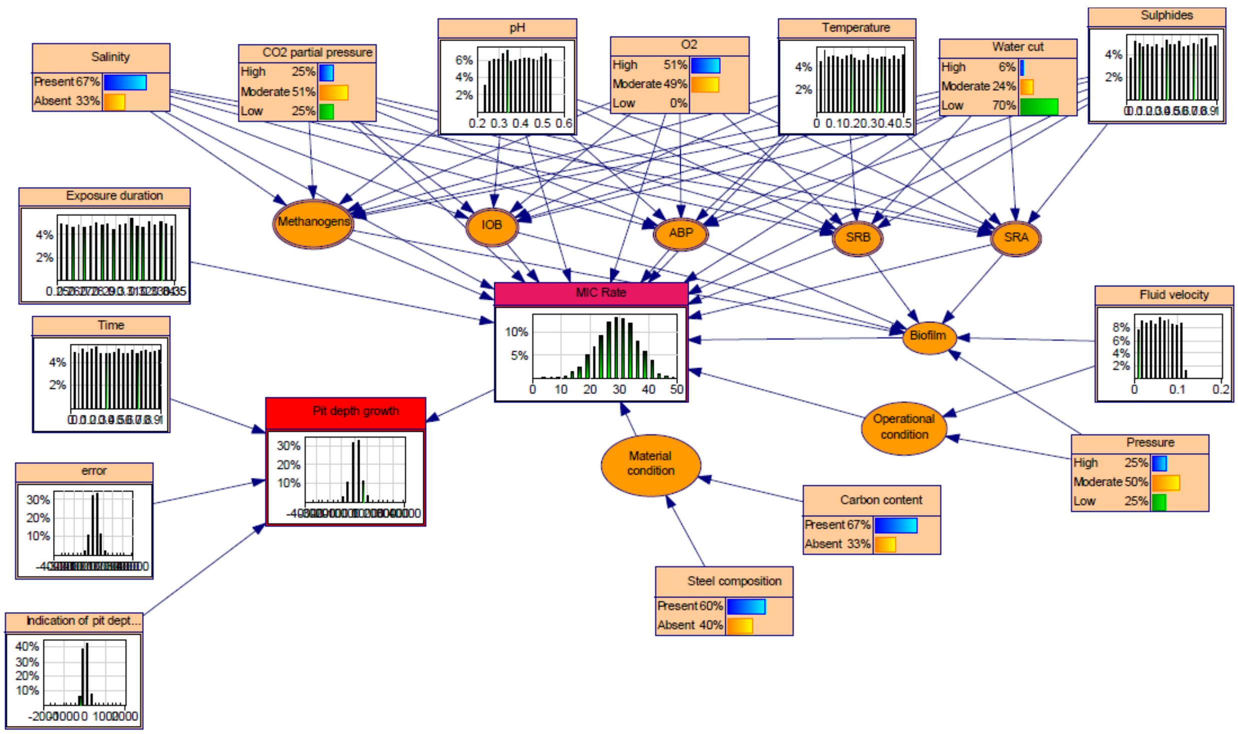


Figure 3.6. The CBN for obtaining a pit depth growth

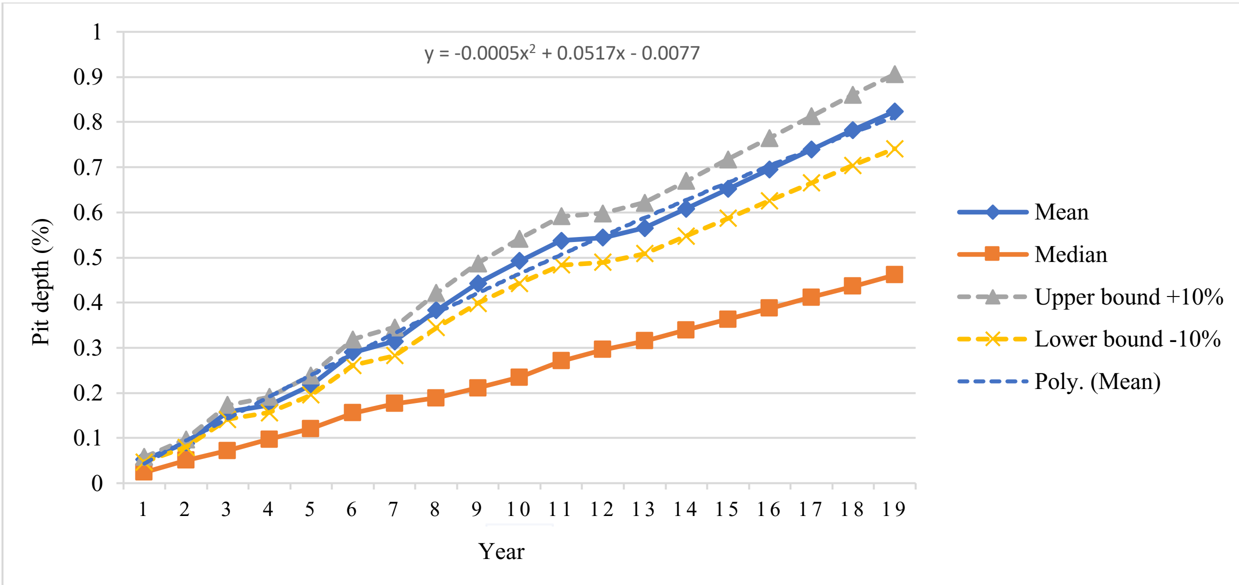


Figure 3.7. The predicted pit depth growth path for the defect

For the fifth step, sensitivity analysis is performed as a forward propagation to understand how proposing a management practice can properly prevent, mitigate, and control MIC. In addition, it can increase the lifetime of the pipeline by decreasing the pit depth growth path over a period. Figure 3.8 presents the possible management practice for the subsea pipelines influenced by MIC [80].

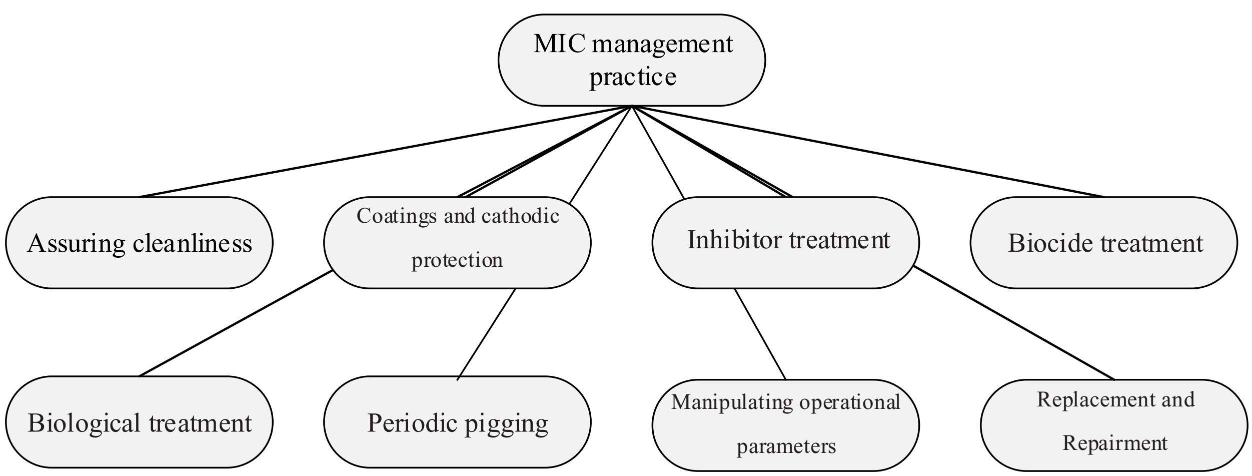


Figure 3.8. MIC preventive, mitigative, and control management practice

The first two management practices are assumed that they are already considered in the pipeline installation. It is known as a method to prevent, or at least limit, internal contamination. The cathodic protection and coatings would be the least difficult, most economically friendly, and proficiently and preventively proactive to deal with MIC [81]. The majority of offshore pipelines have coatings. The Fusion-bonded epoxy (FBE) is the most popular applied coating for North America [82]. Cathodic protection systems are divided into two methods (i) the sacrificial anode, and (ii) the impressed current system. In the latter, an external DC current is used to cathodically polarize the pipeline. This method of cathodic protection can be used to protect bare or poorly coated pipelines because of high current capacity. In the majority of subsea pipelines, the sacrificial anode technique is used.

As a first practice, continuous injecting inhibitors are evaluated. MIC inhibitors are those chemicals that influence anodic (chromates (CrO_4^{2-}), nitrites (NO^{2-}), phosphate, and molybdate), cathodic (Zinc salts ($ZnSO_4$), Polyphosphates ($Na_4P_2O_7$), and Phosphonates), or both types of reactions (polyphosphates, phosphates, silicates, and benzotriazole) to considerably reduce the rate of corrosion, in this case MIC [83]. The selection of MIC inhibitor is a difficult task for subsea industries as different types of aspects need to be taken into consideration such as, but not limited to, partitioning effect, compatibility of MIC inhibitors and other injected chemicals, the composition of produced water, the content of CO_2 and/or H_2S, for example [84,85]. Inhibitors can control MIC in three ways (i) increasing the anodic or cathodic polarization behavior, (ii) reducing the movement or diffusion of ions to the metallic surface, and (iii) increasing the electrical resistance of the metallic surface. Inhibitors can be generally classified as passivating inhibitors, cathodic inhibitors, precipitation inhibitors, organic inhibitors, volatile corrosion inhibitors. In the subsea industry, three types of chemical injection are typically used as inhibitors, 1) Hydrate

Inhibition, 2) Paraffin Inhibitors, and 3) Asphaltene Inhibitors [86]. In this study, a value of 80% for inhibitor efficiency is considered and assumed that the efficiency of inhibitors would be present in the system at the required dosage through the entire pipeline. In such cases, the efficiency of the inhibitor is considered in mechanistic model in which parent node leading to rate of MIC and further pit depth growth are updated. As an example, if a management practice has a specific target such as biofilm, the efficiency of the practice could improve the target parent node. To estimate the pit depth growth path over a period, HBA within the MCMC method is utilized. Figure 3.9 shows the efficiency of selected inhibitors on the pit depth growth path.

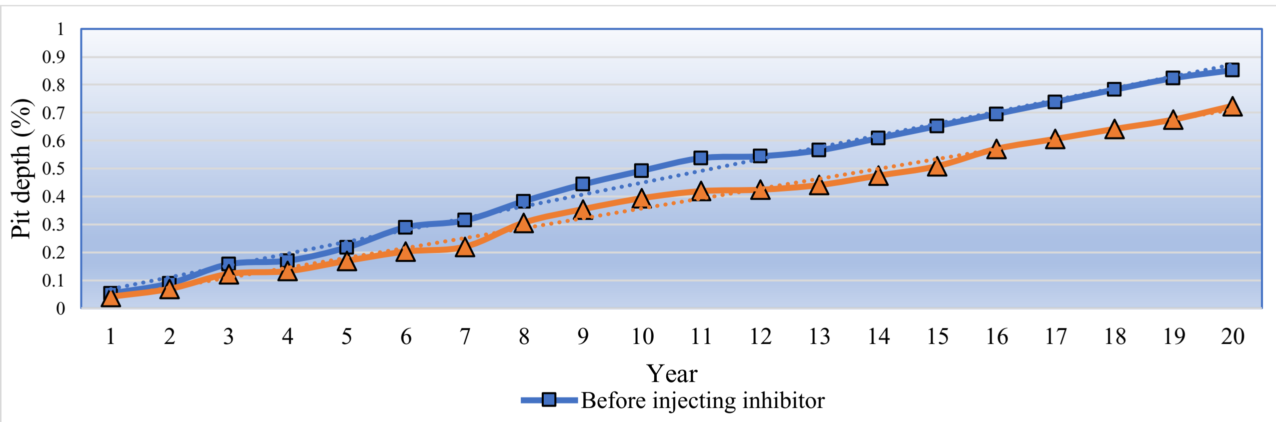


Figure 3.9. The efficiency of selected inhibitors on the pit depth growth path

As a second practice, continuous injecting biocide is evaluated. Biocides mean the killer of those living things which may endorse the mitigation mechanism of MIC. The biocides can be single or a mixture of two or more compounds to kill microbes [87]. To select the biocides in subsea industries, it is necessary to consider the following issues (i) selectivity against target microbes, (ii) biodegradability, and (iii) effectiveness in the presence of different chemical compounds such as inhibitors. The biocides can be categorized into two classes, oxidizing and non-oxidizing biocides. The oxidizing biocides such as chlorine, chlorinating compounds, chlorine dioxide, and bromine are used in water systems. The non-oxidizing biocides use synthetic molecules, which can be used in different environmental conditions. In addition, this type of biocide can reduce hydrocarbon contents. Formaldehyde, Glutaraldehyde, Quaternary amine substances, Carbamates, Metronidazole, and Isothiazolone which all have advantages and disadvantageous, are the common biocides in subsea industries. Among all industry-based biocides, as an example, Formaldehyde is economical, but it is carcinogenic, large quantities are needed, and combines with ammonia, oxygen scavengers, and hydrogen sulfide. In this study, Formaldehyde (CH_2O (H−CHO)) is considered for evaluation, since it is economical and adequate for Desulfo-based microorganism (SRB category) and SRA category [88,89], which together constitute approximately 60% of available microbes in the system. In this study, a value of 60% for laboratory-based biocide efficiency is considered, since it can have efficiencies in the field of >99.9% [89]. It also assumed that Formaldehyde would be present in the system at the required dosage through the the entire pipeline. To estimate the pit depth growth path over a period, HBA within MCMC method is utilized. Figure 3.10 shows the efficiency of selected inhibitors on the pit depth growth path based on Equation 3.4.

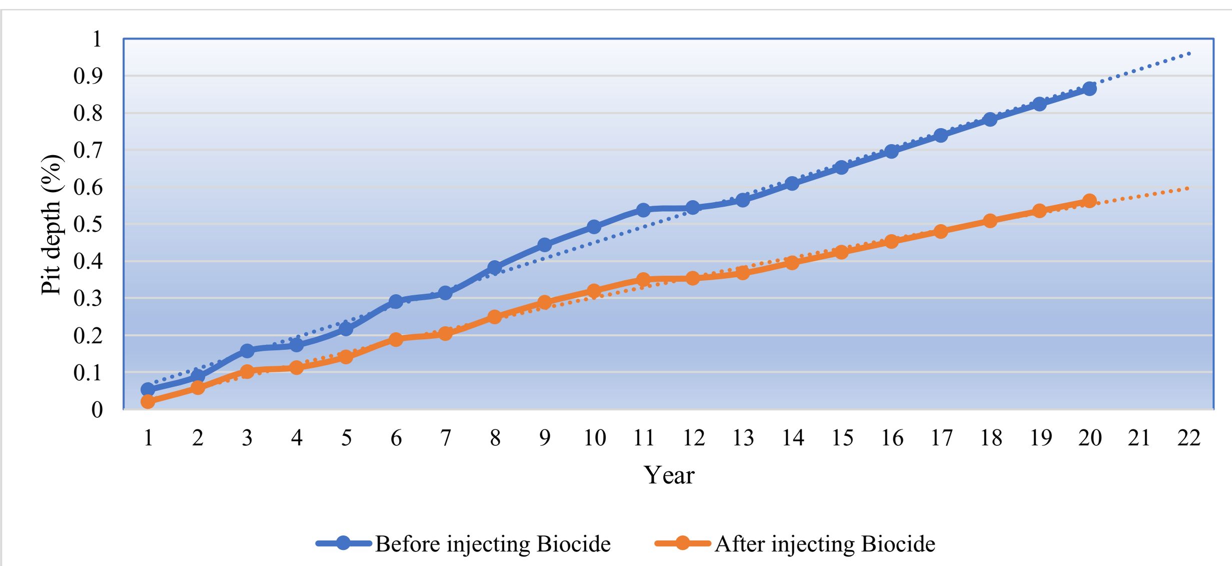


Figure 3.10. The efficiency of Formaldehyde as a biocide on the pit depth growth path

As a third practice, launching periodical pigging is evaluated. Periodical pigging as a mechanical strategy is a way of MIC mitigation. In pipelines, a mechanical pig is used to clean garbage from the interior portion of the pipeline and can be used for investigation purposes. Its mechanism is removing a piece of the biofilm and keeping solid particles [90]. According to the laboratory study, the efficiency of pigging in the rate of MIC is approximately 65% [91]. Figure 3.11 shows the efficiency of periodically launching pig within 3 years on the pit depth growth path based on Equation 3.4.

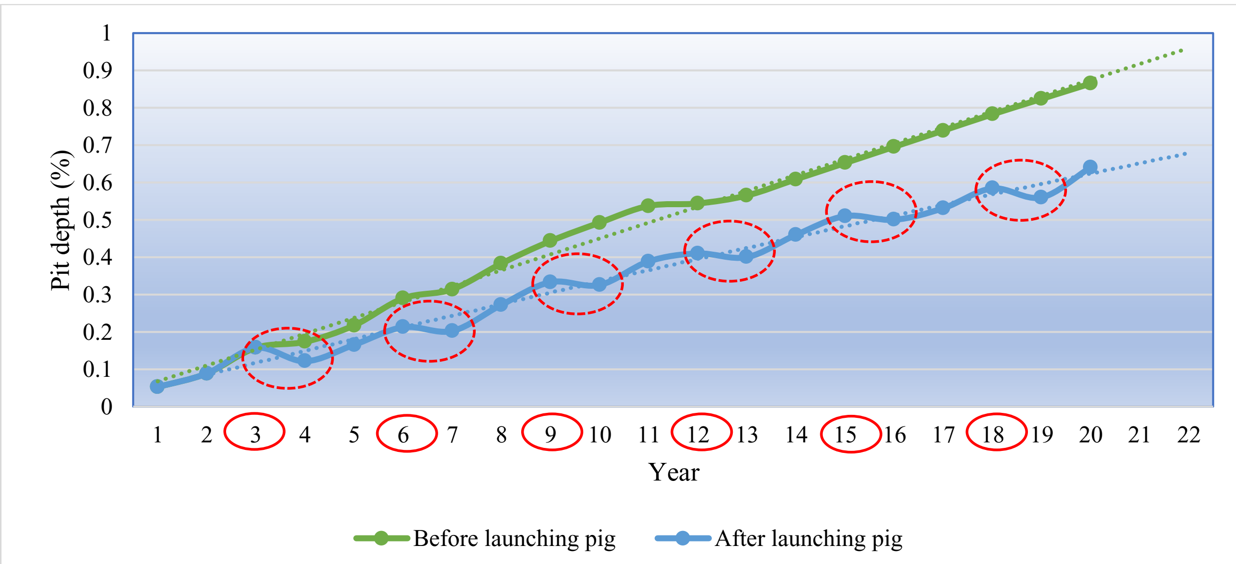


Figure 3.11. The efficiency of periodically launching pig within 3 years on the pit depth growth paths, with and without pigging

As a fourth practice, biological treatment is evaluated. The biological treatment is using a different type of bacteria against the primary bacteria responsible for MIC [80]. Several attempts have been made to use nitrate-reducing bacteria (NRB) fighting against SRB subsea industries. Two examples of methods for NRB against SRB are (i) bio-competitive exclusion and (ii) bio-augmentation. Nitrate induce the heterotrophic NRB (hNRB) sulfide-oxidizing NRB (SO-NRB) development as NRB. The hNRB fights against SRB to obtain a similar carbon variant. The SO-

NRB are autotrophs and do not compete for SRB for electrons' donation [92,93]. A study demonstrated that the practicability of persevering with NRB as a treatment for MIC mitigation can reduce the rate of MIC up to 40 % [94] in the presence of biocides and 50 % without the presence of biocides [95]. To estimate the pit depth growth path over a period, HBA within MCMC method is utilized. Figure 3.12 shows the efficiency of NRB with and without biocides on the pit depth growth path based on Equation 3.4.

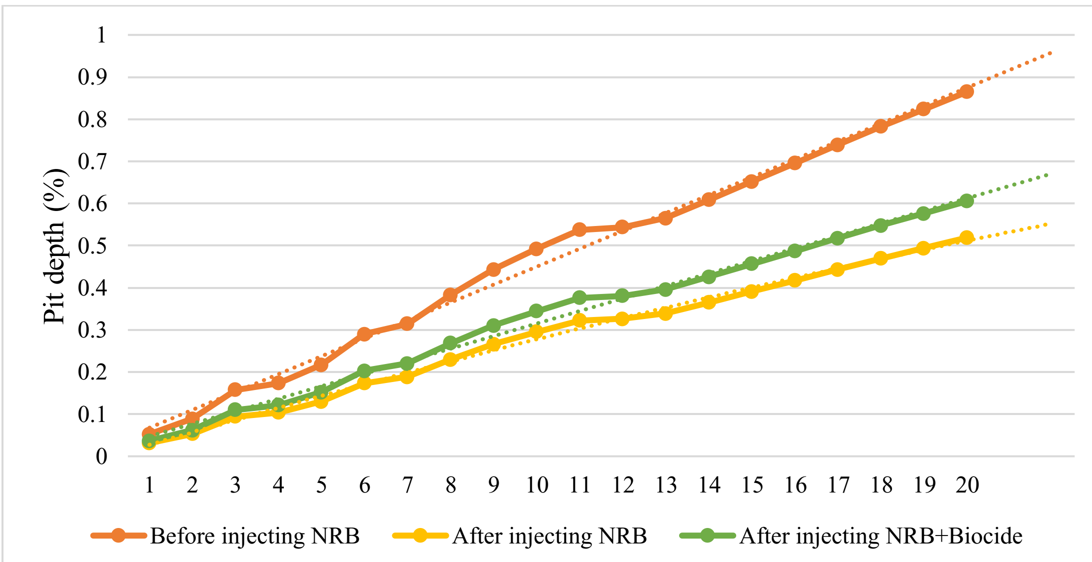


Figure 3.12. The efficiency of NRB with and without biocide on the pit depth growth path

As a fifth practice, manipulating operational parameters including pH, temperature, and fluid velocity are evaluated. In literature, scholars have made numerous efforts to determine the optimum pH value to reduce the rate of corrosion [96]. In a laboratory study, the rate of corrosion for carbon steel coupled with the influence of SRB have been studied [97]. The obtained results suggest that the value of pH=6.5 can highly influence the rate of corrosion because of the presence of sulfates within bacterial activities. Thus, the optimum value of pH is considered in the mechanistic model (Figure 3.6) to update the model. To estimate the pit depth growth path over a period, HBA within the MCMC method is utilized. Figure 3.13 shows the effect of the optimum value of pH on the pit depth growth path according to Equation 3.4. The parameter temperature also highly influences corrosion behavior. The pit depth growth path is a function of temperature and it can be concluded that it would increase with temperature. According to Melchers studies, the temperature in value of 17.5 has influenced the lowest rate of corrosion and further metal loss [98]. Thus, the optimum value of 17.5 is considered for the temperature in the mechanistic model (Figure 3.6) in order to update the model. To estimate the pit depth growth path over a period, HBA within the MCMC method is utilized. Figure 3.13 shows the effect of the optimum value of pH on the pit depth growth path according to Equation 3.4. The parameter velocity also has a high influence on corrosion behavior. The pit depth growth path is a function of velocity and Melchers reported that the velocity nonlinearly increases the rate of corrosion, [99]. The higher level of velocity increases the rate of corrosion. According to the study of Soares et al, [100], the minimum value velocity of 0.1 m/s has the maximum effect on the rate of corrosion in the marine environment, 0.12 mm/yr. Thus, to update the model, the optimum value of 0.1 m/s is considered for the velocity in the mechanistic model (Figure 3.6). To estimate the pit depth growth path over a period, HBA within the MCMC method is utilized. Figure 3.13 shows the effect of optimum value of pH on the pit depth growth path based on Equation 3.4.

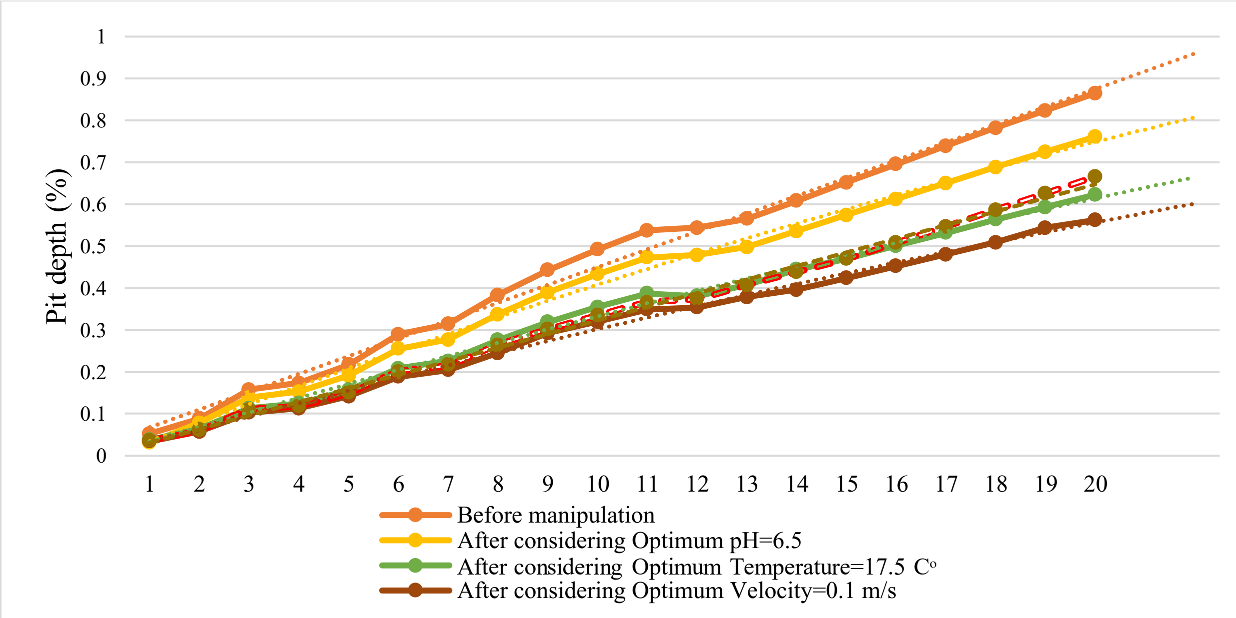


Figure 3.13. The efficiency of operational parameters' manipulation with and without manipulation operational parameters on the pit depth growth path

In the last practice, Replacement and Repair of the corroded pipeline are evaluated. It is considered that once the maximum pit depth growth path reaches 80 % of wall thickness, replacement methods (such as grouted clamp, coupling, sleeve, cladding, welding, *etc*) are required. To evaluate the replacement, as can be seen in Figure 3.14, three defects ($i = 1,2,3$) through the pipeline with the different indications of pit depth growth are considered. As can be seen, the replacement point of maximum pit depth would be in year 18. Replacement is done by using double block isolation tools installed locally on both sides of the defect having maximum depth and depressurizing the entire section of the pipeline to allow safe removal, and repair by installing a new pipeline section. After installing a new section, the defect having maximum pit depth has disappeared, and defect 2 will have maximum pit depth growth and is predicted to need a replacement at year 22. In addition, repair such as grouted clamp can be used instead of the replacement method. Assuming that, the grouted clamp can increase the thickness of the pipeline up to 50%, subsequently, pit depth growth will sharply decrease and defect 2 will have maximum pit depth growth. The pit depth growth considering the replacement and repair for defect 1 is depicted in Figure 3.15.

In step six of our proposed framework, the efficiency of all singular management practice as well as different combinations in several time slices are considered. Thus, the best management practice would be based on optimum operational parameters (pH, temperature, and velocity), injecting NRB and biocide into the system at the required dosage in addition to launching periodical pig in order for the pipeline to survive for 40 years. As can be seen in Figure 3.16, the period of launching pig increases to 5 years instead of 3 years as before, and the last pigging would be in year 30. In addition, if the pipeline still needs to be in operational condition, replacement and repair can be applied, and the second defect monitored within maximum pit depth growth.

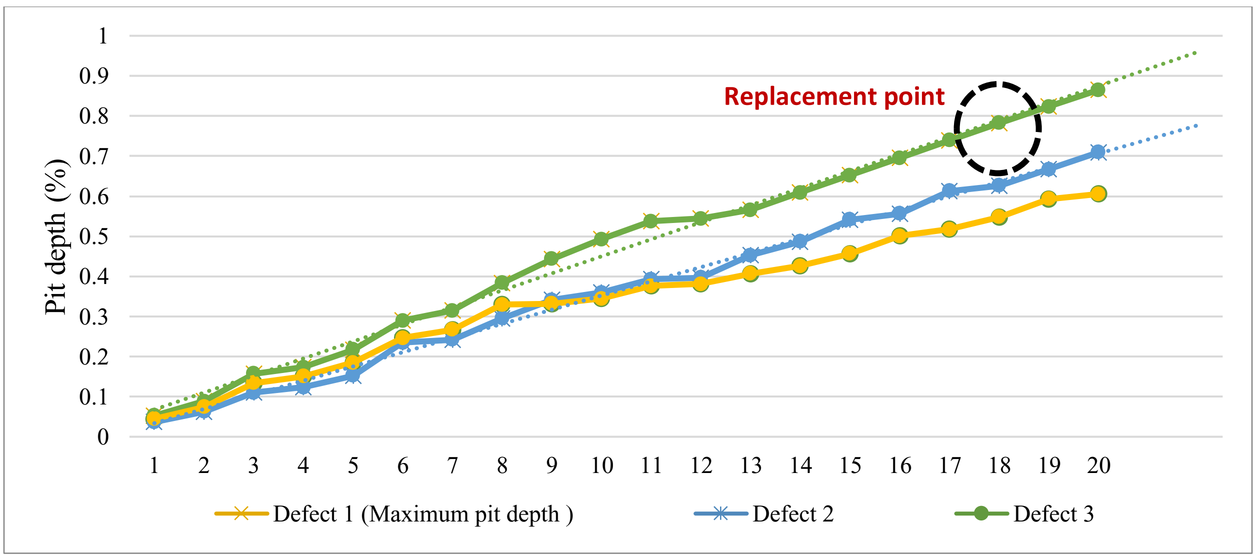


Figure 3.14. The pit depth growth of three different defects

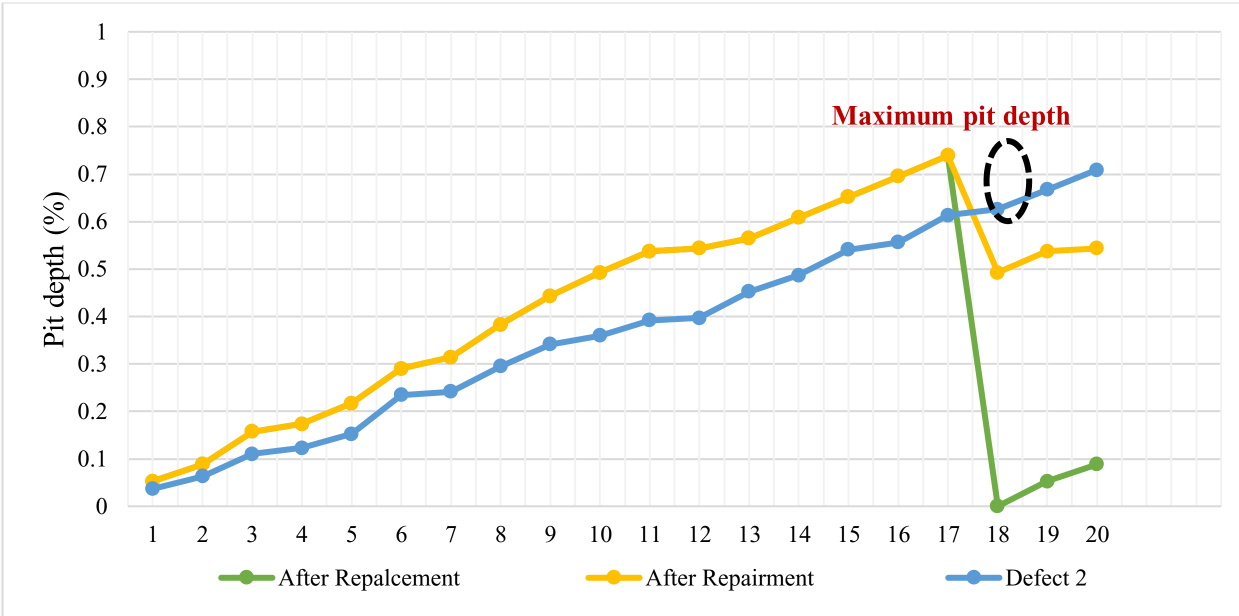


Figure 3.15. The pit depth growth considering the replacement and repair for defect 1

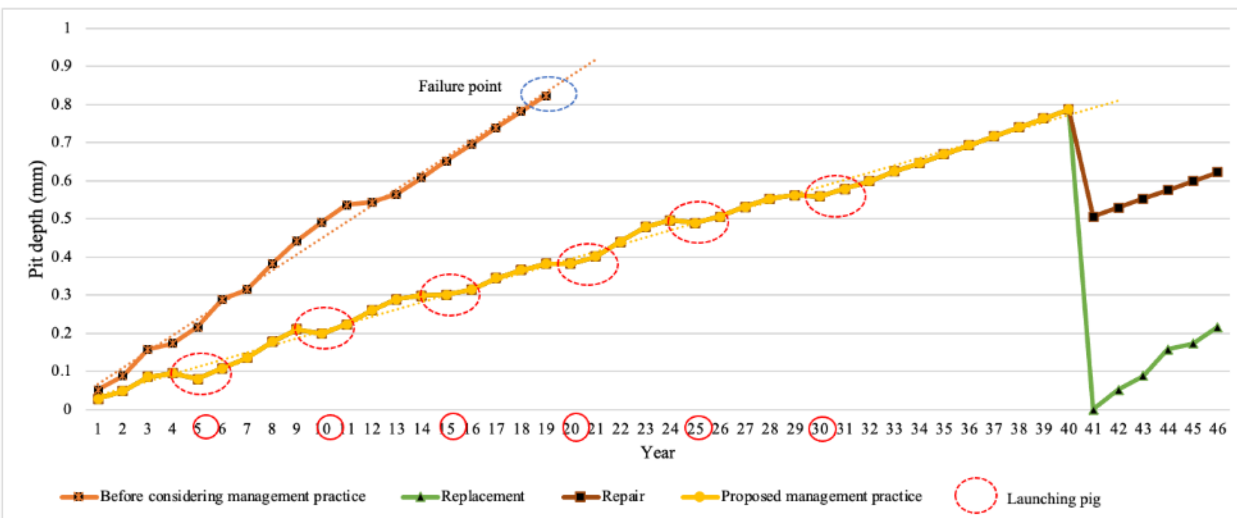


Figure 3.16. The proposed management practice for the defect within maximum pit depth growth

Up to this point, a management practice was proposed at the time of installation of the pipeline to be in an operational condition for at least 40 years. Subsequently, in-line inspection tools are assumed to be used to update the pit depth growth path over a period by input information into the MIC mechanistic model. Therefore, once the new information related to behavior of corrosion is collected, the pit depth growth path would be updated, and accordingly a management practice may be changed.

In the first case scenario, the in-line inspection tool is launched into the pipeline in year 3. Considering the measurement error of the in-line inspection tool [21,35], the actual pit depth of the defect is estimated (as an example 35 % wt), MIC rate (as an example 0.9 mm/yr), and biofilm thickness (High). As can be seen from Figure 3.17, using new data as input into HBA, the pipeline will fail by the end of year 7. This sharp increase in the pit depth growth may be the result of the breakdown of the internal coating. Considering injection of NRB and biocide are in a highly effective manner, immediate launching pigging can be utilized. According to this practice, the pipeline can operate for the extra few years. Observing the efficiency of pigging, it is continued annually until year 13, with the pipeline close to failure point. According to this point, repair and replacement methods have been applied in years 13 and 19, respectively. Thus, the pipeline will work under operational conditions for a longer time.

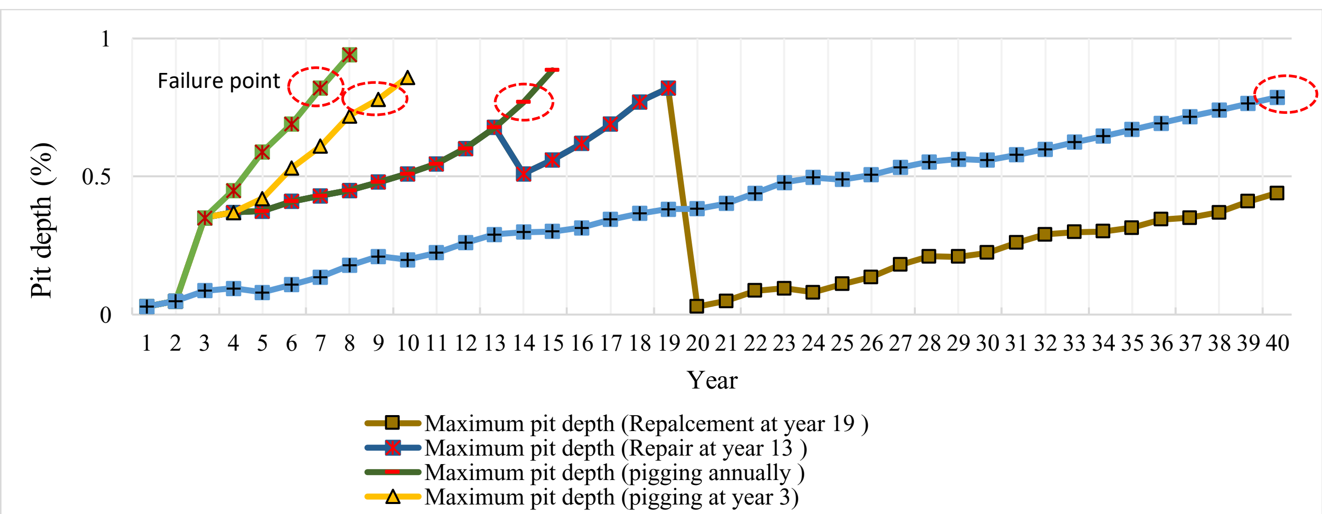


Figure 3.17. Changing management practice based on collected new information by in-line inspection tools

In the second scenario, following the previous scenario, another in-line inspection tool is launched in the pipeline in year 5. The actual pit depth of the defect is estimated (as an example 55% wt), MIC rate (as an example 1.6 mm/yr), and biofilm thickness (high). As can be seen from Figure 3.18, using new data as input into HBA, the pipeline will fail in the middle of year 6. According to the pit depth growth path, the proposed management practice seems to be ineffective. Therefore, the replacement of that area should be considered. After replacement, in year 6, the proposed management practice is continued.

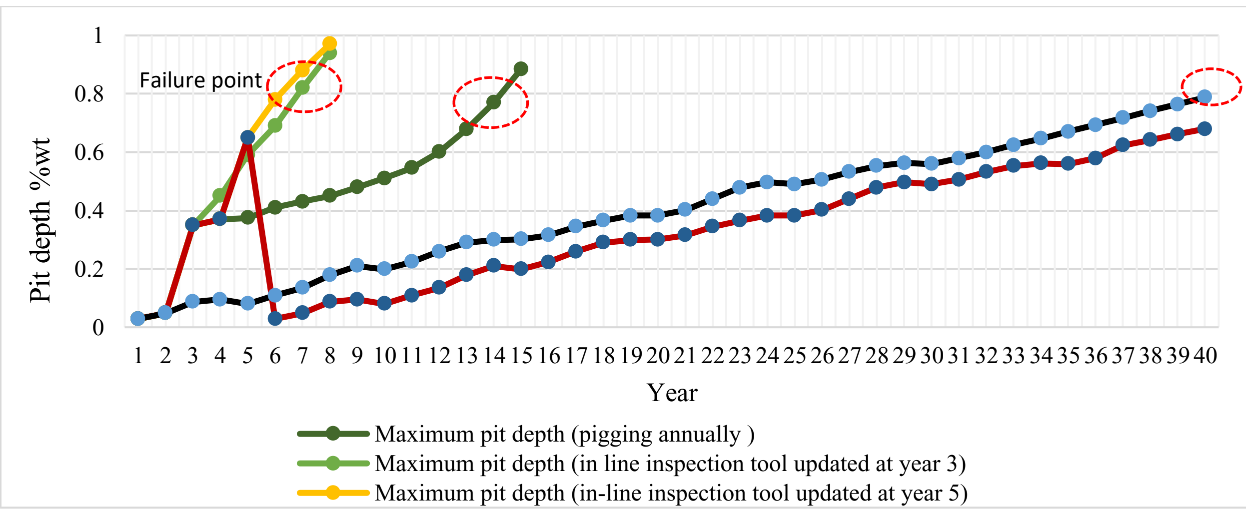


Figure 3.18. Changing management practice based collected new information by in-line inspection tools

3.4. Conclusions

This paper presents individual pit depth growth characterization using a Bayesian model. The pit depth growth of an active corrosion defect influenced by MIC was considered to observe a power-law path. The power-law function parameters are obtained using HBA based on the different effective operational and environmental factors, and material properties. The MCMC method was utilized to perform the Bayesian updating and statistical inferences of the model parameters.

The application of the proposed model was demonstrated in a subsea pipeline currently in service. The parameters of the pit depth growth model were developed for an internal corrosion defect influenced by MIC. The pit depth growth path for a period until reaching the failure point was estimated. Accordingly, different types of management practices to prevent, control, and mitigate MIC for the defect were proposed. The effectiveness of each management practice and the their combination were evaluated. Thus, the best and optimum management practice was selected.

Moreover, HBA can incorporate the value of the parameters that affect pit depth growth as distribution, which shows its effectiveness in dealing with data uncertainty compared with conventional methods. Considering the ability to update probability in CBN and dependency between the parameters, it can adequately deal with the traditional methods' limitation and reduce model uncertainty.

During the study however, some important challenges have arisen. These are necessary to mention and can be improved in further studies. Firstly, the growth of an individual internal defect is assumed to be influenced by MIC, while multiple defects' interactions need to be considered as much more practical. Second, there is a lack of information to understand corrosion growth behaviours under the combination of management practice. Thus, this requires further laboratory-based studies. Lastly, in the current study, the cost, which is an important factor for management strategies, is not considered. This can be regarded as a future research activity. In addition, to show the robustness of the proposed model, it needs to be validated once new information from pigging becomes available.

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References

[1] J.M.B. Technol, T. Gu, Microbial & Biochemical Technology New Understandings of Biocorrosion Mechanisms and their Classifications, J. Microb. Biochem. Technol. 4 (2012). https://doi.org/10.4172/1948-5948.1000e107.

[2] D. Xu, Y. Li, T. Gu, Bioelectrochemistry Mechanistic modeling of biocorrosion caused by bio fi lms of sulfate reducing bacteria and acid producing bacteria, Bioelectrochemistry. 110 (2016) 52–58.

[3] M. Taleb-Berrouane, F. Khan, K. Hawboldt, R. Eckert, T.L. Skovhus, Model for microbiologically influenced corrosion potential assessment for the oil and gas industry, Corros. Eng. Sci. Technol. 53 (2018) 378–392. https://doi.org/10.1080/1478422X.2018.1483221.

[4] T. Gu, R. Jia, T. Unsal, D. Xu, Journal of Materials Science & Technology Toward a better understanding of microbiologically influenced corrosion caused by sulfate reducing bacteria, J. Mater. Sci. Technol. 35 (2019) 631–636. https://doi.org/10.1016/j.jmst.2018.10.026.

[5] A. Ibrahim, K. Hawboldt, C. Bottaro, F. Khan, A. Ibrahim, K. Hawboldt, C. Bottaro, Review and analysis of microbiologically influenced corrosion: the chemical environment in oil and gas facilities environment in oil and gas facilities, Corros. Eng. Sci. Technol. 2782 (2018). https://doi.org/10.1080/1478422X.2018.1511326.

[6] D. Walsh, P. D, D. M, H. T, The effect of microstructure on microbiologically influenced corrosion, Phys. Metall. Corros. 45 (1993) 22–30. https://doi.org/10.1007/BF03222429.

[7] M. De Romero, Z. Duque, O. De Rinc, O. P, I. Araujo, A. Martinez, A.C.-N.A. B-, C. Uns, Online Monitoring Systems of Microbiologically Influenced Corrosion on Cu-10 % Ni Alloy in Chlorinated , Brackish Water, Corros. Eng. Sect. Online. 56 (2000) 867–876.

[8] A. Morshed, An Introduction to Asset Corrosion Management in the Upstream Offshore Industry, Houston, 2011.

[9] T.L. Skovhus, E.S. Andersen, E. Hillier, D.N. V Gl, Management of Microbiologically Influenced Corrosion in Risk-Based Inspection Analysis, in: Int. Oilf. Corros. Conf. Exhib., 2018: pp. 9–10.

[10] T. Lund, R.B. Eckert, E. Rodrigues, Management and control of microbiologically in fl uenced corrosion (MIC) in the oil and gas industry — Overview and a North Sea case study, 256 (2017) 31–45.

[11] T.L. Skovhus, V.I.A. Building, E.S. Andersen, Management of Microbiologically Influenced Corrosion in Risk Based Short introduction to MIC, Soc. Pet. Eng. (2016).

[12] ISO 31000: Risk Management, Int. Stand. Organ. (2009).

[13] R. Javaherdashti, K. Alasvand, Biological Treatment of Microbial Corrosion, Elsevier Inc, 2019. https://doi.org/10.1016/C2017-0-04219-2.

[14] S. Zhang, W. Zhou, Cost-based optimal maintenance decisions for corroding natural gas pipelines based on stochastic degradation models, Eng. Struct. 74 (2014) 74–85. https://doi.org/10.1016/j.engstruct.2014.05.018.

[15] W.J.S. Gomes, A.T. Beck, T. Haukaas, Optimal inspection planning for onshore pipelines subject to external corrosion, Reliab. Eng. Syst. Saf. 118 (2013) 18–27. https://doi.org/10.1016/j.ress.2013.04.011.

[16] W. Zhou, Optimal Design of Onshore Natural Gas Pipelines, J. Press. Vessel Technol. 133 (2011). https://doi.org/10.1115/1.4002496.

[17] W. Zhou, International Journal of Pressure Vessels and Piping System reliability of corroding pipelines, Int. J. Press. Vessel. Pip. 87 (2010) 587–595. https://doi.org/10.1016/j.ijpvp.2010.07.011.

[18] K. Zhao, S. Nesic, M. Technology, A NEW MECHANISTIC MODEL FOR MIC, NACE Int. (2009) 1–12.

[19] A.P. Teixeira, C.G. Soares, T.A. Netto, S.F. Estefen, Reliability of pipelines with corrosion defects, Int. J. Press. Vessel. Pip. 85. 85 (2008) 228–237. https://doi.org/10.1016/j.ijpvp.2007.09.002.

[20] W.J.S. Gomes, A.T. Beck, Optimal inspection and design of onshore pipelines under external corrosion process, Struct. Saf. 47 (2014) 48–58. https://doi.org/10.1016/j.strusafe.2013.11.001.

[21] S. Zhang, W. Zhou, M. Al-Amin, S. Kariyawasam, H. Wang, Time-Dependent Corrosion Growth Modeling Using Multiple In-Line Inspection Data, J. Press. Vessel Technol. 136 (2014) 1–7. https://doi.org/10.1115/1.4026798.

[22] M. Ahammed, Probabilistic estimation of remaining life of a pipeline in the presence of active corrosion defects, Int. J. Press. Vessel. Pip. 75 (1998) 321–329.

[23] M. Ahammed, R.E. Melchers, Reliability estimation of pressurised pipelines subject to localised corrosion defects, Int. J. Press. Vessel. Pip. 0161 (1996).

[24] J.M. Van Noortwijk, J.A.M. Van Der Weide, M.J. Kallen, M.D. Pandey, Gamma processes and peaks-over-threshold distributions for time-dependent reliability, Reliab. Eng. Syst. Saf. 92. 92 (2007) 1651–1658. https://doi.org/10.1016/j.ress.2006.11.003.

[25] J.M. Van Noortwijk, A survey of the application of gamma processes in maintenance, Reliab. Eng. Syst. Saf. 92. 94 (2009) 2–21. https://doi.org/10.1016/j.ress.2007.03.019.

[26] M.D. Pandey, X. Yuan, J.M. Van Noortwijk, The influence of temporal uncertainty of deterioration on life-cycle management of structures The influence of temporal uncertainty of deterioration on life-cycle management of structures, Reliab. Eng. Syst. Saf. 92. 2479 (2009). https://doi.org/10.1080/15732470601012154.

[27] M.A. Maes, M. Dann, Hierarchical Bayes methods for systems with spatially varying condition states, Can. J. Civ. Eng. 1298 (2007) 1289–1298. https://doi.org/10.1139/L07-049.

[28] A. Valor, F. Caleyo, Stochastic modeling of pitting corrosion : A new model for initiation and growth of multiple corrosion pits, Corros. Sci. 49 (2007) 559–579. https://doi.org/10.1016/j.corsci.2006.05.049.

[29] F. Caleyo, J.C. Velázquez, A. Valor, J.M. Hallen, Markov chain modelling of pitting corrosion in underground pipelines, Corros. Sci. 51 (2009) 2197–2207. https://doi.org/10.1016/j.corsci.2009.06.014.

[30] H.P. Hong, Application of the Stochastic Process to Pitting Corrosion, Corros. Sci. (1999) 10–16.

[31] W. Xiang, W. Zhou, CORROSION GROWTH MODELING BY LEARNING A DYNAMIC BAYESIAN, in: 12th Int. Pipeline Conf., Alberta, 2018: pp. 1–11. https://doi.org/IPC2018-78118.

[32] Y. Zhang, W.G. Weng, Bayesian network model for buried gas pipeline failure analysis caused by corrosion and external interference, Reliab. Eng. Syst. Saf. 203 (2020) 107089. https://doi.org/10.1016/j.ress.2020.107089.

[33] O.G. Palencia, A.P. Teixeira, C.G. Soares, Safety of Pipelines Subjected to Deterioration Processes Modeled Through Dynamic Bayesian Networks, Int. J. Press. Vessel. Pip. 141 (2019) 1–11. https://doi.org/10.1115/1.4040573.

[34] A.P. Teixeira, O.G. Palencia, C.G. Soares, Reliability Analysis of Pipelines With Local Corrosion Defects Under External Pressure, Int. J. Press. Vessel. Pip. 141 (2019) 1–10. https://doi.org/10.1115/1.4042384.

[35] M. Al-Amin, H. Wang, S. Zhang, S. Kariyawasam, Hierarchical Bayesian Corrosion Growth Model Based on In-Line Inspection Data, J. Press. Vessel Technol. 136 (2014) 1–8. https://doi.org/10.1115/1.4026579.

[36] H. Qin, W. Zhou, S. Zhang, Bayesian inferences of generation and growth of corrosion defects on energy pipelines based on imperfect inspection data, Reliab. Eng. Syst. Saf. 144 (2015) 334–342. https://doi.org/10.1016/j.ress.2015.08.007.

[37] K. Pesinis, K.F. Tee, Bayesian analysis of small probability incidents for corroding energy pipelines, Eng. Struct. 165 (2018) 264–277. https://doi.org/10.1016/j.engstruct.2018.03.038.

[38] K.M. Groth, A hybrid model of internal pitting corrosion degradation under changing operational conditions for pipeline integrity management, Struct. Heal. Monit. (2019). https://doi.org/10.1177/1475921719877656.

[39] G. Song, F. Khan, M. Yang, H. Wang, Predictive Abnormal Events Analysis Using Continuous Bayesian Network, ASCE-ASME J. Risk Uncertain. Eng. Syst. 3 (2017). https://doi.org/10.1115/1.4035438.

[40] S. Kabir, T.A.N.K.I.M. Geok, M. Kumar, M. Yazdi, F. Hossain, A Method for Temporal Fault Tree Analysis Using Intuitionistic Fuzzy Set and Expert Elicitation, IEEE Access. 8 (2020) 980–996. https://doi.org/10.1109/ACCESS.2019.2961953.

[41] N.U.I. Hossain, F. Nur, S. Hosseini, R. Jaradat, M. Marufuzzaman, S.M. Puryear, A Bayesian network based approach for modeling and assessing resilience: A case study of a full service deep water port, Reliab. Eng. Syst. Saf. 189 (2019) 378–396. https://doi.org/10.1016/j.ress.2019.04.037.

[42] N. Khakzad, F. Khan, P. Amyotte, Risk-based design of process systems using discrete-time Bayesian networks, Reliab. Eng. Syst. Saf. 109 (2013) 5–17. https://doi.org/10.1016/j.ress.2012.07.009.

[43] A. Misuri, N. Khakzad, G. Reniers, V. Cozzani, Tackling uncertainty in security assessment of critical infrastructures: Dempster-Shafer Theory vs. Credal Sets Theory, Saf. Sci. 107 (2018) 62–76. https://doi.org/10.1016/j.ssci.2018.04.007.

[44] S. Kabir, M. Yazdi, J.I. Aizpurua, Y. Papadopoulos, Uncertainty-Aware Dynamic Reliability Analysis Framework for Complex Systems, IEEE Access. 6 (2018) 29499–29515. https://doi.org/10.1109/ACCESS.2018.2843166.

[45] D.L. Kelly, C.L. Smith, Bayesian inference in probabilistic risk assessment-The current state of the art, Reliab. Eng. Syst. Saf. 94 (2009) 628–643. https://doi.org/10.1016/j.ress.2008.07.002.

[46] N. Khakzad, F. Khan, N. Paltrinieri, On the application of near accident data to risk analysis of major accidents, Reliab. Eng. Syst. Saf. 126 (2014) 116–125.

[47] M. Yang, F.I. Khan, L. Lye, Precursor-based hierarchical Bayesian approach for rare event frequency estimation : A case of oil spill accidents, Process Saf. Environ. Prot. 91 (2012) 333–342. https://doi.org/10.1016/j.psep.2012.07.006.

[48] N.O. Siu, D.L. Kelly, Bayesian parameter estimation in probabilistic risk assessment, Reliab. Eng. Syst. Saf. 0 (1998) 89–116.

[49] M. Abimbola, F. Khan, N. Khakzad, Risk-based safety analysis of well integrity operations, Saf. Sci. 84 (2016) 149–160. https://doi.org/10.1016/j.ssci.2015.12.009.

[50] A. Noroozi, N. Khakzad, F. Khan, S. Mackinnon, R. Abbassi, The role of human error in risk analysis: Application to pre- and post-maintenance procedures of process facilities, Reliab. Eng. Syst. Saf. 119 (2013) 251–258. https://doi.org/10.1016/j.ress.2013.06.038.

[51] E. Zarei, M. Yazdi, R. Abbassi, F. Khan, A hybrid model for human factor analysis in process accidents: FBN-HFACS, J. Loss Prev. Process Ind. (2019) 142–155. https://doi.org/10.1016/j.jlp.2018.11.015.

[52] E. Arzaghi, R. Abbassi, V. Garaniya, J. Binns, C. Chin, N. Khakzad, G. Reniers, Developing a dynamic model for pitting and corrosion-fatigue damage of subsea pipelines, Ocean Eng. 150 (2018) 391–396. https://doi.org/10.1016/j.oceaneng.2017.12.014.

[53] M. Yazdi, F. Khan, R. Abbassi, R. Rusli, Improved DEMATEL methodology for effective safety management decision- making, Saf. Sci. 127 (2020) 104705. https://doi.org/10.1016/j.ssci.2020.104705.

[54] A. Zinetullina, M. Yang, N. Khakzad, B. Golman, Dynamic resilience assessment for process units operating in Arctic environments, Saf. Extrem. Environ. (2019).

[55] K.A. Adesina, A. Nedjati, M. Yazdi, A Short communication Improving marine safety management system by addressing common safety program, Res. Mar. Sci. 5 (2020) 671–680.

[56] M. Taleb-Berrouane, F. Khan, P. Amyotte, Bayesian Stochastic Petri Nets (BSPN) - A new modelling tool for dynamic safety and reliability analysis, Reliab. Eng. Syst. Saf. 193 (2020) 106587. https://doi.org/https://doi.org/10.1016/j.ress.2019.106587.

[57] S. Adumene, F. Khan, S. Adedigba, Operational safety assessment of offshore pipeline with multiple MIC defects, Comput. Chem. Eng. (2020) 106819. https://doi.org/10.1016/j.compchemeng.2020.106819.

[58] N. Xia, P.X.W. Zou, X. Liu, X. Wang, R. Zhu, A hybrid BN-HFACS model for predicting safety performance in construction projects, Saf. Sci. 101 (2018) 332–343. https://doi.org/10.1016/j.ssci.2017.09.025.

[59] J. Bhandari, R. Abbassi, V. Garaniya, F. Khan, Risk analysis of deepwater drilling operations using Bayesian network, J. Loss Prev. Process Ind. 38 (2015) 11–23. https://doi.org/10.1016/J.JLP.2015.08.004.

[60] S. Adumene, S. Adedigba, F. Khan, S. Zendehboudi, An integrated dynamic failure assessment model for offshore components under microbiologically influenced corrosion, Ocean Eng. 218 (2020) 108082. https://doi.org/10.1016/j.oceaneng.2020.108082.

[61] S. Adumene, F. Khan, S. Adedigba, S. Zendehboudi, H. Shiri, Dynamic risk analysis of marine and offshore systems suffering microbial induced stochastic degradation, Reliab. Eng. Syst. Saf. 207 (2020) 107388. https://doi.org/10.1016/j.ress.2020.107388.

[62] M. Yazdi, S. Kabir, M. Walker, Uncertainty handling in fault tree based risk assessment: State of the art and future perspectives, Process Saf. Environ. Prot. 131 (2019) 89–104. https://doi.org/10.1016/j.psep.2019.09.003.

[63] E. Zarei, F. Khan, M. Yazdi, A dynamic risk model to analyze hydrogen infrastructure, Int. J. Hydrogen Energy. 46 (2021) 4626–4643. https://doi.org/https://doi.org/10.1016/j.ijhydene.2020.10.191.

[64] W.R. Gilks, Markov Chain Monte Carlo in Practice, Chapman & Hall, London, 1996. https://doi.org/10.1007/978-1-4899-4485-6.

[65] S. Banerjee, B.P. Carlin, A.E. Gelfand, Hierarchical Modeling and Analysis for Spatial Data, Chapman & Hall/CRC, New York, 2014.

[66] C.P. Robert, The Bayesian Choice: From Decision-Theoretic Foundations to Computational Implementation, Springe, New York, 2007.

[67] F. Demichelis, P. Magni, P. Piergiorgi, M.A. Rubin, R. Bellazzi, A hierarchical Naïve Bayes Model for handling sample heterogeneity in classification problems : an application to tissue microarrays, BMC Bioinformatics. 12 (2006) 1–12. https://doi.org/10.1186/1471-2105-7-514.

[68] N.E. Fenton, M. (Martin D.. Neil, Risk assessment and decision analysis with Bayesian networks, 2013.

[69] M. El-gheriani, F. Khan, D. Chen, R. Abbassi, Major accident modelling using spare data, Process Saf. Environ. Prot. 6 (2016) 52–59. https://doi.org/10.1016/j.psep.2016.12.004.

[70] M. El-Gheriani, F. Khan, M.J. Zuo, Rare event analysis considering data and model uncertainty, ASCE-ASME J. Risk Uncertain. Eng. Syst. Part B Mech. Eng. 3 (2017). https://doi.org/10.1115/1.4036155.

[71] N. Khakzad, S. Khakzad, F. Khan, Probabilistic risk assessment of major accidents : application to offshore blowouts in the Gulf of Mexico, Nat Hazards. (2014) 1759–1771. https://doi.org/10.1007/s11069-014-1271-8.

[72] P.D. Congdon, Applied Bayesian Hierarchical Methods, CRC Press, 2020.

[73] I. Ntzoufras, Bayesian Modeling Using WinBUGS, John Wiley & Sons, 2011.

[74] A. Saltelli, Sensitivity analysis for importance assessment, in: Risk Anal., John Wiley & Sons, Ltd, 2002: pp. 579–590. https://doi.org/10.1111/0272-4332.00040.

[75] A. Saltelli, M. Ratto, T. Andres, F. Campolongo, J. Cariboni, D. Gatelli, M. Saisana, S. Tarantola, Global Sensitivity Analysis. The Primer, 2008. https://doi.org/10.1002/9780470725184.

[76] D. Dubois, Representation, propagation, and decision issues in risk analysis under incomplete probabilistic information: Commentary, Risk Anal. 30 (2010) 361–368. https://doi.org/10.1111/j.1539-6924.2010.01359.x.

[77] U. Bhardwaj, A.. Teixeira, C. Guedes Soares, Uncertainty in reliability of thick high strength pipelines with corrosion defects subjected to internal pressure, Int. J. Press. Vessel. Pip. 188 (2020) 104170. https://doi.org/10.1016/j.ijpvp.2020.104170.

[78] U. Bhardwaj, A.P. Teixeira, C.G. Soares, Reliability assessment of a subsea pipe-in-pipe system for major failure modes, Int. J. Press. Vessel. Pip. 188 (2020) 104177. https://doi.org/10.1016/j.ijpvp.2020.104177.

[79] A.-W. Dawuda, M. Taleb-berrouane, F. Khan, A probabilistic model to estimate microbiologically influenced corrosion rate, Process Saf. Environ. Prot. 148 (2021) 908–926. https://doi.org/https://doi.org/10.1016/j.psep.2021.02.006.

[80] R. Javaherdashti, K. Alasvand, Biological Treatment of Microbial Corrosion Opportunities and Challenges, Elsevier Inc, 2019. https://doi.org/10.1016/C2017-0-04219-2.

[81] T.L. Skovhus, D. Enning, J.S. Lee, Microbiologically Influenced Corrosion in the Upstream Oil and Gas Industry, Taylor & Francis, 2017.

[82] E.M. Orazem, Underground pipeline corrosion, Detection, analysis and prevention, Elsevier, Woodhead Publishing, 2014.

[83] B. Chugh, S. Thakur, A.K. Singh, Microbiologically Influenced Corrosion Inhibition in Oil and Gas Industry, Corros. Inhib. Oil Gas Ind. (2020) 321–338. https://doi.org/10.1002/9783527822140.ch13.

[84] J. Sonke, W.D. Grimes, Guideline for corrosion inhibitor selection for oil and gas production – Part 2: Corrosion inhibition performance validation, in: NACE Corros., NACE International, 2017. https://doi.org/Paper no. 178842.

[85] J. Sonke, W.D. Grimes, Guidelines for corrosion inhibitor selection for oil and gas production – Part 1: Corrosion inhibition management, in: EuroCorr, NACE International, 2016.

[86] Y. Bai, Q. Bai, Subsea Engineering Handbook, 2010.

[87] NACE, Selection, Application, and Evaluation of Biocides in the Oil and Gas Industry, Houston, 2006. https://doi.org/TR 31205.

[88] C.W.S. Cheung, I.B. Beech, The use of biocides to control sulphate-reducing bacteria in biofilms on mild steel surfaces, Biofouling. 9 (1996) 231–249. https://doi.org/10.1080/08927019609378305.

[89] J.L. Dawson, Chemical treating in oil and gas production, Shreir’s Corros. (2010) 2900–2929. https://doi.org/10.1016/B978-044452787-5.00160-8.

[90] R. Javaherdashti, How is MIC treated, in: Microbiol. Influ. Corros. An Eng. Insight, Springer, London, 2008.

[91] J. Mand, J. Longwell, D. Enning, Observations on the Effect of Simulated Pigging and Corrosion Inhibitor Exposure on Microbiologically Influenced Corrosion of Carbon Steel, in: NACE Int., Houston, 2019. https://doi.org/Paper No. 13103.

[92] M. Nemati, T.J. Mazutinec, G.E. Jenneman, G. Voordouw, Control of biogenic H2S production with nitrite and molybdate., J. Ind. Microbiol. Biotechnol. 26 (2001) 350–355.

[93] T.J. DiChristina, Effects of nitrate and nitrite on dissimilatory iron reduction by Shewanella putrefaciens 200, J. Bacteriol. (1994) 1891–1896. https://doi.org/10.1128/jb.174.6.1891-1896.

[94] G. Bødtker, T. Thorstenson, B.L.P. Lillebø, B.E. Thorbjørnsen, R.H. Ulvøen, E. Sunde, T. Torsvik, The effect of long-term nitrate treatment on SRB activity, corrosion rate and bacterial community composition in offshore water injection systems, J. Ind. Microbiol. Biotechnol. 35 (2008) 1625–1636. https://doi.org/10.1007/s10295-008-0406-x.

[95] E. Sunde, G. Bodtker, B.-L.. Lillebo, T. Thorstenson, H2S inhibition by nitrate injection on the Gullfaks field, in: NACE Int., New Orleans, 2004.

[96] R. Javaherdashti, A review of some characteristics of MIC caused by sulfate-reducing bacteria: past, present and future, Anti-Corrosion Methods Mater. 46 (1999) 173–180. https://doi.org/10.1108/00035599910273142.

[97] M. Ismail, N.M. Noor, N. Yahaya, A. Abdullah, R.M. Rasol, A.S.A. Rashid, Effect of pH and Temperature on Corrosion of Steel Subject to Sulphate-reducing Bacteria, J. Environ. Sci. Technol. (2014) 209–217. https://doi.org/https://scialert.net/fulltext/?doi=jest.2014.209.217.

[98] R.E. Melchers, Pitting Corrosion in Marine Environments: A Review, University of Newcastle, 1994.

[99] R.E. Melchers, Pitting Corrosion of Mild Steel in Marine Immersion Environment—Part 2: Variability of Maximum Pit Depth, CORROSION. 60 (2004) 937–944. https://doi.org/10.5006/1.3287827.

[100] C.. Soares, Y. Garbatov, A. Zayed, Effect of environmental factors on steel plate corrosion under marine immersion conditions, Corros. Eng. Sci. Technol. 46 (2011) 524–541. https://doi.org/10.1179/147842209X12559428167841.

Chapter 4

Operational Subsea pipeline Assessment Affected by Multiple Defects of Microbiologically Influenced Corrosion

Preface

A version of this chapter has been published in the ***Process Safety and Environmental Protection, 2022; 158: 159-171****. I am the primary author along with the Co-authors, Faisal Khan, and Rouzbeh Abbassi. I developed the conceptual framework for the operational subsea pipeline assessment model and carried out the literature review. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' feedbacks. Co-author Faisal Khan helped in the concept development and testing the model, reviewing, and revising the manuscript. Co-author Rouzbeh Abbassi provided support in implementing the concept and testing the model. The co-authors also contributed to the review and revision of the manuscript.*

Abstract

This paper presents a systematic approach to evaluate the time interval of optimal maintenance strategy for the subsea process system influenced by Microbiological Influenced Corrosion (MIC) within multiple defects. The proposed method incorporates the non-homogeneous Poisson, homogeneous gamma, and non-homogeneous Markov processes for modeling the generation of multiple defects, the average pit depth growth, and maximum pit depth, respectively. The maintenance strategy comprises industrial procedure, probability of failure detection, errors sizing in-line inspection tools, management actions costs, and failure cost. The developed framework

simulates maintenance strategies considering time interval, cost, probability of detection, average pit depth, and maximum pit depth and identifies the optimal strategy. The practical application is demonstrated in a North Sea subsea pipeline system under MIC's influence. This work assists decision-makers in selecting the optimal conditioned-based maintenance strategy for the processing system. While the application is demonstrated to subsea process systems under MIC influence, the developed approach is equally applicable to other process systems.

Keywords: MIC management; reliability-based maintenance; multiple defects; Markov process; Condition Modelling

4.1. Introduction

The marine environment is one of the significant challenges of engineering infrastructures, which increase the risk of metal degradation. The two biotic and abiotic factors influence metal degradation depending on operational and environmental conditions [1–4]. The bacteria, fungi, and algae as abiotic factors play a significant role in metal degradation in offshore industrial sectors, e.g., pipeline corrosion [5–15], and souring of the reservoir [16]. Thus, facing a catastrophic accident resulting from microbial-influenced degradation by impacting asset losses, environmental pollution, and the system's reputation indicates that there is still a necessity for more attempts to manage offshore integrity. The microbial-influenced corrosion (MIC) is stochastic and uncertain; therefore, MIC propagation and formation are complicated by considering multispecies biofilm architecture [17–25]. Due to limited and insufficient understanding of MIC stochastic behavior, this may result in risky improper decisions made by onsite decision-makers.

There are several models for MIC risk assessment in the existing literature and a limited number of MIC management. As an example, in the case of MIC risk assessment, Melchers et al. studied the MIC assessment, including studying (i) the corrosion of mooring chain under the influence of

MIC [26], (ii) MIC loss and pit depth growth path on the carbon steel coupons considering the similar operational parameters [27], (iii) the corrosion of floating storage and offloading unit mooring systems under the influence of MIC [28], (iv) MIC of steel water injection pipelines at the six o'clock position using extreme value distributions [29], (v) MIC of offshore water injection pipelines by assessing the service lifetime [30]. Adumene et al. (2020a) [31] proposed an integrated dynamic failure assessment model for subsea systems under the influence of MIC. In this work, a combination of Bayesian Network (BN) and Markov chain is utilized to predict the rate of MIC and failure probability of the system. In another study, Adumene et al. (2020c) [32] integrated the dynamic Bayesian network (DBN) with loss aggregation tools to estimate the risk of MIC. Additionally, in the case of MIC risk management, Torben Lund Skovhus et al. (2017) [33] reviewed the MIC management on North Sea case studies. In the study, the authors proposed three step-based approaches based on biotic and abiotic MIC mechanisms, including assessment, mitigation, and monitoring. Salgar-Chaparro et al. (2020) [34] introduced a MIC management approach based on nutrient-level biocide treatment, which determines biofilm characteristics. Eckert and Skovhus (2018) [35] proposed the three core activities of the corrosion management process as (i) assessing threats, (ii) identifying barriers, and (iii) measuring the effectiveness. In another study, Wang and Melchers (2017b) [36] studied Nitrate addition into the system by managing bacterial H_2S production oil reservoirs, which further help in pipeline integrity management.

Reviewing the advanced methods to improve the corrosion risk-based models and other similar application domains, they fall into two categories which use probabilistic-based models, including Markov, Petri nets, Bayesian belief network (BBN) [37–40], Monte Carlo simulation, Markov Chain Monte Carlo (MCMC) [41–45], and fuzzy-based models such as fuzzy experts system and fuzzy inference [46–51]. For example, using DBN, Arzaghi et al. (2018) [51] developed a dynamic damage model for fatigue and pitting corrosion of offshore facilities. In another study, Arzaghi et al. (2017) [52] developed a risk-based maintenance technique applicable to the subsea pipelines considering fatigue corrosion using BN. Singh and Pokhrel (2018) [53] introduced a fuzzy logic-based methodology to predict the MIC rate of carbon steel systems (i.e., pipelines and pressure vessels). Considering all the advantages of proposed models in the literature to deal with stochastic behavior of different corrosion types, MIC management is still a challenging task in practice. It should be noted that MIC creates multiple defects through the pipeline in realistic cases. However, most of the attempts performed by scholars mainly focused on estimating a single maximum pit depth growth path. The multiple defects in a specific area can interact with each other, and multispecies biofilms architecture has a high impact on multiple defects interactions. Therefore, MIC management practices should be performed with consideration of MIC multiple defects. Adumene et al. (2020b) [54] developed a stochastic-based formulation model to estimate MIC rate and obtain the remaining strength and safe operating pressure with multiple MIC defects. A combination of BN and Markov Mixture (MM) was utilized for this purpose. Shekari et al. (2017) [55] proposed a framework to predict pit depth growth on equipment under insulation in offshore sectors. The average pit density referring to the multiple defects using the Markov process is obtained. In other studies, Adumene et al. (2021) [56] proposed a methodology to integrate the Bayesian Network with Copula-based Monte Carlo (BN-CMC) simulation. The BN captures the dynamic interactions among physio-chemical parameters and microbes to predict the corrosion rate of an offshore system. The random corrosion parameters dependencies and the failure modes that define the performance functions under microbial corrosion are modeled using CMC. Adumene et al. (2021b) [57] presented a framework to combine a "semi-empirical corrosion model" with a probabilistic steel structural failure behavior assessment considering the material and parametric uncertainties. The semi-empirical models are used to assess the asset's susceptibility, system degradation rate, and defect growth overtime under a harsh corrosive environment. A limited number of studies have been worked on reliability-based approaches considering multiple defects assets such as, but not limited to, [58,59]. However, to the best of our understanding, there has been no study to propose a model for corrosion management within multiple defects. Therefore, there is still room to make more attempts to model MIC maintenance management induced multiple defects asset.

The critical contribution of the present study is in proposing an approach for scheduling conditioned-based maintenance management actions considering multiple defects caused by MIC (MIC-based defects) through the pipeline. In addition, another contribution is to use a combination of three stochastic tools such as non-homogeneous Poisson process, homogeneous gamma process, and non-homogeneous Markov process to appropriately deal with the stochastic behavior of multiple defects in nature. The third contribution is developing new reliability and cost functions for maintaining pipelines under the influence of MIC.

The rest of the paper is prepared as follows. In Section 2, a framework is developed to estimate the average pit depth growth path from multiple defects, maximum pit depth, and the corresponding total management cost rate by time. Section 3 describes the application of the proposed methodology with a case study as well as presenting results. In Section 4, the discussion is provided to put the results into context. In Section 4, the conclusion, including recent work challenges and a direction for future research, is discussed.

4.2. The proposed methodology

It is vital to accurately predict the pit depth growth path in the early stage of the subsea pipeline under the influence of multiple MIC defects to help decision-makers provide reliable condition-based management actions(s) and preventing/controlling the failure occurrence. Therefore, it is essential to propose a framework to predict the pit depth growth for multiple defect paths over time. Due to the lack of information from in-line inspection tools, the estimation process is challenging for decision-makers. Therefore, stochastic tools should be employed to estimate pit depth growth paths and obtain reliable condition-based management actions(s). The main objective of this work is to develop a framework to capture the stochastic nature of MIC multiple defects and the safety management of the corroded subsea pipeline. Therefore, a model can provide a more robust tool for risk assessment, evaluation, and management of offshore systems under complex features such as multiple defects and biofilm architecture. As shown in Figure 4.1, three steps methodology is proposed to manage the subsea pipeline under multiple defects. This framework enables decision-makers to obtain acceptable management actions by a trade-off between the efficiency of management actions and the corresponding cost.

In step one, the unique elements of MIC that are taken into account and modeled in the introduced corrosion prediction model are as the following (i) modeling the generation of new defects, (ii) modeling the pit depth growth path, and (iii) modeling the pit density and maximum pit depth. In step two, the limit state function based on pipeline thickness is defined. Finally, as maintenance decisions, the optimum condition-based management actions are obtained by defining the management actions' performance policy and evaluating the expected cost of the management actions. The descriptions of every single step in the developed methodology are presented as follows.

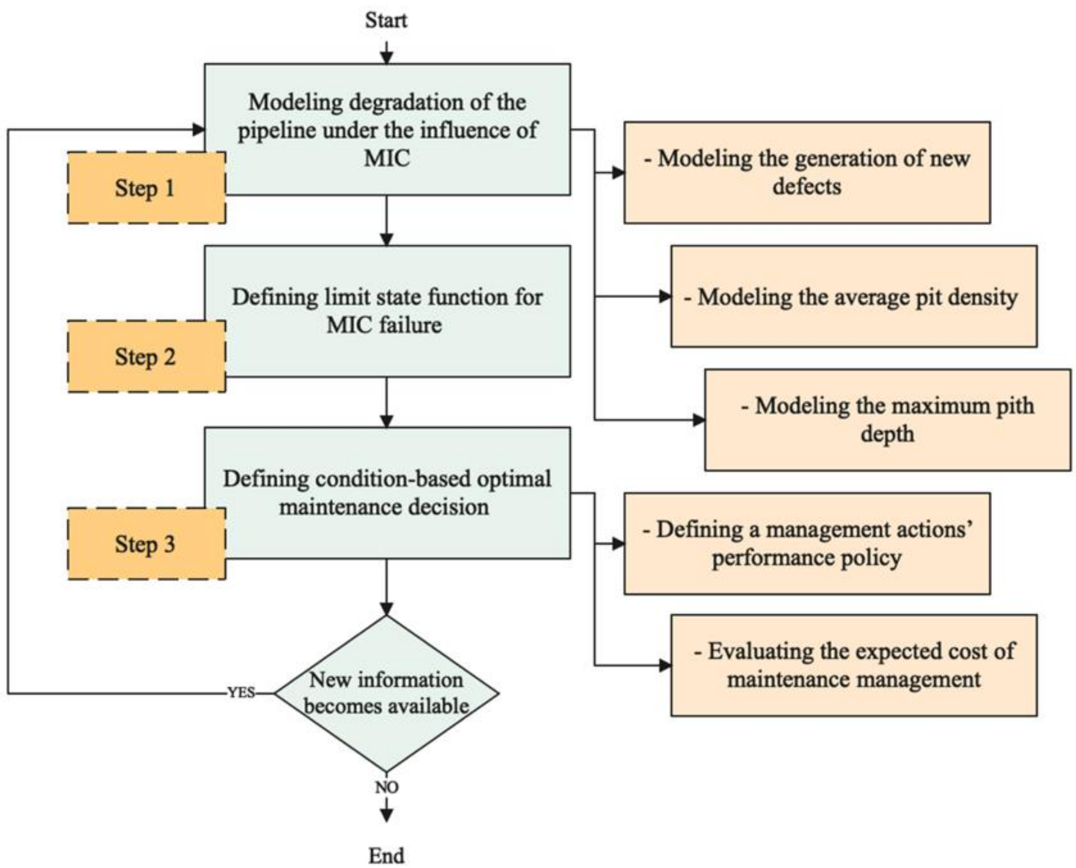

Figure 4.1. The developed framework to obtain conditioned-based MIC management actions

Step one: Modeling degradation of the pipeline under the influence of MIC

In this step, three tasks, (i) modeling the generation of new defects, (ii) modeling the average pit density, and (iii) modeling the pit depth growth path and maximum pit depth, are explained.

(i) Modeling the generation of new defects

In order to generate new defects, consideration should be made to the defects that are not generated uniformly by time and should be random. Thus, in this study, the non-homogenous Poisson process is utilized for modeling the generation of new defects [60]. Let us assume that, $\mathcal{N}(t)$ shows that the total number of defects and $\mathcal{N}(t)$ is generated between zero and 1. The time $t = 0$ stands for the pipeline's installation time, and time $t = 1$ is indicating that the last year of assessment. The total number of defects in the time interval [0,1] is following a Poisson distribution having a PMF $\mathcal{F}_P\,(\mathcal{N}(t)|\,\nabla(t))$ and is defined by Equation (4.1):

$$\mathcal{F}_P\big(\mathcal{N}(t)\big|\nabla(t)\big) = \frac{\nabla(t)^{\,\mathcal{N}(t)}e^{-\nabla(t)}}{\mathcal{N}(t)!} \quad \text{for } t > 0 \tag{4.1}$$

The abovementioned Equation, $\nabla(t)$ shows the expected number of defects, which are generated in the interval $[0\,,t]$, and $\nabla(t) = \int_0^t \lambda(\tau)d\tau$, in which $\lambda(\tau)$ is taken into account as intensity function (i.e., it can be named instantaneous generation rate). As an example, it can be considered that $\lambda(\tau) = \lambda_0\,\tau^{\,a}$, where λ_0 and a are positive values and can be obtained according to the objective data or subjectively from experts. If we consider $a = 0$, Equation (4.1) is shortened to the homogenous Poisson process. It simply means that the intensity function would be time-independent and constant. In this work, the quantification of pit locations in time, space, and pit spatially dependency is not considered to simplify model defect generation.

Three examples considering $\lambda_0 = 1, 2, and$ 3 and the exponent a is assumed to be 1 (i.e., $\nabla(t) = \frac{\lambda_0\tau^2}{2}$) are simulated with MATLAB (R2020b). The results are then connected with the expected values of 2.5 and 97.5 percentile. There would be a relatively narrow confidence interval for the number of defects in the subsea pipeline. In some cases, with the availability of inspection results over time, using the Poisson process might not suit the generation of new defects. Those Processes with higher variance to mean ratios may provide better reflection to generate new defects.

The initiation times for all single n defects can be signified as T_1 , T_2 , … T_n ($T_1 < T_2 < \cdots < T_n < T$) in the exact accordance. The joint PDF (probability density function) of (T_1, T_2 , … T_n), conditioned on $\mathcal{N}(t) = n$ can be expressed by adopting Equation 4.2.

$$\mathcal{F}_{T_1\,,\,T_2\,,\ldots\,T_n|\,\mathcal{N}(t)}(T_1, T_2\,, \ldots T_n|\, n) = \frac{n!\prod_{i=1}^{n} \lambda\,(t_i)}{(\nabla(t))^{\,n}} \quad (0 < t_1 < t_2 < \cdots < t_n \le T) \tag{4.2}$$

For comparison purposes, the HPP (homogeneous Poisson process) where $a = 0$ in the instantaneous generation rate, Equation (4.2) updated into $\frac{n!}{\mathrm{t}^n}$ [60]. This shows that the joint probability density function of the initiation times for homogeneous Poisson process conditioned on $\mathcal{N}(T) = n$ is equivalent to the joint PDF of the statistics ordering samples $(\mathrm{i.e.}, R1, R2, \ldots., Rn)$, where $R1\,, R2\,, \ldots., Rn$ are the n identically distributed and independent and the random variables, which are entirely uniformly distributed in the time interval $[0\,, T]$. The remarks mentioned above for homogeneous Poisson process can be generalized to non-homogeneous Poisson process, R $(i\ = 1\,, 2\,, \ldots., n)$ as the following equation:

$$P(\,R_i \le t) = \frac{\nabla\,(t)}{\nabla\,(T)} \quad (0 \le t \le T) \tag{4.3}$$

where $P(\,R_{\,i} \le t)$ is the independent and identically distributed random variables.

Let us assume that the expected service life of the pipeline is T, τ $(\tau = 1\,, 2\,, 3\,, \ldots, T)$ is standing for a single year T, n_T indicates the total number of defects, which are generated by time T. The problem is coded in MATLAB to induce the new defects and their initiation time.

It should be highlighted that a couple of previous studies particularly consider the interaction between the defects according to the different interaction rules such as, but not limited to [54]. Therefore, the present work focuses on n independent multiple defects by utilizing average pit density, explained in the next step.

(ii) Modeling the average pit density

The average pit density stands for the number of pits per unit area of the metal surface in the present study. The average pit density $\overline{ad}(t)$ is estimated from the average number of predicted pits in the pipeline area. A review study was conducted by Shekari et al. (2017), and in the present work, the equations provided by Shekari have been used.

In this case, a combination of exponential and power models is utilized in this study to obtain the average pit depth density [61], as explained by adopting Equation 4.4.

$$\overline{ad}(t) = \frac{\mathrm{A}}{\psi}\left[1 - e^{-\psi t}\right] + wt^{\eta} \tag{4.4}$$

from equation (4.4), there are four parameters - A , w , ψ , and η in the $\overline{ad}(t)$ model. Equation (4.4) has enough flexibility to deal with MIC pits' complex and uncertain behaviors. Additionally, the distribution of pit density is assumed to follow a homogeneous gamma process. Furthermore, the distribution of pit density at time t, which is $\overline{ad}(t)$, is pursuing a gamma distribution with the probability density function, $f_G(\,\overline{ad}(t))|\,\alpha(t - t_0)\,,\beta)$, is given by the following equation:

$$\mathcal{F}_G\left(\,\overline{ad}(t)\middle|\,\alpha(t - t_0)\,,\beta\right) = \frac{\beta^{\,\alpha\,(t - t_0)}\,\overline{ad}(t)^{\,\alpha\,(t - t_0) - 1}e^{-\,\overline{ad}(t)\beta}}{\Gamma\left(\alpha\,(t - t_0)\right)\,(I_{\,0\,,\infty}(\,\overline{ad}(t)))} \tag{4.5}$$

where $\overline{ad}_n = \int_{t2}^{t1} \frac{\mathrm{A}}{\psi}\left[1 - e^{\,-\psi t}\right] + w\eta t^{\,\eta - 1}\,dt$,

(iii) Modeling the maximum pith depth

In this study, the maximum pit depth at time t is denoted as d_{Max}, characterized by a non-homogeneous Markov process, where $t = 0$ means pipeline's installation time [61,62]. Markov process has been widely used previously to estimate the pit depth such as [63], and in all, it is assumed that the pit depth growth path would be determined in the varieties of time slices (i.e., intervals). In addition, the pit depth growth path for the following years only depends on the pit depth at the current time [64]. Another assumption is that the initiation and growth of pits are independent. The dependency between the pits can only be considered once the reactions occur in a single pit, and this depends on the area of pits and what is taking place in that area [64]. Figure 4.2 illustrates the visual exemplification of the Markov states processing in simple cylindrical-based assets.

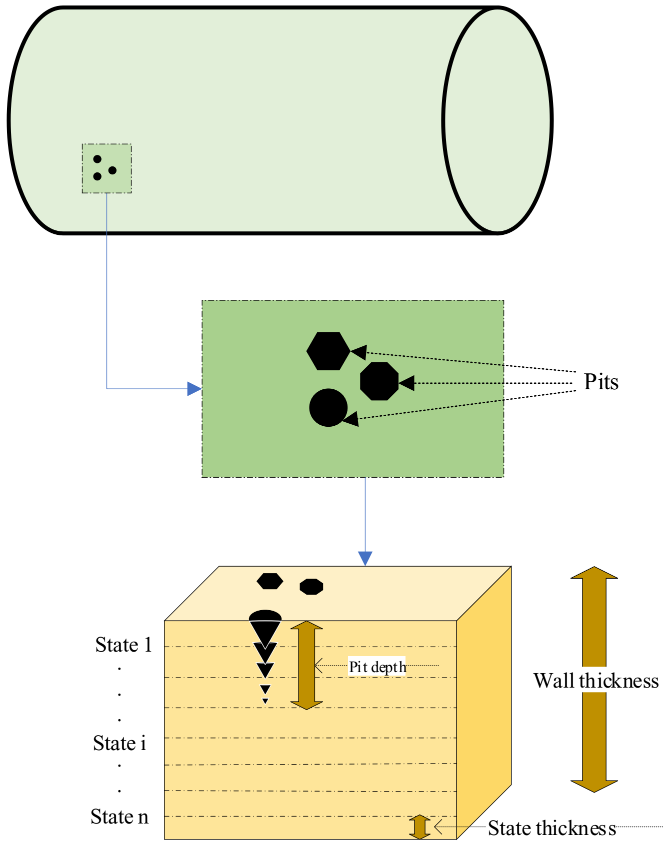

Figure 4.2. The Markov states process for pitting on the surface of the cylindrical asset

Let us assume that $\gamma_i\,(i \mid \chi\,, \omega)$, $i = 1\,, 2\,, \ldots, n$, shows the probabilities in which the maximum pit depth growth should be in the state, satisfying that $state \leq i$ at time t. This can be characterized within χ having the distance dimensions as well as ωth time power-law. Due to the fact that the two parameters χ and ω describe $\vartheta(t)$ as this is the times of transited states for a single pit. It is considered to follow a power-law function and is presented in the following equation [62]:

$$\vartheta(t) = \chi\,(\,t - \,t_{\,k}\,)^{\,\omega} \tag{4.6}$$

Subsequently, the CDF (cumulative distribution function) for maximum pit depth growth path is defined as predicted in the following equation:

$$\gamma_H = (i\,,t \mid \chi\,,\omega) = \prod_{k=1}^{m} \{\,1 - [1 - \exp(-\vartheta(t\ - t_k))]^{\,i}\,\}$$

$$\forall \quad i = 1\,,2\,,\ldots,n \tag{4.7}$$

in which, t indicates the assessment time based on the year, month, week, and day, t_k shows the initiation time of pit depth growth path, i is standing for the total counted states in the Markov process, m denotes the $\overline{ad}(t)$ at assessment time, and $\vartheta(\,t - t_k)$ indicates the total transited states of pit depth growth path in the time interval $(t_{\,k}\,,t)$. This equation provides a predictive model, which can be utilized to approximate the CDF of maximum pit depth growth in different time slices. The PDF can be defined by using Equation 4.8.

$$\mathcal{F}_i = (i\,,t|\,\chi\,,\omega) = \frac{d\gamma_{H\,i}}{di} \cong \frac{\gamma_{H\,i} - \gamma_{H\,i-1}}{1} \tag{4.8}$$

in which, $\mathcal{F}_i$ is presenting the PDF function as state i, $\gamma_{H\,i}$ and $\gamma_{H\,i-1}$ are the CDF function on the states $i,$ and $i-1$, respectively. To get more details related to Equation (4.8), one can refer to the study of Valor et al. (2013). The equation for probability distribution function is further developed in the present study by integrating with the average pit density model from Equation (4.5). It should be added; the average pit density would help to obtain maximum pit depth over time. More defects (maximum pit density) will lead to more defects in the pipeline and, therefore, to higher pit depth value [55,64].

Step two: Defining limit state function for MIC failure

For a given pipeline containing different pipe joints, which are all under the influence of MIC pits, the limit state function equivalent to the area of pits based on average pit density, in which penetrating the pipeline wall at time τ, is defined as the following equation:

$$g(\tau) = sf.wt - d_{Max} \tag{4.9}$$

where wt denotes the thickness of the pipeline at the area of defects; d_{Max} signifies the maximum pith depth growth in the area of defects with time t. The constant factor sf is a safety factor (i.e., $80\,\%, 60\,\%, etc.$), which accounts for the residual ligament of the pipeline thickness at a maximum depth of MIC defect(s), which is likely to develop a pinhole that causes leakage.

It is also essential to see how maximum pit depth can be determined. Therefore, probability of detection (PoD) is defined as the ability of a proper in-line inspection tool to adequality and is purely used to identify defects based on the actual depth of the defect. For large pits, PoD is close to 100 %. This ability depends on defect size and many characteristic parameters. The PoD function is usually considered as the exponential function for the maximum pit depth d_{Max} in the available literature, and is defined as the following equation:

$$PoD(d_{Max}) = 1 - e^{qd_{Max}} \tag{4.10}$$

where q is the constant value and represents the inherent in-line inspection tool capability. The value of q can be quantified from a vendor such as $80\,\%\ PoD$ of a pit within a pit depth growth of $20\,\%$ of pipeline thickness. In this paper, considering unavailability, it is tried to show how PoD is working.

It should be highlighted that the uncertainty for the detected defect is commonly described by the random scattering errors and biases connected to the in-line inspection tools. In the following, the pit depth of MIC defect measured by in-line inspection tool is presented as an example for maximum pit depth [60]:

$$d_{Max}^{ili} = R + Bd_{Max} + \varepsilon \tag{4.11}$$

Where R and B are representing the biases which are stable and non-stable, connected to the pit depth (i.e., $R = 0$, and $B = 1$, this is unbiased), they are considered as having deterministic quantities, and ε is random scattering error connected with the measured pit depth growth path, in which it is commonly characterized with normal distribution with zero mean as well as unknown standard deviation. The present work assumes that the ransom scattering error connected to a different area of defects is mutually independent. According to this point, the three-dimensional correlation connected to the ε is disregarded. This can be acceptable since an area of defects is not in close proximity close spaces to other areas.

However, to see how one could use PoD, d_{Max}^{ili}, and d_{Max} to make a reliable decision, two essential steps are required to be performed as follows:

(i) Generating a random number called u from an entirely uniform distribution in the interval [0 , 1], then computing the value of PoD connected with the area of defects and showing as PoD_{ς}. Utilizing equation (4.10), we have $PoD_{\varsigma} = 1 - e^{qd_{Max,\ \varsigma}}$;

(ii) If $u < PoD_{\varsigma}$, compute $d_{Max,\varsigma}^{ili}$; if $d_{Max,\ \varsigma}^{ili} > sf.wt$, the cost of management actions needs to be computed and the total number of defects regenerated, step one.

Step three: Defining condition-based optimal maintenance decision

Once the limit state function is defined from step two, in this step, a combination of condition-based optimal maintenance management decisions would be obtained in two different sub-steps, being: (i) defining a management actions performance policy and (ii) evaluating the expected cost of maintenance management. In the following, the detail for every single sub-step is described.

(i) Defining a management actions' performance policy

In this study, it is assumed that the pipeline failure (i.e., pinhole) in the understudy defect(s) is caused by MIC (MIC-based defects) and does not impact other types of defects(s).

Therefore, the pinhole through the pipeline will be examined and replaced as soon as recognition for pipeline failure. In addition, the maintenance management actions are assumed to be based on common industry practices and utilize a periodic in-line inspection tool. The following management actions' performance policies are considered in this study. The pit corroded area of the pipeline will be examined and replaced immediately if one can see the pinhole and fluid leakage or $d_{Max}^{ili} \geq wt$. The reason for considering greater than nominal pipeline wall thickness is that errors of in-line inspection tools may show higher thickness measurement than nominal pipeline wall thickness.

- The pit corroded area of the pipeline will be examined and maintained immediately if $d_{Max}^{ili} \geq sf.wt$, in which safety factor sf ($sf < 1$) is considered as 80 %. Repair and replacement can be performed for maintenance. A goal is set in which the pipeline's expected service life would e only for at least 30 years. Therefore, it is essential to minimize the cost of maintenance actions. Typically, the total cost of replacement is more than repair actions and also has greater efficacy. Therefore, another goal is the performance of maintenance action repair M_{Repair} (sleeving), if $d_{Max}^{ili} \geq sf.wt$ and $T \geq 20$, where T is standing for the service life of the pipeline, and the unit is a year. Moreover, performing maintenance action replacement $M_{\text{Replacement}}$ (replace the corroded area of the pipeline completely), if $d_{Max}^{ili} \geq sf.wt$ and $T < 20$.

- Recoating or recoating plus maintenance action repair can be done based on the severity of the corroded area. First of all, all coating should be removed; thereafter, the recoating or recoating plus maintenance action repair will be applied. It should be added that the risk of coating the wrong section of a subsea pipeline is usually very high; however, in this work, these risks are not considered for assessment as it is out of scope. The selection between these two is based on the actual difference size of maximum pit depth (d_{Max}) and the in-line inspection tool (d_{Max}^{ili}). A simple suggestion to apply recoating is that the corroded area satisfying $d_{Max} < sf.wt$ (actual size of maximum pit depth) and recoating plus maintenance action repair will be performed if $d_{Max} \geq sf.wt$.
- Is it assumed that the corroded area's recoating plus maintenance action repair is fully reinstated into the initial pipeline condition.
- It is also assumed that the likelihood of maintenance management actions with low quality is negligible. Thus, the likelihood is disregarded in the current work.
- Finally, no maintenance actions would be performed at the end of the pipeline service lifetime, and no inspection would be applied if the scheduled inspections upon a failure.

(ii) Evaluating the expected cost of maintenance management

To evaluate the expected cost of maintenance management, it is assumed that the pipeline is under periodic inspection and maintenance with a specified time interval (T_i). Given units cost of the different maintenance management actions (inspection (C_{IN}), sleeving repair (C_{SR}), recoating repair (C_{RR}), pipeline surface examination (C_{SE}), replacement (C_R), and failure cost (C_F), the total cost can be obtained. Different types of up to date cost function models are available , such as, but not limited to [65,66]; however, in this study, we utilized the cost rate function (the total cost per unit service time, $C_T(T_i)$ utilized by Zhang and Zhou [60], which can be further determined from the following equation:

$$C_T(T_i) = \frac{1}{T}\Big(\sum_{i=1}^{n_{IN}} C_{IN}e^{-\delta t_i} + \sum_{i=1}^{n_F} C_F e^{-\delta t_{F_i}} + \sum_{i=1}^{n_{RR}} C_{RR}e^{-\delta t_{RR_i}} + \sum_{i=1}^{n_{SE}} C_{SE}e^{-\delta t_{SE_i}} + \sum_{i=1}^{n_{SR}} C_{SR}e^{-\delta t_{SR_i}} + \sum_{i=1}^{n_R} C_R e^{-\delta t_{R_i}}\Big) \quad (4.12)$$

in which δ is standing for discount rate (where $\delta = 0$, $C_T(T_i)$ will increase as the maintenance actions' cost increase, t_i indicates the time of ith action/failure, n_{IN} denotes the total number of inspections, n_F shows the total number of failures in the service lifetime of the pipeline, n_{RR} shows the total number of recoating repairs, n_{SE} denotes the total number of pipeline surface examinations, n_{SR} shows the total number of sleeve repairs, and n_R represents the total number of replacements. In this study, the failure cost is considered as both direct cost and indirect cost by placing different failure costs into the model (parametric analysis), and the cost model would help assessors to construct the risk-based decision-making model [65,67,68].

As understood so far, pit depth growth process, material properties, the capability of a limit state function, and t_i for the mentioned cost are uncertain and stochastically based. Therefore, it is a challenging task to compute and solve Equation (4.12) analytically. According to this point, in the present study, the numerical simulation is used to estimate the $C_T(T_i)$, which is further called $S[C_T(T_i)]$.

To obtain the $S[C_T(T_i)]$ and other essential parameters, the problem is coded in MATLAB. Let it be assumed that $C(T_i)$ indicates the total cost related to an inspection time of T_i. By giving the specific amounts for T, T_i, C_{IN}, C_{SR}, C_{RR}, C_{SE}, C_R, C_F, δ, and cf, the stepwise programming code has been done with MATLAB. In general, the Pseudocode helps assessors learn how to program the proposed approach to solve the problem. The expectation is that the Pseudocode should be as simple as possible, and by following step by step, their codes can be provided and the same results obtained as those achieved in the present work. By reviewing the literature, there are a couple of Pseudocodes to estimate pit characteristics and associated costs such as [60,69,70]; however, in the current study, the pit characteristic is unique when using the Markov process.

4.3. Application of study

In order to find condition-based MIC maintenance management actions, the proposed methodology in Section 2 was utilized using a subsea hydrocarbon transmission pipeline (API 5L, Grade X42 steel within the wall thickness of 20 mm and selected joint pipeline length 12.5 m). This subsea pipeline carries co-mingled fluids depicting two or more fluid phases from different offshore resources. It is considered that the subsea pipeline at the installation time is free of any defects.

A chemical analysis of produced water according to the operational and chemical analysis from an offshore facility off the East Coast of Canada shows the total number of microorganisms using the qPCR (quantitative Polymerase Chain Reaction) method (3.19E+06 (16S rRNA copies/mL sample)), different types of microorganisms percentage (Methermicoccus 4.79 %, Desulfovibrio 8.72 %, Dethiosulfatibacter 10.14 %, Archaeoglobus 38.36 %, Thermoanaerobacter 1.35 %, Thermococcus 9.9 %, Thermosipho 3.6 %, Methermicoccus 4.79 %), and sulfate reduction rate (SRR) (0.52 in situ). The characteristic of biofilm architecture in the present research analysis is provided in Table 4.1.

Table 4.1. The characteristic of biofilm architecture

Group	Mode	Product	Performance
SRB [1]	Anaerobic	H_2S, HS^-, and FeS	Active state
ABP [2]	Aerobic/anaerobic	Organic-based acids	Active state
IRB [3]	Aerobic/anaerobic	Soluble Fe ions	Active state
1- Sulfur reducing bacteria, 2- Acid-producing bacteria, 3- Iron reducing bacteria			

4.4. Discussion

According to the first step, the number of defects on the pipeline surface is described using Equation 4.1, in which λ_0 and a are assumed to be 4, and 1, respectively. The values λ_0 and a denote that in the 40 years lifespan of the subsea pipeline, the expected number of multiple defects with 97.5 % and 2.5 % confidence level and simulation will be 3312, 3039, and 3200 defects, respectively. The numerical results show that the confidence interval for the number of defects at 40 years is narrow due to using the specific values of the new defect generation model with $\lambda_0 = 4$, and $a = 1$. This assumption has been made to simplify the problem as well as consider different environmental conditions.

Considering the number of defects, the corresponding initiation times from Equation (4.2), the parameters of the model, and a couple of assumptions are presented in Table 4.2 to obtain the average pit density and maximum pit depth growth path. The assumptions are utilized from the literature [55,64,71,72] and subjective opinions from decision-makers. Decision-makers are defined as a group of experts who are qualified within enough knowledge of technical practices, training, and experiences. If the empirical data are not available such as new installation having a lack of inspection and operational background, experts' judgment seems to be the best alternative to empirical data. This means that experts with relevant backgrounds are employed to express their opinions qualitatively about unknown parameters that we are looking for. Next, the aggregation process will be performed to obtain a single value parameter (see Yazdi et al. (2019)). There are a couple of tools to minimize the subjective uncertainty from the experts' judgment in practice.

Table 4.2. The characteristic parameters to estimate pit depth growth path

Characteristic	Definition of equations	Parameters values
Average pit density	$\overline{ad}(t) = \frac{A}{\psi}\left[1 - e^{-\psi t}\right] + wt^{\eta}$	$A = 35$, $\eta = 1$, $\psi = 0.09$, and $w = 0$
Transited states	$\vartheta(t) = \chi(t - t_k)^{\omega}$	$\chi = 0.940$, and $\omega = 0.102$
Maximum pit depth	$\gamma_H = (i, t \mid \chi, \omega) = \prod_{k=1}^{m}\{1 - [1 - \exp(-\vartheta(t - t_k))]^{i}\}$	$i = 100$

In addition, the partial unit costs of inspection (C_{IN}), sleeving repair (C_{SR}), recoating repair (C_{RR}), pipeline surface examination (C_{SE}), replacement (C_{R}), and failure cost (C_{F}), which are all representative of the common industry practices in Canada, are provided in Table 4.3. Moreover, to obtain the total cost rate $S[C_T(T_i)]$, the discount rate δ is assumed to be zero. Table 4.4 also provides a value for the rest of the model parameters. In this study, the pit depth reported by in-line inspection tools is considered unbiased ($\mathrm{i.e.}, R = 0\ ,\ B = 1$), and the random scattering error according to the study report of [60] is assumed to be 0.078 mm. This means that a confidence level of the actual pit depth is somehow $\pm$ % 10 wt within 0.8 measured probability for the pit depth growth path. The PoD value is assumed to be 90 % for the pit depth of $\pm$ % 10 wt, which is 5.73 mm. The safety factor for all management actions is 80 %, which is consistent with industry practices.

Table 4.3. The summary of all unit costs

Item	Partial costs (CAD)
Inspection (C_{IN})	4,876
Sleeving repair (C_{SR})	35,000
Recoating repair (C_{RR})	20,000
Pipeline surface examination (C_{SE})	5,000
Replacement (C_{R})	68,000
Failure cost (C_{F})	543,407

Table 4.4. The values of model parameters

Parameters	Value
R	0
B	1
sf	80 %
α	1
β	2
ε	0.078 mm
q	2.57 mm

According to the published works, the obtained CDF and PDF of maximum pit depth growth path would be varied and moved into the right side particular time [55,64,72]. This signifies that the probability of the pits with maximum depth has increased with time. However, this also means that there will be resulting further thickness loss.

As highlighted in the methodology section, there are a couple of variables, which are changed by service lifetime of the understudy pipeline, including the probability of detection (PoD), cost rate, ($\overline{ad}(t)$), (d_{Max}), average maximum pit depth based on in-line inspection tools (d_{Max}^{ili}), and thickness loss. The variation of each parameter, as well as its combinations, is depicted in Figure 4.3. According to the obtained results, managing multiple MIC defects within conditioned-based management actions can be understood. Corresponding to the obtained results, the policies of performing management actions presented in Section 2 are feasible because the service lifetime of the subsea pipeline underlies the idea of the set goal being more than 30 years. Thus, the sensitive analysis (SA) should be performed by varying all essential factors in the formulation of the framework, including sf, λ, δ , q , ε, $C_T(T_i)$, and using HPP instead of NHPP in the modeling process. Based on the results obtained from SA, it would be clear to see how the pipeline being studied, under the influence of multiple MIC defects, is behaving under different conditions. Thus, it helps assessors to discover the feasible results and those optimum ones. This may further cause the policies of performing management actions to be revised and improved according to management actions scheduling.

According to the updated results, this would help the system to improve its policies in three different categories as (i) safety, (ii) cost reduction, and (iii) improving the system efficiency. This would help in safety because the system works with hydrocarbon material, potential fire, and explosion. The pipeline would be susceptible to corrosion over time and rescued its resistance to harsh environmental conditions (e.g., temperature and pressure). Therefore, increasing system safety would prevent accidents in which the types of equipment, employees, and environments are kept safe. This also would help in cost reduction since replacing the section of pipeline prematurely by MIC is costly. Thus, the system should avoid such costs by contributing to the long-term corrosion management and maintaining the pipeline for many years. Finally, the obtained results would assist system policies to improve the general efficiency of the system considering the following aspects, (a) providing insight for the decision-makers to purchase and invest in the less likely corroded materials in the future, (b) reducing the number of system shutdowns which would satisfy connected industries as customers, (c) recognizing different cost-effective approach for remedying the MIC pit depth growth and similar concerns, (d) surviving the pipeline and related operational types of equipment (e.g., pumps, valve, and so on), and recognizing the conditions that make MIC worse, and then can be used for purchasing in future and maintenance decisions.

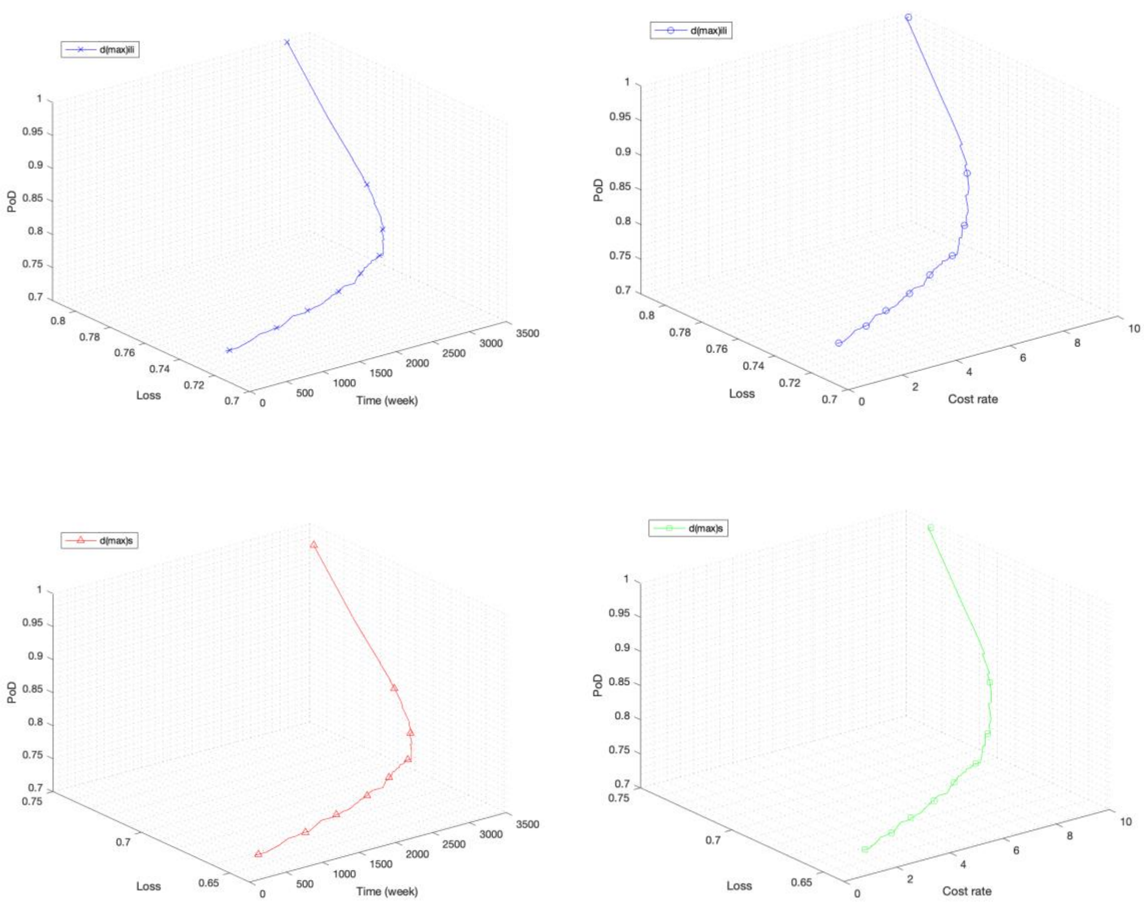

Figure 4.3. Analysis of the model parameters varying over service lifetime of the pipeline under study (the Loss thickness is in percentage %)

4.5. Sensitivity analysis

Sensitivity analysis (SA) is a systematic methodology with considerable proficiency in describing information about quantitative evaluation by identifying the system's weakness and designing much better options for the system and the significant foundations of subjective and objective uncertainty in a stochastic-based problem [74]. In this study, the SA is performed by varying different types of parameters in the management process.

(i) Evaluating the effect λ_0 in the total number of defects over the service lifetime

According to Equation (4.1), it can be considered that $\lambda(\tau) = \lambda_0 \tau^a$ where λ_0 is a positive value and it can be obtained according to the objective data or subjective information from experts. In the present study, it is assumed that $\lambda_0 = 4$, that is while for performing SA, two different values λ_0 are taken into account as $\lambda_0 = 0.5$, and $\lambda_0 = 2$. To simplify this, the main changes of considering $\lambda_0 = 0.5$, and $\lambda_0 = 2$ on thickness loss and the probability of detection are depicted for further discussion. The reason for this selection is that this is much better from an uncertainty propagation perspective to have uncertainty on the parameters that control the models.

As can be seen, by varying λ_0 the value of model parameters is changed; however, the changes are not considered. λ_0 affects the total number of defects, which does not necessarily make the system worse in the case of maximum pit depth, and cost rate. The results are depicted in Figure 4.4.

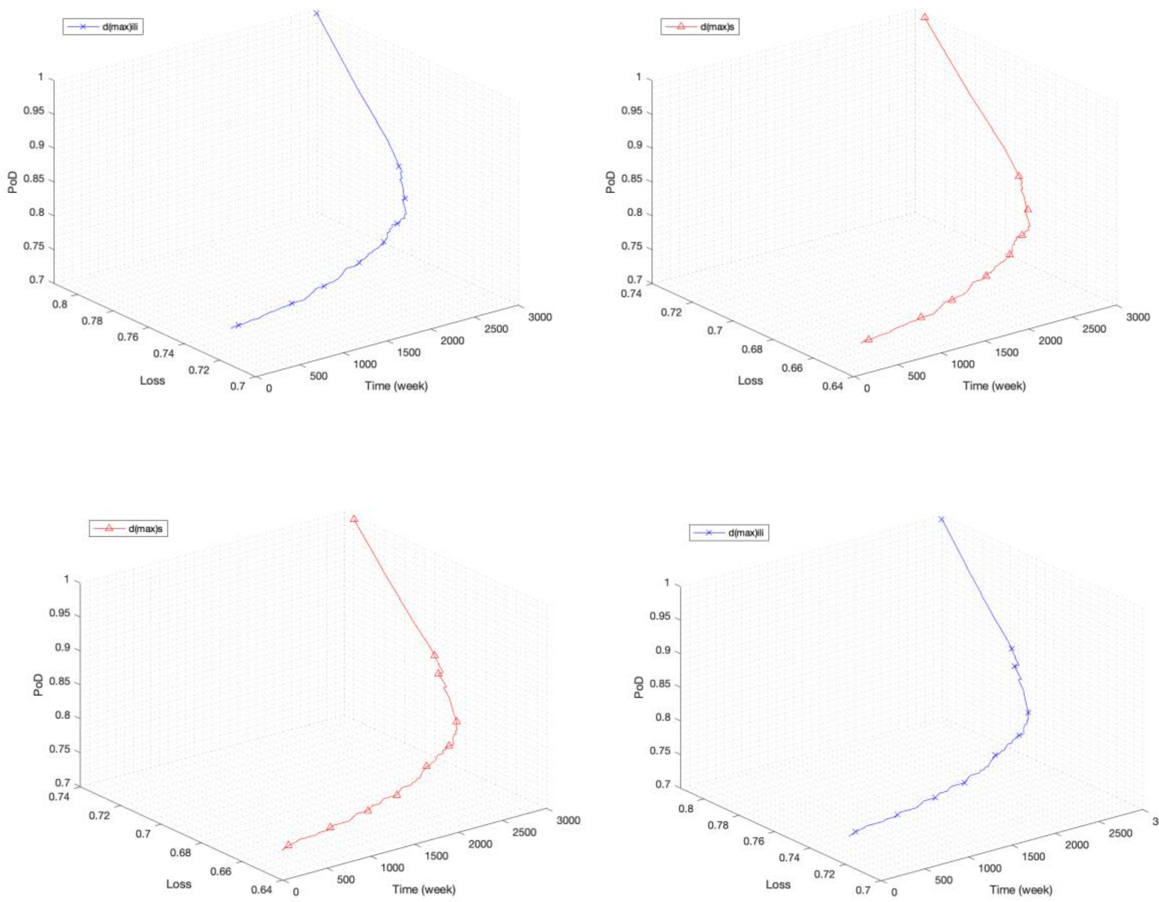

Figure 4.4. The model parameters analysis by varying over service lifetime with consideration of $\lambda_0 = 0.5$ (top) and $\lambda_0 = 2$ (bottom) (the Loss thickness is in percentage %)

(ii) Evaluating the effect the Poisson process ($a = 0$) has on model parameters

According to equation (4.1), it can be considered that $\lambda(\tau) = \lambda_0 \tau^a$, if we consider $a = 0$, the equation (4.1) is shortened to the homogenous Poisson process. Figure 4.5 represents the expected total number of defects related to HPP and NHPP for comparison purposes. For the $\lambda_0 = 4$ and $a = 1$ (NHPP), the $\nabla(t)$ is obtained as $\nabla(t) = 2t^2$, and for $\lambda_0 = 4$ and $a = 0$, the $\nabla(t)$ is obtained as $\nabla(t) = 100t$. From this finding as well as from the support of literature [60], it can be highlighted that all values based on the HPP model-results should be more than all values based on the NHPP model-results excluding the 50th year, where HPP and NHPP are equal, and after the 50th year, NHPP passes the HPP model. Using NHPP is much more realistic, and therefore, the results of the HPP-based model are skipped here.

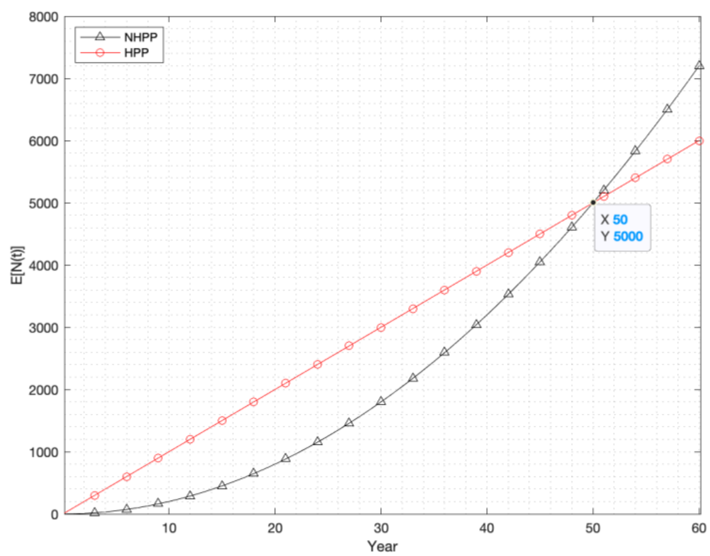

Figure 4.5. Analysis of the total number of defects with consideration of HPP and NHPP based models

(iii) Evaluating the effect of different management action costs on cost rate parameter

In order to perform SA (iii), in Table 4.5, two different sets of management action costs are provided. First, the cost rate over service lifetime is updated by modifying the relevant MATLAB code and depicted in Figure 4.6. As can be seen, once the management costs have been changed in Case 1, the total cost rate decreases without considerable change in the probability of detection. In addition, by increasing the management costs from Case 1 to Case 2, the total cost rate is almost consistent with the initial assessment. Therefore, it is clear that the obtained changes are partial, and varying all costs in the same pattern does not necessarily affect scheduling management actions over the service lifetime of the pipeline under study.

Table 4.5. The summary of all unit costs

Item	Partial costs (partial unit cost)	
	Case 2	Case 1
Inspection (C_{IN})	5000	300
Sleeving repair (C_{SR})	25000	400
Recoating repair (C_{RR})	18000	550
Pipeline surface examination (C_{SE})	4000	350
Replacement (C_{R})	50000	700
Failure cost (C_{F})	2000	3000

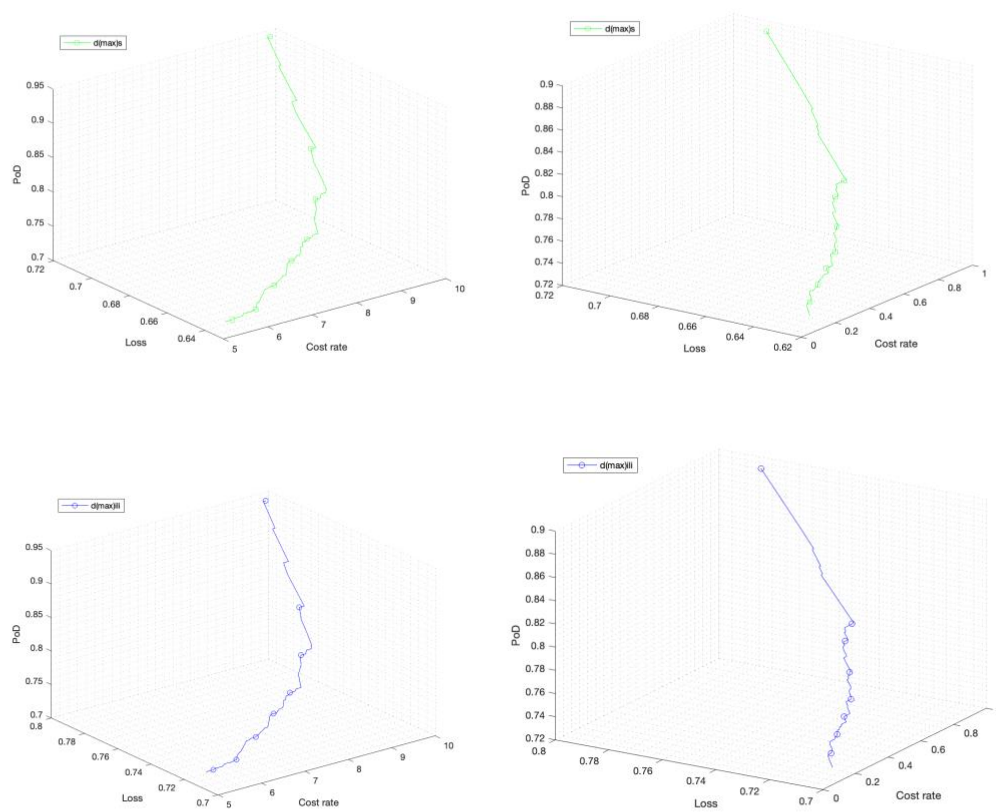

Figure 4.6. Analysis of the model parameters varying over service lifetime with two sets of management actions cost (Right side: Case 1, Left side: Case 2, (the Loss thickness is in percentage %))

(iv) Evaluating the effect of discount rate on cost rate parameter

In the original form of assessment, the discount rate δ is assumed to be zero. Here it is assumed that $\delta = 10$ %. Figure 4.7 depicts the results of $C_T(T_i)$ based on the new discount rate value. It can be seen that when $\delta = 10$ %. The new model makes a lower cost rate, and therefore it makes for a longer optimal service lifetime of the pipeline than the model when the $\delta = 0$. In addition, where $\delta = 10$ %, it means that $C_T(T_i)$ decreases as the highest cost value (i.e., failure cost) decreases as is expected.

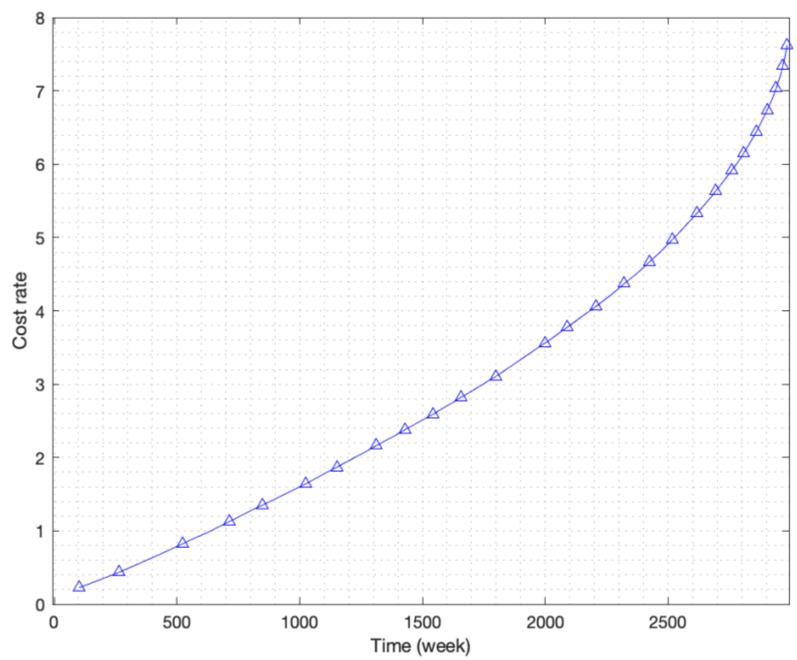

Figure 4.7. Analysis of expected $C_T(T_i)$ in term of discount rate

(v) Evaluating the effect of safety factors on the parameter cost rate

The effect of safety factor on the model parameter $C_T(T_i)$ is evaluated by varying it with two values being $sf = 50$ % and $sf = 70$ %. The results of this analysis are presented in Figure 4.8. Similar to the industrial practice, it can be seen that by decreasing the value of the safety factor, the cost of assessing integrity increases, and subsequently, the cost rate increases. Therefore, selecting a reliable safety factor is a critical task considering the asset's annual budget and acceptable service lifetime. In the present study, it is assumed that there is no limit for spending assets integrity cost.

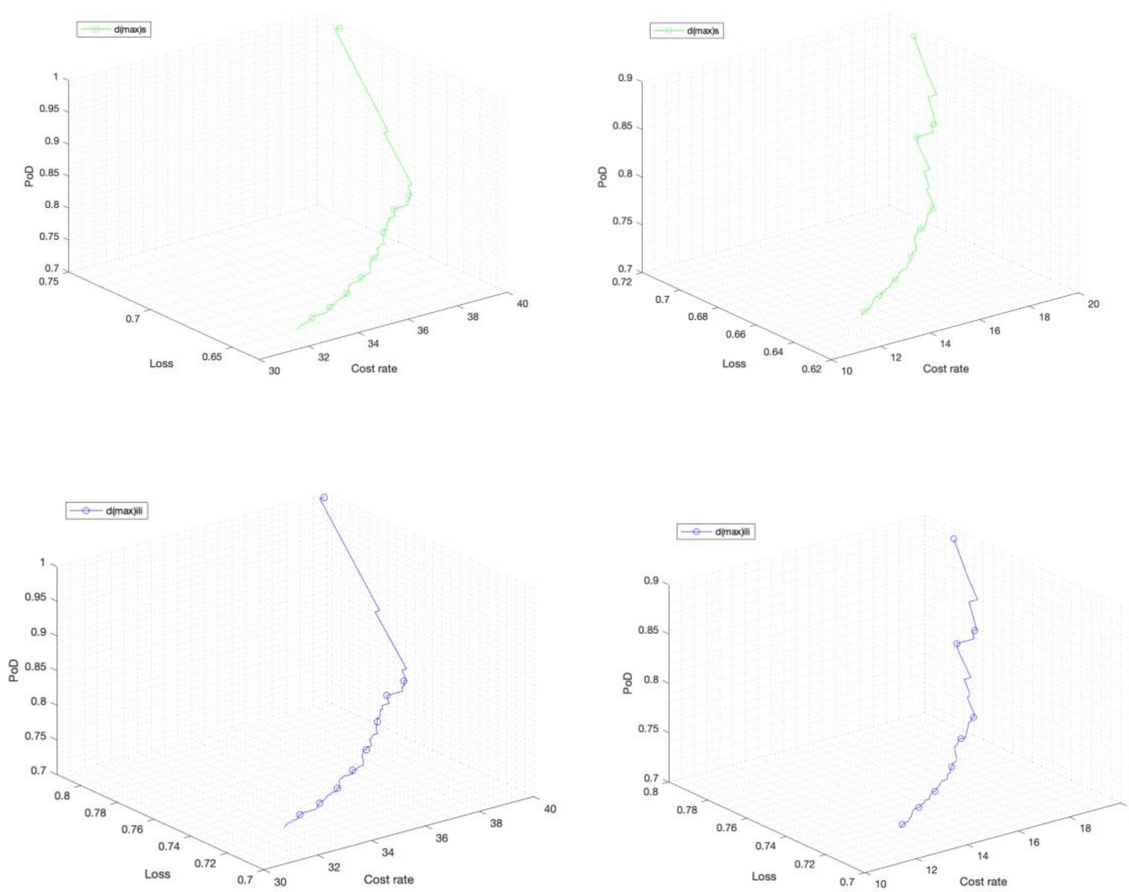

Figure 4.8. Evaluating the effect of safety factor on the parameter cost rate (Right: $sf = 70$ %. Left: $sf = 50$ %, (the Loss thickness is in percentage %))

(vi) Evaluating the effect of ε (random scattering error) on the probability of detection and thickens loss

To perform this SA, two different values are assigned to the random scattering error being $\varepsilon = 0.01$ and $\varepsilon = 0.001$. Figure 4.9 depicts the results of POD, maximum depth, and thickness loss over the service lifetime of the pipeline. The critical point is that as much as the random scattering error decreases, the results of measured depth from in-line inspection tools fall. Therefore, it is essential to use an accurately calibrated inspection tool.

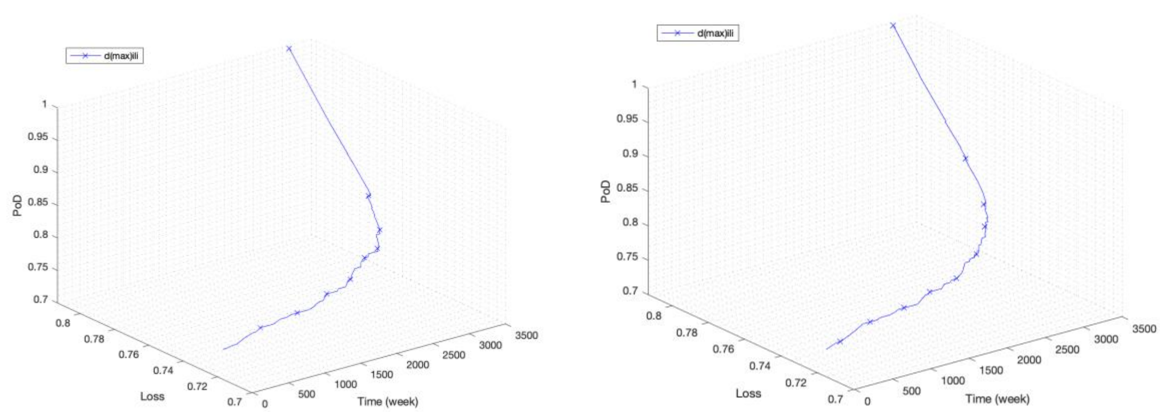

Figure 4.9. Evaluating the effect of ε (random scattering error) on the PoD and thickness loss (Right: $\varepsilon = 0.01$ and Left: $\varepsilon = 0.001$, (the Loss thickness is in percentage %))

(vii) Evaluating the effect of average pit depth density $\overline{ad}(t)$ overtime

Different environmental conditions and different types of coating may cause different pit rates, which further influences average pit density. By varying the paraments of average pit depth density (equation (4.4)), this can evaluate the different behaviors of the management model over time. Two scenarios are considered, and relevant modifications are presented in Table 4.5. By assuming t stands for the year, Figure 4.10 illustrates the average pit density based on two defined scenarios. As depicted in Figure 4.10, the average number of pits in a unit area in scenario #S1 is initiated in the early service lifetime of the pipeline. This can be used to signify the harsh environmental conditions. Therefore, by varying the Equation parameters (Equation (4.4)), the $\overline{ad}(t)$ can be correctly reflected by various environmental circumstances.

Table 4.5. Varying the parameters for average pit depth density in the model

Scenario tag	Parameters' value	Modified equation
# S1	$\mathrm{A} = 0 , \eta = 1 , \psi = 2 , w = 30$	$\overline{ad}(t) = wt$
# S2	$\mathrm{A} = 2 , \eta = 2 , \psi = 4 , w = 0$	$\overline{ad}(t) = \frac{\mathrm{A}}{\psi} \left[1 - e^{-\psi t}\right]$

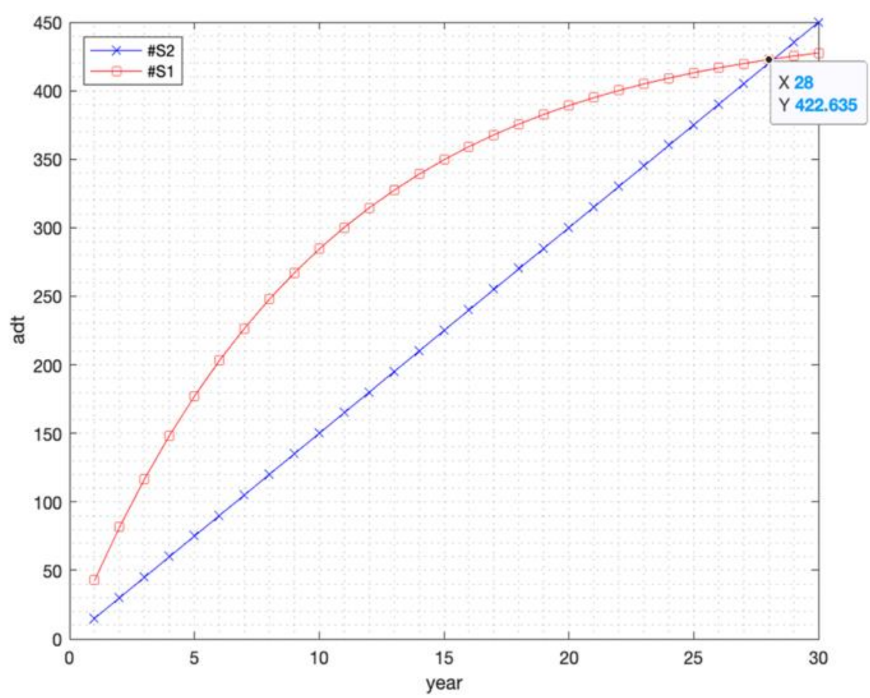

Figure 4.10. Evaluating the effect of average pit depth density $\overline{ad}(t)$ overtime

4.6. Conclusion

MIC appears extensively in the broad range of metals in marine and offshore environments, stochastically. The present work delivers a comparative study of models to characterize the multiple MIC defects, including the generation of defects, initiation times, the average pit density, and the maximum pit depth growth path. This paper considers the uncertainties for modeling the number of defects, defects' size, and uncertainty of in-line inspection tools. In addition, this study determines the optimal time of subsea pipeline inspections. The non-homogeneous Poisson process is utilized to obtain the number of defects over the service life of the pipeline. The combination of homogenous Gamma process and exponential and power equations is used to model average pit depth through a pipeline thickness (i.e., pit depth). The Markov process is then engaged for modeling the dynamic feature of pit depth growth over time. The uncertainty associated with in-line inspection tools is also considered with the probability of detection, random scattering, and bias errors. By reading the existing literature, and the obtained results in current work highlighted that: (i) the presence of microorganisms in the pipeline does not mean that there would be any evidence of MIC activities, (ii) most of the studies suffer from using off-site facilities, and they are restricting to rapid assessment due to the high cost of simulation environmental conditions, (iii) the microbiological evaluation-based method (e.g., metabolomic and metagenomic) is the most robust tool for MIC determination, (iv) the significant point to detect MIC in a short period is the characterizing the diversity of microorganisms on suspectable field sites, (v) the data mining on the microbiological data set may provide a valuable understanding for the greatest possible and proliferation of MIC impacts, (vi) the probabilistic and fuzzy-based methods can be employed to enhance the system's capabilities to assess MIC treatments. Thus, an intelligent system can provide a much more realistic timeline for decision-makers and operators to obtain the level of risk, (vii) utilizing such qPCR techniques to derive the total numbers of a single gene (16S rRNA), bacteria, and archaea is the critical performing indicator of consistent reporting in the system, (viii) engaging the nano-material tools can provide insights for robust detection sensors, such as smart pigs and miniaturized kits, (ix) reducing the cost of MIC management can only be applied in case using multi-disciplinary approaches between chemical, corrosion, and safety engineering, and (x) There is a requirement for research tasks to obtain the solutions for MIC in dynamic environmental circumstances.

Moreover, the cost of maintenance actions in the given inspection time interval over the service life of the pipeline is formulated. The Monte Carlo simulation technique is used to examine the cost rate by service lifetime of the pipeline. Finally, different sensitivity analyses are performed to show how the proposed models behave in a couple of scenarios.

However, a couple of challenges have arisen during the study that needs further work to direct future studies. First of all, there are a couple of parameters in the stochastic equations such as A, ψ, w, and η in average pit depth equation for which there is no empirical data available to estimate them. Experts' judgment elicitation procedure as an alternative needs to be improved by correctly dealing with subjective uncertainties. Secondly, the direct cost of system failure and maintenance actions assessment were the only considerations in the present work. In real applications, the indirect costs are required to be determined using methods such as parametric analysis. In addition, this work focused on the external surface of the subsea pipeline under the influence of MIC. As a direction for further study, the internal MIC can be examined considering relevant maintenance management actions such as biocide, inhibitors treatment, and periodical pigging.

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References

[1] B.J. Little, D.J. Blackwood, J. Hinks, F.M. Lauro, E. Marsili, A. Okamoto, S.A. Rice, S.A. Wade, H.-C. Flemming, Microbially influenced corrosion—Any progress?, Corros. Sci. 170 (2020) 108641. https://doi.org/https://doi.org/10.1016/j.corsci.2020.108641.

[2] P. Kannan, S.S. Su, M.S. Mannan, H. Castaneda, S. Vaddiraju, A Review of Characterization and Quantification Tools for Microbiologically Influenced Corrosion in the Oil and Gas Industry: Current and Future Trends, Ind. Eng. Chem. Res. 57 (2018) 13895–13922. https://doi.org/10.1021/acs.iecr.8b02211.

[3] A. Marciales, Y. Peralta, T. Haile, T. Crosby, J. Wolodko, Mechanistic microbiologically influenced corrosion modeling — A review, Corros. Sci. 146 (2019) 99–111. https://doi.org/10.1016/j.corsci.2018.10.004.

[4] U.S. Thomsen, R.L.C. Meng, J. Larsen, Monitoring and Risk Assessment of Microbiologically Influenced Corrosion in Offshore Pipelines , (2016).

[5] D. Yuhua, Y. Datao, Estimation of failure probability of oil and gas transmission pipelines by fuzzy fault tree analysis, J. Loss Prev. Process Ind. 18 (2005) 83–88. https://doi.org/10.1016/j.jlp.2004.12.003.

[6] A. Shahriar, R. Sadiq, S. Tesfamariam, Risk analysis for oil & gas pipelines: A sustainability assessment approach using fuzzy based bow-tie analysis, J. Loss Prev. Process Ind. 25 (2012) 505–523. https://doi.org/10.1016/j.jlp.2011.12.007.

[7] X. Li, L. Zhang, F. Khan, Z. Han, A data-driven corrosion prediction model to support digitization of subsea operations, Process Saf. Environ. Prot. 153 (2021) 413–421. https://doi.org/https://doi.org/10.1016/j.psep.2021.07.031.

[8] A.U. Ebenuwa, K.F. Tee, Y. Zhang, Fuzzy-Based Multi-Objective Design Optimization of Buried Pipelines, Int. J. Uncertainty, Fuzziness Knowledge-Based Syst. 29 (2021) 209–229. https://doi.org/10.1142/S0218488521500104.

[9] J. Larsen, K.B. Sørense, S. Juhler, D.S. Pedersen, The Application of Molecular Microbiological Methods for early Warning of MIC in Pipelines , (2013).

[10] E.M. Orazem, Underground pipeline corrosion, Detection, analysis and prevention, Elsevier, Woodhead Publishing, 2014.

[11] X. Song, Y. Yang, D. Yu, G. Lan, Z. Wang, X. Mou, Studies on the impact of fluid flow on the microbial corrosion behavior of product oil pipelines, J. Pet. Sci. Eng. 146 (2016) 803–812. https://doi.org/https://doi.org/10.1016/j.petrol.2016.07.035.

[12] S. Al-jaroudi, A. Ul-hamid, M.M. Al-Gahtani, Failure of crude oil pipeline due to microbiologically induced corrosion, Corros. Eng. Sci. Technol. 46 (2011) 568–579. https://doi.org/10.1179/147842210X12695149033819.

[13] X. Li, H. Zhu, G. Chen, R. Zhang, Optimal maintenance strategy for corroded subsea pipelines, J. Loss Prev. Process Ind. 49 (2017) 145–154. https://doi.org/10.1016/j.jlp.2017.06.019.

[14] C. Gong, W. Zhou, Multi-objective maintenance strategy for in-service corroding pipelines using genetic algorithms, Struct. Infrastruct. Eng. 14 (2018) 1561–1571. https://doi.org/10.1080/15732479.2018.1459744.

[15] M. Al-Amin, W. Zhou, S. Zhang, S. Kariyawasam, H. Wang, Bayesian model for calibration of ILI tools, Proc. Bienn. Int. Pipeline Conf. IPC. 2 (2012) 201–208. https://doi.org/10.1115/IPC2012-90491.

[16] L.M. Gieg, T.R. Jack, J.M. Foght, Biological souring and mitigation in oil reservoirs, Appl. Microbiol. Biotechnol. 92 (2011) 263–282. https://doi.org/10.1007/s00253-011-3542-6.

[17] T.L. Skovhus, D. Enning, J.S. Lee, Microbiologically Influenced Corrosion in the Upstream Oil and Gas Industry, Taylor & Francis, 2017.

[18] T.L. Skovhus, E.S. Andersen, E. Hillier, D.N. V Gl, Management of Microbiologically Influenced Corrosion in Risk-Based Inspection Analysis, in: Int. Oilf. Corros. Conf. Exhib., 2018: pp. 9–10.

[19] R.B. Eckert, T.L. Skovhus, Advances in the application of molecular microbiological methods in the oil and gas industry and links to microbiologically influenced corrosion, Int. Biodeterior. Biodegradation. 126 (2018) 169–176. https://doi.org/https://doi.org/10.1016/j.ibiod.2016.11.019.

[20] T.L. Skovhus, K.B. Sørensen, J. Larsen, K. Rasmussen, M. Jensen, Rapid Determination of MIC in Oil Production Facilities with a DNA-based Diagnostic Kit , (2010). https://doi.org/10.2118/130744-MS.

[21] R. Javaherdashti, Microbiologically Influenced Corrosion, 2nd Editio, Springer International Publishing Switzerland, 2017.

[22] R. Javaherdashti, K. Alasvand, Biological Treatment of Microbial Corrosion Opportunities and Challenges, Elsevier Inc, 2019. https://doi.org/10.1016/C2017-0-04219-2.

[23] R. Javaherdashti, How is MIC treated, in: Microbiol. Influ. Corros. An Eng. Insight, Springer, London, 2008.

[24] R. Javaherdashti, Technical Mitigation of Corrosion: Corrosion Management, in: 2017: pp. 9–15. https://doi.org/10.1007/978-3-319-44306-5_2.

[25] R. Javaherdashti, C. Nwaoha, Henry Tan, Corrosion and Materials in the Oil and Gas Industries, CRC Press, 2013.

[26] A.E. Potts, E. Fontaine, R. Melchers, Investigation of severe corrosion of mooring chain in west African waters, Annu. Conf. Australas. Corros. Assoc. 2012. (2012) 992–1001.

[27] I. Comanescu, C. Taxen, R.E. Melchers, Assessment of MIC in carbon steel water injection pipelines, Soc. Pet. Eng. - SPE Int. Conf. Exhib. Oilf. Corros. 2012. (2012) 227–234. https://doi.org/10.2118/155199-ms.

[28] J. Rosen, A.E. Potts, R.E. Melchers, MIC and pitting corrosion on field recovered mooring chain links, Annu. Conf. Australas. Corros. Assoc. 2014 Corros. Prev. 2014. (2014) 1–13.

[29] X. Wang, R.E. Melchers, Long-term under-deposit pitting corrosion of carbon steel pipes, Ocean Eng. 133 (2017) 231–243. https://doi.org/https://doi.org/10.1016/j.oceaneng.2017.02.010.

[30] I. Comanescu, R.E. Melchers, C. Taxen, Life Time Assessment of Offshore Water Injection Pipelines As a Function of Microbiologically Influenced Corrosion , (2012).

[31] S. Adumene, S. Adedigba, F. Khan, S. Zendehboudi, An integrated dynamic failure assessment model for offshore components under microbiologically influenced corrosion, Ocean Eng. 218 (2020) 108082. https://doi.org/10.1016/j.oceaneng.2020.108082.

[32] S. Adumene, F. Khan, S. Adedigba, S. Zendehboudi, H. Shiri, Dynamic risk analysis of marine and offshore systems suffering microbial induced stochastic degradation, Reliab. Eng. Syst. Saf. 207 (2020) 107388. https://doi.org/10.1016/j.ress.2020.107388.

[33] T.L. Skovhus, R.B. Eckert, E. Rodrigues, Management and control of microbiologically influenced corrosion (MIC) in the oil and gas industry—Overview and a North Sea case study, J. Biotechnol. 256 (2017) 31–45. https://doi.org/10.1016/j.jbiotec.2017.07.003.

[34] S.J. Salgar-Chaparro, K. Lepkova, T. Pojtanabuntoeng, A. Darwin, L.L. Machuca, Nutrient level determines biofilm characteristics and subsequent impact on microbial corrosion and biocide effectiveness, Appl. Environ. Microbiol. 86 (2020) 1–23. https://doi.org/10.1128/AEM.02885-19.

[35] R.B. Eckert, T.L. Skovhus, Advances in the application of molecular microbiological methods in the oil and gas industry and links to microbiologically influenced corrosion, Int. Biodeterior. Biodegrad. 126 (2018) 169–176. https://doi.org/10.1016/j.ibiod.2016.11.019.

[36] X. Wang, R.E. Melchers, Corrosion of carbon steel in presence of mixed deposits under stagnant seawater conditions, J. Loss Prev. Process Ind. 45 (2017) 29–42. https://doi.org/10.1016/j.jlp.2016.11.013.

[37] M. Yazdi, S. Kabir, A fuzzy Bayesian network approach for risk analysis in process industries, Process Saf. Environ. Prot. 111 (2017) 507–519. https://doi.org/10.1016/j.psep.2017.08.015.

[38] X. Li, G. Chen, S. Jiang, R. He, C. Xu, H. Zhu, Developing a dynamic model for risk analysis under uncertainty: Case of third-party damage on subsea pipelines, J. Loss Prev. Process Ind. 54 (2018) 289–302. https://doi.org/10.1016/j.jlp.2018.05.001.

[39] M. Gao, M.C. Zhou, X. Huang, Z. Wu, Fuzzy Reasoning Petri Nets, IEEE Trans. Syst. Man, Cybern. Part ASystems Humans. 33 (2003) 314–324. https://doi.org/10.1109/TSMCA.2002.804362.

[40] A. Nedjati, M. Yazdi, R. Abbassi, A sustainable perspective of optimal site selection of giant air - purifiers in large metropolitan areas, Springer Netherlands, 2021. https://doi.org/10.1007/s10668-021-01807-0.

[41] H. Qin, S. Zhang, W. Zhou, Inverse Gaussian process-based corrosion growth modeling and its application in the reliability analysis for energy pipelines, Front. Struct. Civ. Eng. 7 (2013) 276–287. https://doi.org/10.1007/s11709-013-0207-9.

[42] L. Leoni, A. BahooToroody, M.M. Abaei, F. De Carlo, N. Paltrinieri, F. Sgarbossa, On hierarchical bayesian based predictive maintenance of autonomous natural gas regulating operations, Process Saf. Environ. Prot. 147 (2021) 115–124. https://doi.org/https://doi.org/10.1016/j.psep.2020.08.047.

[43] H. Su, E. Zio, J. Zhang, X. Li, L. Chi, L. Fan, Z. Zhang, A method for the multi-objective optimization of the operation of natural gas pipeline networks considering supply reliability and operation efficiency, Comput. Chem. Eng. 131 (2019) 106584. https://doi.org/https://doi.org/10.1016/j.compchemeng.2019.106584.

[44] G. Weidl, A.L. Madsen, S. Israelson, Applications of object-oriented Bayesian networks for condition monitoring, root cause analysis and decision support on operation of complex continuous processes, Comput. Chem. Eng. 29 (2005) 1996–2009. https://doi.org/https://doi.org/10.1016/j.compchemeng.2005.05.005.

[45] M. Yazdi, F. Khan, R. Abbassi, Microbiologically influenced corrosion (MIC) management using Bayesian inference, Ocean Eng. (2021). https://doi.org/10.1016/j.oceaneng.2021.108852.

[46] M. Singh, M. Pokhrel, A Fuzzy logic-possibilistic methodology for risk-based inspection (RBI) planning of oil and gas piping subjected to microbiologically influenced corrosion (MIC), Int. J. Press. Vessel. Pip. 159 (2018) 45–54. https://doi.org/10.1016/j.ijpvp.2017.11.005.

[47] T.J. Ross, Fuzzy Logic with Engineering Applications, 2009. https://doi.org/10.1002/9781119994374.

[48] A.S. Markowski, M.S. Mannan, Fuzzy logic for piping risk assessment (pfLOPA), J. Loss Prev. Process Ind. 22 (2009) 921–927. https://doi.org/10.1016/j.jlp.2009.06.011.

[49] A.S. Markowski, M.S. Mannan, A. Kotynia (Bigoszewska), D. Siuta, Uncertainty aspects in process safety analysis, J. Loss Prev. Process Ind. 23 (2010) 446–454. https://doi.org/10.1016/j.jlp.2010.02.005.

[50] H. Li, J.-Y. Guo, M. Yazdi, A. Nedjati, K.A. Adesina, Supportive emergency decision-making model towards sustainable development with fuzzy expert system, Neural Comput. Appl. 33 (2021) 15619–15637. https://doi.org/10.1007/s00521-021-06183-4.

[51] G.-J. Jiang, H.-X. Chen, H.-H. Sun, M. Yazdi, A. Nedjati, K.A. Adesina, An improved multi-criteria emergency decision-making method in environmental disasters, Soft Comput. (2021). https://doi.org/10.1007/s00500-021-05826-x.

[52] E. Arzaghi, R. Abbassi, V. Garaniya, J. Binns, C. Chin, N. Khakzad, G. Reniers, Developing a dynamic model for pitting and corrosion-fatigue damage of subsea pipelines, Ocean Eng. 150 (2018) 391–396. https://doi.org/10.1016/j.oceaneng.2017.12.014.

[53] E. Arzaghi, M.M. Abaei, R. Abbassi, V. Garaniya, C. Chin, F. Khan, Risk-based maintenance planning of subsea pipelines through fatigue crack growth monitoring, Eng. Fail. Anal. 79 (2017) 928–939. https://doi.org/10.1016/j.engfailanal.2017.06.003.

[54] S. Adumene, F. Khan, S. Adedigba, Operational safety assessment of offshore pipeline with multiple MIC defects, Comput. Chem. Eng. (2020) 106819. https://doi.org/10.1016/j.compchemeng.2020.106819.

[55] E. Shekari, F. Khan, S. Ahmed, Probabilistic modeling of pitting corrosion in insulated components operating in offshore facilities, ASCE-ASME J. Risk Uncertain. Eng. Syst. Part B Mech. Eng. 3 (2017) 1–11. https://doi.org/10.1115/1.4034603.

[56] S. Adumene, F. Khan, S. Adedigba, S. Zendehboudi, Offshore system safety and reliability considering microbial influenced multiple failure modes and their interdependencies, Reliab. Eng. Syst. Saf. (2021) 107862. https://doi.org/https://doi.org/10.1016/j.ress.2021.107862.

[57] S. Adumene, F. Khan, S. Adedigba, S. Zendehboudi, H. Shiri, Offshore pipeline integrity assessment considering material and parametric uncertainty, J. Pipeline Sci. Eng. (2021). https://doi.org/https://doi.org/10.1016/j.jpse.2021.09.005.

[58] C. Gong, W. Zhou, First-order reliability method-based system reliability analyses of corroding pipelines considering multiple defects and failure modes, Struct. Infrastruct. Eng. 13 (2017) 1451–1461. https://doi.org/10.1080/15732479.2017.1285330.

[59] S. Haladuick, M.R. Dann, Risk-Based Maintenance Planning for Deteriorating Pressure Vessels With Multiple Defects, J. Press. Vessel Technol. Trans. ASME. 139 (2017). https://doi.org/10.1115/1.4036428.

[60] S. Zhang, W. Zhou, Cost-based optimal maintenance decisions for corroding natural gas pipelines based on stochastic degradation models, Eng. Struct. 74 (2014) 74–85. https://doi.org/10.1016/j.engstruct.2014.05.018.

[61] J. Zhao, Risk Management for Pitting Corrosion, The University of Akron, 2014.

[62] A. Valor, F. Caleyo, L. Alfonso, J.C. Velázquez, J.M. Hallen, Markov chain models for the stochastic modeling of pitting corrosion, Math. Probl. Eng. 2013 (2013). https://doi.org/10.1155/2013/108386.

[63] F. Caleyo, J.C. Velázquez, A. Valor, J.M. Hallen, Markov chain modelling of pitting corrosion in underground pipelines, Corros. Sci. 51 (2009) 2197–2207. https://doi.org/10.1016/j.corsci.2009.06.014.

[64] E. Shekari, F. Khan, S. Ahmed, A predictive approach to fitness-for-service assessment of pitting corrosion, Int. J. Press. Vessel. Pip. 137 (2015) 13–21. https://doi.org/10.1016/j.ijpvp.2015.04.014.

[65] V. Hernández-Chover, Á. Bellver-Domingo, F. Hernández-Sancho, The influence of oversizing on maintenance cost in wastewater treatment plants, Process Saf. Environ. Prot. 147 (2021) 734–741. https://doi.org/https://doi.org/10.1016/j.psep.2020.12.033.

[66] S. Ramya, V. Devadas, Integration of GIS, AHP and TOPSIS in evaluating suitable locations for industrial development: A case of Tehri Garhwal district, Uttarakhand, India, J. Clean. Prod. 238 (2019) 117872. https://doi.org/10.1016/j.jclepro.2019.117872.

[67] M. Yazdi, F. Khan, R. Abbassi, R. Rusli, Improved DEMATEL methodology for effective safety management decision-making, Saf. Sci. 127 (2020) 104705. https://doi.org/https://doi.org/10.1016/j.ssci.2020.104705.

[68] P. Chemweno, L. Pintelon, A.M. De Meyer, P.N. Muchiri, A. Van Horenbeek, J. Wakiru, A Dynamic Risk Assessment Methodology for Maintenance Decision Support, Qual. Reliab. Eng. Int. 33 (2017) 551–564. https://doi.org/10.1002/qre.2040.

[69] S. Zhang, W. Zhou, M. Al-Amin, S. Kariyawasam, H. Wang, Time-Dependent Corrosion Growth Modeling Using Multiple In-Line Inspection Data, J. Press. Vessel Technol. 136 (2014) 1–7. https://doi.org/10.1115/1.4026798.

[70] H. Qin, W. Zhou, S. Zhang, Bayesian inferences of generation and growth of corrosion defects on energy pipelines based on imperfect inspection data, Reliab. Eng. Syst. Saf. 144 (2015) 334–342. https://doi.org/10.1016/j.ress.2015.08.007.

[71] R.B. Miller, A. Sadek, A.L. Crouch, J.G. Floyd, C.A. Drake, B.S. Stevenson, W. Crookes-Goodson, C.N. Monty, J.M. Senko, Novel Mechanism of Microbially Induced Carbon Steel Corrosion at an Aqueous/Non-aqueous Interface, Ind. Eng. Chem. Res. 59 (2020) 15784–15790. https://doi.org/10.1021/acs.iecr.0c02497.

[72] E. Shekari, Risk-based evaluation of pitting corrosion in process facilities, Memorial University of Newfoundland, 2017. http://research.library.mun.ca/id/eprint/13051.

[73] M. Yazdi, S. Kabir, M. Walker, Uncertainty handling in fault tree based risk assessment: State of the art and future perspectives, Process Saf. Environ. Prot. 131 (2019). https://doi.org/10.1016/j.psep.2019.09.003.

[74] H. Christopher Frey, S.R. Patil, Identification and Review of Sensitivity Analysis Methods, Risk Anal. 22 (2002) 553–578. https://doi.org/https://doi.org/10.1111/0272-4332.00039.

Chapter 5

A dynamic model for Microbiologically Influenced Corrosion (MIC) Integrity Risk Management of Subsea Pipelines

Preface

A version of this chapter has been submitted to the journal of ***Ocean Engineering****. I am the primary author along with the Co-authors, Faisal Khan, and Rouzbeh Abbassi. I developed the conceptual framework for the integrity risk management of subsea pipelines model and carried out the literature review. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' feedbacks. Co-author Faisal Khan helped in the concept development and testing the model, reviewing, and revising the manuscript. Co-author Rouzbeh Abbassi provided support in implementing the concept and testing the model. The co-authors also contributed to the review and revision of the manuscript.*

Abstract

Microbiologically Influenced Corrosion (MIC) is a severe problem for offshore oil and gas facilities. MIC causes pinholes, which become a source of the leak. The pipeline integrity management requires preventive (proactive) (i.e., coatings, cathodic protection) and mitigative (reactive) actions (i.e., inhibitor treatment, biocide treatment). The efficiency and the cost of these integrity management actions play a critical role in overall integrity risk management. A multi-objective functional methodology involving Dynamic Continuous Bayesian Network modeling to minimize the operational risk associated with the MIC is proposed. The Meta-heuristic algorithm as Genetic Algorithm (GA) is used to obtain the optimum schedule for performing integrity management actions. The application of the proposed model is illustrated in a subsea pipeline

under the influence of MIC. The results identify a series of solutions allowing decision-makers to select the optimal combination of integrity management actions with the tradeoff between reliability and cost.

Keywords: Optimization, Bayesian network, Meta-heuristic algorithm, Pipelines, MIC integrity management

5.1. Introduction

Microbiologically Influenced Corrosion (MIC) is one of the most significant metal degradation mechanisms, which further affects subsea pipelines' long-term availability and integrity [1–4]. MIC causes different incidents in the oil and industrial sectors, such as hazardous hydrocarbon containment loss leading to fire and explosion as well as environmental and economic impact [5]. Steel deterioration is a common cause of loss in the subsea pipeline in Canada [6]. To ensure the pipeline integrity for a specific period, considering the preventive (proactive) and mitigative (reactive) practices are the key components for the MIC integrity management program [7]. Determination of optimal practices times and interval are vital for decision-makers. Since performing the integrity management practices in a long time interval will result in extreme integrity management action, it could be costly in time, human resources, and finances. In contrast, the short time interval may ignore the critical defects through the pipeline and lead to serious safety and economic impacts. Therefore, it is vital to derive the best interval to perform management practices.

Therefore, optimizing the time interval for applying certain integrity management practices is challenging for site operators. Firstly, the metal deterioration mechanism under the influence of MIC is still under discussion and uncertain with time-variation, which assessors face to model uncertainty. Secondly, the pit depth growth of individual defects and the number of defects is uncertain with time variation. According to the challenges mentioned above, scheduling and selecting optimum integrity management actions have been investigated by considering different reliability-based models. Early studies developed a framework to estimate pit depth growth and further determine the optimum interval of the inspection schedule [8]. Following the Hong study [8], Gomes et al. [9] proposed a cost-effective safety integrity management framework that includes assigning the cost to determine the optimum inspection period for onshore pipelines subjected to external corrosion. Gomes and Beck [10] designed an objective function to minimize the total expected life-cycle costs. They considered different types of variables such as thickness, time to the first inspection, the time between successful inspections, and expected numbers of failures. Similarly, Zhang and Zhou [11] considered the minimum expected life-cycle costs to obtain the optimum inspection intervals by attending to the set of defects.

In order to investigate the optimum integrity management practices over a period, two primary objectives should be considered. These objectives are (i) maximizing the reliability/availability of the pipeline under study and (ii) minimizing the cost associated with the integrity management practices. In a realistic case, decision-makers need to consider multiple objectives with or without the same importance weight. Then, decision-makers can find all possible solutions using multi-objective functions, which tradeoff between the two objectives as mentioned above. According to this point, Gong and Zhou [12] provided objective functions with conditional probabilities of burst and small leak for an in-service corroded pipeline within a limited annual budget. Latif et al. [13] formulated optimum condition-based maintenance scheduling for metal structures using multidisciplinary algorithmic approaches. A comprehensive outline for managing an underground pipeline was proposed to optimize the reliability and cost factors using Monte Carlo simulation [14]. Ghimire et al. [15] addressed the challenges of identifying the optimal location of gas network maintenance centers in natural gas transmission systems. A combination of Bayesian network (BN) and Genetic Algorithm (GA) are utilized to propose a methodology for the inspection scheduling of pipelines under the influence of corrosion [16].

Since corrosion defect under the influence of MIC grows over time, the MIC defects are not critical at a certain point but may become much more critical over time. This denotes that the MIC defects might not be prevented, controlled, or mitigated simultaneously because of the limited annual budget, resources, and access limitations. Therefore, to manage the MIC defect, the application of a management practice may not be sufficient over a period, and different types of integrity management actions should be employed over time.

This study's main contribution in MIC management for subsea systems proposes a framework for scheduling integrity management actions over time. In addition, the dynamic Continuous Bayesian network (CBN) is used in the assessment framework for MIC integrity management. Thus, the proposed framework takes into account both model and data uncertainty. Another contribution is developing the reliability and cost functions for pit depth growth under the influence of MIC, and the third is using the mathematical optimization modeling technique over a period to obtain optimum integrity management practices.

The remainder of the paper is structured as follows. A reliable framework to determine the optimum integrity management practices is proposed in Section 2 for the subsea pipeline under the influence of MIC. The application of the developed framework to a case study of a subsea pipeline is discussed in Section 3. Finally, Section 4 is devoted to the present study's conclusions, highlighting the challenges and the direction for further research in this field.

5.2. The Proposed Microbiologically Influenced Corrosion (MIC) Integrity Management Methodology

It is essential to predict the rate of MIC and pit depth growth in the early stage of subsea pipeline development to provide appropriate integrity management actions(s), which can prevent, mitigate, and control the occurrence of a pipeline failure. However, MIC integrity management is challenging for decision-makers due to the lack of information required in the probabilistic risk analysis, such as the problematic data availability from in-line inspection tools. Thus, as demonstrated in Figure 5.1, the seven steps methodology is proposed to find the optimum time interval for performing the required integrity management practices. This framework enables decision-makers to tradeoff between reliability and cost. In step one, the mechanistic model of MIC and all required information for developing the models will be obtained. Different integrity management practices will be presented in step two, including preventive and mitigative. In steps three and four, reliability functions and cost functions for each integrity management practice will be derived. In addition, failure cost is also considered in the case of comparison purposes. The multi-objective functions are then defined with consideration of different constraints in step five. In step six, all possible solutions will be derived. Finally, the optimal decision will be implemented in step seven. The details of the steps are provided in the following sections.

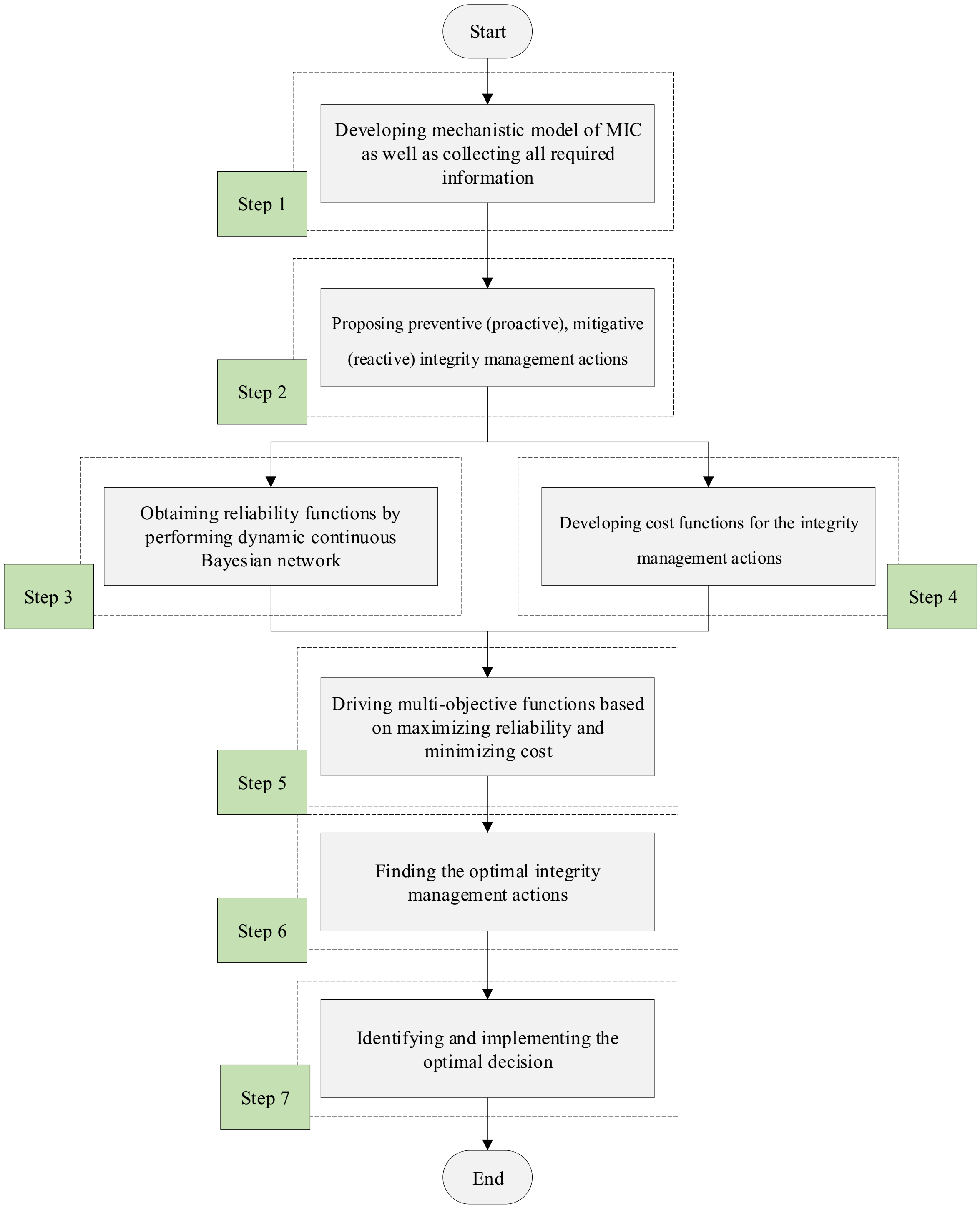

Figure 5.1. The developed framework to implement the optimal integrity management actions

Step 1: Developing a mechanistic model of MIC as well as collecting all required information

In this step, mechanistic modeling of individual pit initiation influenced by MIC is developed. The mechanistic model considers the type of corrosion (which is MIC), chemical compositions of internal fluid, material type, alloy composition, mechanic characteristics of the system (e.g., subsea, onshore), and effective environmental and operational conditions. This can further lead but is not limited to the corrosion rate, material strength properties, depth and width of the pits, and remaining age of the pipeline.

After identifying all potential factors impacting the MIC, the BN tool is used to reflect the relationship between different parameters in the mechanistic model developed for MIC. Thus, developing BN by considering the dependency and interrelationships between the potential factors is the first step in providing the mechanistic model of MIC.

The related data for each node in developed BN are obtained from various sources, including different industrial sectors, operational conditions, multiple regions, or subjective opinions from experts in the field. Once all the necessary data/information is collected, they are further processed into intervals to approximate their probabilities for identified ranges. Therefore, the predicted probabilities can be used as input data for the BN model.

The BN based on discrete and continuous nodes has enough capacity to analyze each node's behavior over time, given new data, making it one of the most effective and robust tools. Common BN-based approaches have been widely used in different engineering domains, such as [17–22]. BN-based techniques can employ different input data (objective or subjective) to estimate the probability centered event by reducing the model uncertainty with consideration of interdependency between all the participating nodes [23,24]. However, the discrete BN-based models ignore the precision and modeling flexibility. In other words, the discrete BN-based approaches consider the continuous nature of causal factors in the network as discrete variables. Therefore, this type of estimation provides uncertainty during the analysis process [25–28]. In real-world applications, there are often variables that continuously change over time. Therefore, they cannot be modeled by adopting standard BN-based models with discrete variables, such as the case for MIC.

Once continuous nodes are used in BN, the computation of posterior distribution becomes much more complicated. Therefore, the analytical methods or Monte Carlo simulations cannot compute the posterior distributions. Markov Chain Monte Carlo (MCMC) is a robust tool and has a high capacity to calculate the posterior distribution with high dimensions [29–31]. To elaborate, MCMC has two main parts: (i) Monte Carlo and (ii) Markov Chain. Monte Carlo refers to a method that relies on the generation of random numbers, and Markov Chain refers to a sequence of numbers in which each number depends on the last number in the sequence. However, Monte Carlo simulations fail to sample from the complicated distribution, which has different dependent variables. To handle this issue, Markov Chain is used to assist Monte Carlo, and therefore MCMC is utilized. To obtain more details about MCMC and its algorithms, one can refer to [32].

Step 2: Proposing preventive (proactive), mitigative (reactive) integrity management actions

In this step, the possible integrity management actions to maintain the understudied pipelines are proposed. The first maintenance plan is preventive actions. Preventive actions refer to decreasing the occurrence probability of a more hazardous event [33]. The primary motivation for preventive actions is to avoid nonconformances, which means it can improve the efficiency of the system [34]. These intervention actions highlight the technical requirements associated with the product or service supplied or the internal integrity management system. Preventive (proactive) actions are typically used in different fields, including using firewalls and encryption computers-based technologies; modeling and simulating playing the roles of preventive actions in information systems; having a healthy lifestyle, and regular check-ups to prevent risk factors of different diseases in the healthcare system and varieties of safeguards in industrial sectors. Finally, mitigative (reactive) actions can be taken in three different ways (i) providing reactive barriers which are able to stop or reduce the energy rate released by the hazardous event, (ii) separating the assets with coating, lining, and painting, (iii) making the assets less vulnerable to impacts (e.g., hard hats, protective clothing), and (iv) improving first aid and rehabilitation systems (e.g., ambulances, hospitals) [33].

In order to define the policy of performing integrity management practices, it is assumed that there is only one pit at the particular location, and it is not merged with other pits in the duration of the process.

Step 3: Developing reliability functions using dynamic continuous Bayesian network

Thomas Bayes, a British mathematician, proposed Bayes' rule [1701-1761] [35]. Bayes' rule shows that both probabilities of X and Y as two variables can occur when the production of X and Y give X in term of probability. The expression mentioned above can be stated as the following equation:

$$P(X,Y) = P(X) \times P(Y|X) \tag{5.1}$$

where $P(X,Y)$ represents the probability of both variables X and Y, which can occur.

With consideration of symmetry law, Equation (5.1) can be modified into Equation (5.2) as:

$$P(X|Y) = \frac{P(Y|X) \times P(X)}{P(Y)} \tag{5.2}$$

where $P(Y|X)$ represents the probability of evidence Y when the hypothesis of X is true, $P(X)$ is denoted as the prior probability of variable X, $P(Y)$ is the prior probability when the evidence Y occurs (true), and $P(Y|X)$ is the posterior probability of X given the evidence of variable Y.

To show the operational features of BN, assume that in a typical BN, n variables as $X_1, X_2, X_3, \dots, X_n$, are included. Accordingly, the joint probability distribution of variables can be decomposed as Equation (5.3):

$$P(X_1, X_2, X_3, \dots, X_n) = P(X_1 \mid X_2, X_3, \dots, X_n) \times P(X_2 \mid X_3, \dots, X_n) \dots \times P(X_{n-1} \mid X_n) \tag{5.3}$$

Subsequently, by simplification, Equation (5.3) can be streamlined into Equation (5.4):

$$P(X_1, X_2, X_3, \dots, X_n) = \prod_{i=1}^{n} P(X_i \mid X_{i+1}, X_{i+2}, \dots, X_n) = \prod_{i=1}^{n} P(X_i \mid \text{Parrents } (X_i)) \tag{5.4}$$

Assume that a typical BN is structured having a set of limited variables as $M = \{X_1, X_2, X_3, X_4\}$, and consists of arcs that illustrate the interdependency and relationships between the existing variables. To get more details related to BN structuring, BN implementation, and BN computations, one can refer to the previous studies and literature [36–38]. Generally, when BN is constructed based on a combination of continuous and discrete nodes, it cannot be solved using single analytical methods such as Monte Carlo simulation or first/second-order momentum over a period. The computation can perform MCMC as explained in step 1 [30].

As illustrated in Figure 5.2, dynamic continuous BN is established for computing as well as updating the failure probability of the pipeline under the influence of MIC in the current work. The left-hand side of the constructed BN at time $t = 0$ illustrates the initial rate of MIC, pit depth growth, and failure probability of the pipeline for a single defect. The right-hand side shows the growth of pit depth and dynamic failure probability.

In Figure 5.2, the parameter a_i ($a_i > 0$) is an indication of pit depth growth for defect i in one year from the initiation time of the defect. The parameter t_{0i} represents the MIC initiation time (the proceed time from installation date to the time defect i starts to grow). In practice $t_{0i} > t_j$, the parameter b_i ($b_i > 0$) denotes the MIC rate of growth path, in which $b_i = 0$, $b_i > 0$, and $b_i < 1$ are representing the linear, acceleration, and deceleration pit depth growth path, respectively. η_{ij} denotes the model error of the pit depth growth connected with defect i at time and j, da_{ij} is the pit depth growth path, and is the probability of failure of the corroded pipeline.

Once the probability of failure is obtained over a period, the reliability function for each single integrity management practice can be derived.

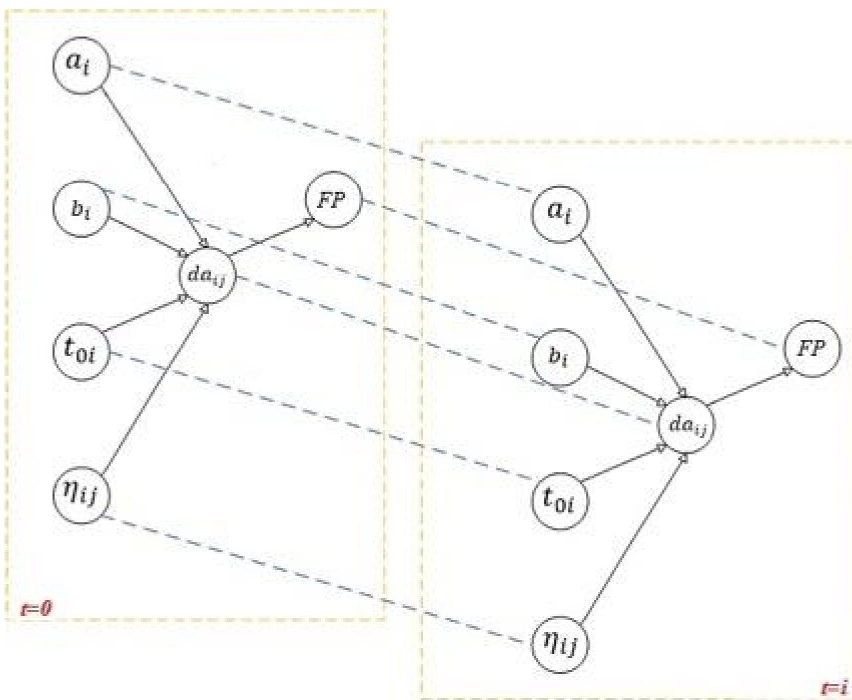

Figure 5.2. The dynamic structure of BN for the corroded pipeline under the influence of MIC

Step 4: Developing cost functions for integrity management actions

In this step, the associated parameters with the cost for all integrity management practices will be provided. In addition, the interest rate, as well as the annual budget, will be considered. A reference pipeline defect is also assumed to be subjected to periodic inspection and maintenance with a fixed time interval. Corresponding to this point, the unit cost of all integrity management practices and periodic inspection fall into the integrity management policy in step two, with the total cost of all integrity management practices over a while able to be estimated.

Step 5: Driving multi-objective functions based on maximizing reliability and minimizing cost

Multi-objective optimization is an essential field of multi-criteria decision-making. This is based on mathematical optimization problems, including more than one objective function to be optimized simultaneously. In addition, the objective functions may be on opposite sides. Therefore, no exact solution optimizes each objective simultaneously, and there is possibly an infinite number of Pareto optimal solutions. Without ignoring the supplementary subjective preference information, all optimal Pareto distribution solutions would be considered similarly reliable [39]. The reason for constructing a multi-objective function is that obtaining Pareto optimal solutions with consideration of different objectives.

Based on step three, the rate of MIC, pit depth growth, and the probability of failure will be obtained over a period for each integrity management practice. Every year, all integrity management practices are evaluated to observe which one has the highest probability of failure and minimize the maximum probability of failure for each year. Thus, the first objective is reducing the highest probability of failure over time. According to step 4, the second objective function would be minimizing the total cost of all integrity management practices over time.

Once the multi-objective optimization is provided, constraints need to be presented to solve the provided multi-objective functions. A constraint is a circumstance of an optimization problem that the solution needs to be satisfied. There are three sorts of constraints, equality, inequality, and integer constraints. The set of candidate solutions as feasible solutions should satisfy the constraints [40].

Our study's constraints would be the annual budget for each year, the cost of integrity management practices, reliability function for each integrity management practice over time, and integrity management policy.

Step 6: Finding optimal integrity management actions

In order to solve the optimization model, two different algorithms can be utilized. Firstly, using an algorithm based on those methods that provide the exact optimum values such as Branch and bounds; secondly, using Meta-Heuristic algorithms such as genetic, gray wolf, bees, whale, ant lions, etc. Considering the complexity of the multi-objective functions, the optimal solutions can only be determined by adopting enumeration and random methods that fall under Meta-Heuristic algorithms' idea. Meta-Heuristic algorithms are the higher-level procedures to find, generate, or select a heuristic (partial search algorithm), which might represent an adequate solution to the multi-objective functions [39,41–44].

The Genetic Algorithm (GA) as a random method is selected to obtain optimum solutions because of its widely effective capabilities and its efficient global search capability [45]. In GA, Darwin's theory of biological evolution is considered to construct the computational model. GA can also be used as a methodology of optimum solution searching with simulations of the natural evolutionary process [16,46–49]. The simple form of the GA solving process is depicted in Figure 5.3, underlying the idea of study [16].

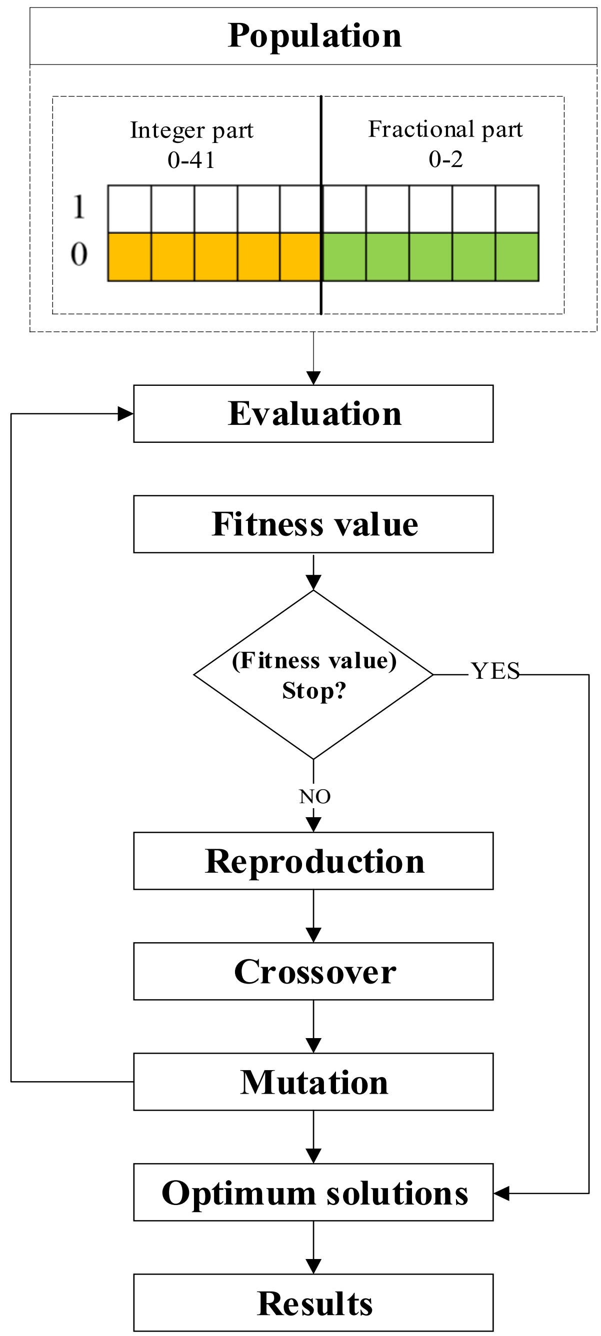

Figure 5.3. The performing procedure of the GA

As illustrated in Figure 5.3, six steps are required, including (i) population generation, (ii) evaluation, (iii) fitness value, (iv) reproduction, (v) crossover, and (vi) mutation. The solutions have to be encoded in a fixed-width form as a first step, called "genetic strings". The number of "bit" has to be employed to properly present the solutions to the optimization problem in the Genetic Algorithm. For example, for a corroded pipeline under the influence of MIC, a 10 bits binary is used to encode the optimal time interval for performing all integrity management practices during a set goal of 40 years. In addition, the accuracy of the optimal time interval is assumed as one or two decimal places. The 5 bits of the 10 bits binary located in the first-order show the integer part (this means that they are searchable 0-41, which are more than the set goal). The 5 bits of the 10 bits binary located last illustrate fractional parts (this means that they are searchable from 0-2). When performing different types of integrity management practices over time, the encoding of subsequent integrity management practices is ordered before in the queue. Therefore, the fitness value of the initial population is computed according to objective functions. The population with proper fitness value are then selected for the next step of reproduction. Subsequently, the reproduced population is then utilized in the following steps as the cross-over and mutation, respectively. A set of the evolved population is then assessed in the cycle of optimization. This cycle is sustained until the evolved population is satisfied with the termination criteria set. The relevant programming model can also be developed using MATLAB as it has useful features.

Step 7: Identifying and Implementing the optimal decision

In this step, decision-makers can select the best time interval for combining integrity management practices by a tradeoff between reliability and cost. The optimum series of solutions will be presented in optimal Pareto distributions. Decision-makers can also give importance weights to the objective functions to allow balance. In the present study, the importance weights of both reliability and cost functions are equal.

5.3. Application of the proposed methodology: A case study

The introduced method is applied to an APL 5L grade X42 subsea hydrocarbon transition pipeline that is highly suspect to internal MIC and must be in operational condition for at least 40 years. The pipeline carries co-mingled fluids from a different number of subsea resources.

Step 1: Developing a mechanistic model of MIC as well as collecting all required information

According to the first step of the developed methodology, the mechanistic model of maximum pit depth growth influence by MIC appears in Figure 5.4. The mechanistic model of MIC is drawn with consideration of (i) environmental conditions, including salinity, CO_2 partial pressure, pH, O_2, temperature, water cut, and Sulphides, (ii) operational conditions including fluid velocity and pressure, (iii) material conditions including steel composition and Carbon content, (iv) biofilm, and (v) exposure duration.

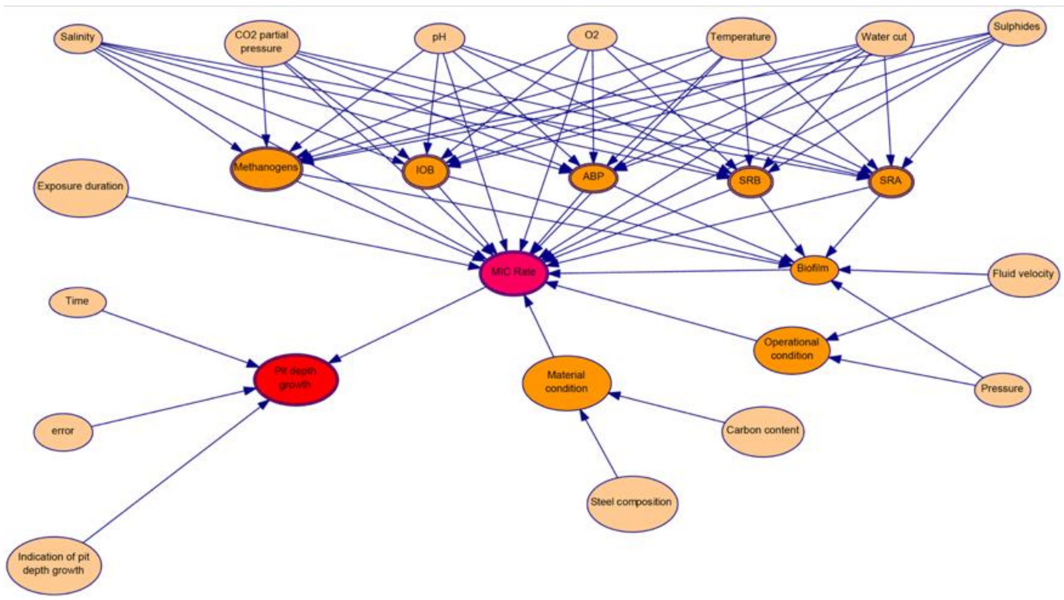

Figure 5.4. The influence diagram of the mechanistic model of maximum pit depth growth influence by MIC (SRB (sulfate-reducing bacteria), SRA (sulfate-reducing Archaea), and IOB (iron-oxidizing bacteria)

The data presented in Table 5.1 are based on literature [19,27,50–52], and mean values of continuous variables are based on operational and chemical analysis from an offshore facility off the East Coast of Canada. A chemical analysis of produced water shows the total number of microorganisms using the qPCR (quantitative Polymerase Chain Reaction) method (3.19E+06 (16S copies/mL sample)), different types of microorganisms percentage (Methermicoccus 4.79 %, Desulfovibrio 8.72 %, Dethiosulfatibacter 10.14 %, Archaeoglobus 38.36 %, Thermoanaerobacter 1.35 %, Thermococcus 9.9 %, Thermosipho 3.6 %, Methermicoccus 4.79 %), and sulfate reduction rate (SRR) (0.52 in situ).

Table 5.1. The pipeline operational parameters' data range

Variables	Descriptions
pH	Distribution: 3.2 - 7.86

Temperature (degree)	Distribution: 0 - 50
Flow rate (m^3/s)	Distribution: 0.01 - 1.116
Exposure time (yrs)	Distribution: 2.5 - 3.5
Salinity	Discrete: Present/ Absent
Steel composition	Discrete: Present/ Absent
Carbon content	Discrete: Present/ Absent
Pressure	Discrete: High/ Moderate/ Low
O_2	Discrete: High/ Moderate/ Low
Sulfate ion (ppm)	Distribution: 0.01 - 32000
CO_2 partial pressure	Discrete: High/ Moderate/ Low
Water cut	Discrete: High/ Moderate/ Low
Biofilm	Discrete: High/ Moderate/ Low thickness

Step 2: Proposed preventive (proactive), mitigative (reactive) integrity management actions

As mentioned earlier, proactive practices, also called a frequency-reducing barrier, are barriers that prevent or reduce the probability of a failure. Moreover, reactive practices, moreover named a mitigating or consequence-reducing barrier, are a barrier that avoids or reduces the consequences of failure. These practices prevent the occurrence of defects influenced by MIC falling into proactive integrity management practices. Once pit depth starts to grow, the reactive integrity management practices play their roles.

Figure 5.5 presents the possible integrity management practices for the subsea pipelines influenced by MIC [53]. The efficiency of each integrity management practice is studied in the previous study [54].

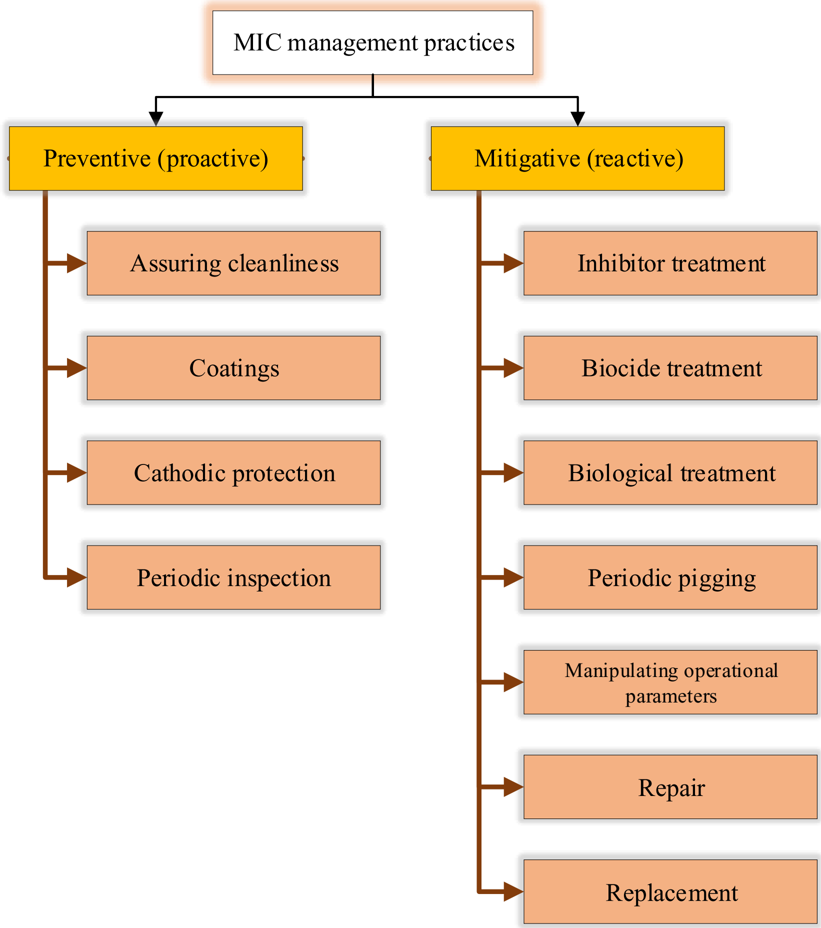

Figure 5.5. MIC preventive and mitigative integrity management actions

Step 3: Developing reliability functions by performing dynamic continuous Bayesian network

In the study's conducted application, it is assumed that the pipeline's lifetime is equal to 40 years. Besides, the lowest accuracy of searching the in-line inspection design is equal to 12 months based on industrial practice. As soon as the lifetime of the pipeline and lowest accuracy of searching are set, the dynamic continuous BN is developed to estimate the rate of MIC, pit depth growth path, and failure probability over a period, as depicted in Figure 5.6.

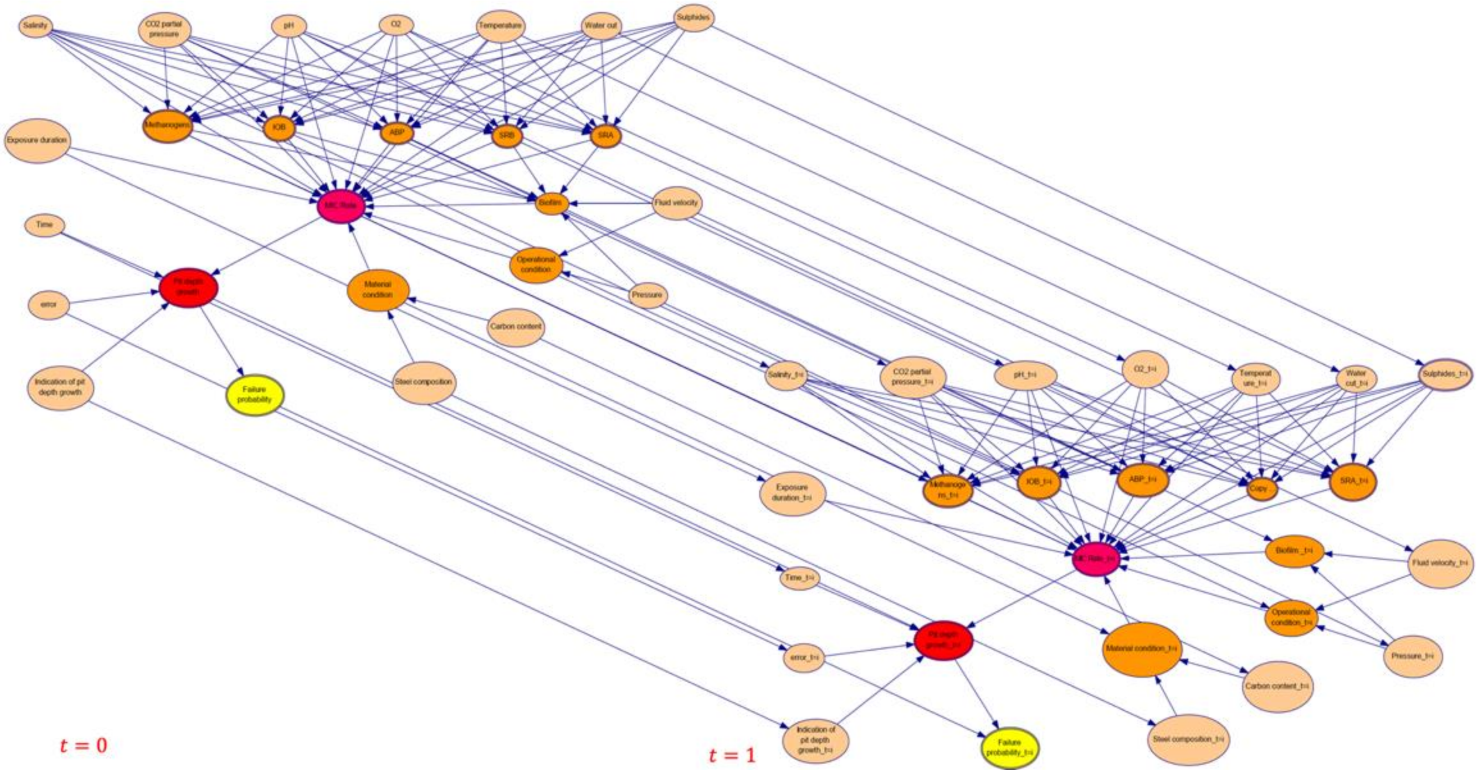

Figure 5.6. Developed dynamic continuous BN

The non-informative distributions (i.e., distributions with small means and very large variances) are considered for the pit depth growth factors a_i , t_{oi} , and η_{ij} . In order to obtain pit depth growth and accordingly failure probability, Bayesian updating software such as OpenBugs (www.openbugs.net) using MCMC methods is utilized by 1000000 iterations within interval two tinning, in which the estimated parameters of the growth models were then used to estimate the failure probability of the defect. The failure probability of the pipeline under the influence of MIC will be further developed and updated using BN in all possible discrete time intervals with one year. Once the failure probability function is derived, the same procedure is applied with consideration of each single integrity management practice's efficiency.

The first three integrity management practices (assuring cleanness, coating, and cathodic protection) are assumed to have been already performed and considered in the pipeline installation

[54]. The reliability or failure probability functions for the rest of integrity management practices can then be derived and provided. It is also assumed that the three integrity management practices Pigging, Repairing, and Replacing, are performing desecrate, and the rest of the actions are performing continuously.

$$R_{\text{Periodic inspection}} = 1 - 5.00 \times e - 4 \times X \times e - 2 + X - 7.70 \times e - 3$$
$$R_{\text{Inhibitors treatment}} = 1 - 2.00 \times e - 5 \times X \times e - 2 + 3.58 \times e - 02X + 1.80 \times e - 3$$
$$R_{\text{Biocide treatment}} = 1 - 3.00 \times e - 4 \times X \times e - 2 + 3.40 \times e - 02X - 9.00 \times e - 3$$
$$R_{\text{Biological treatment}} = 1 - 2.00 \times e - 4 \times X \times e - 2 + 3.04 \times e - 02X - 2.90 \times e - 3$$
$$R_{Manipulating\ operational\ parameters\ (Temperature)} = 1 - 3.00 \times e - 04 \times X \times e - 2 + 3.62 \times e - 02X - 2.90 \times e - 03$$
$$R_{Manipulating\ operational\ parameters\ (pH)} = 1 - 4.00 \times e - 4 \times X \times e - 02 + 4.58 \times e - 2 \times e - 1.11 \times e - 2$$
$$R_{\text{Manipulating operational parameters (Velocity)}} = 1 - 3.00 \times e - 4 \times X \times e - 02 + 3.31 \times e - 2X - 3.80 \times e - 3$$
$$R_{\text{Pigging}} = 1 - 1.00 \times e - 4 \times X \times e - 2 + 3.29 \times e - 2X + 1.96 \times e - 2$$
$$R_{\text{Repairment}} = 1 - 2.40 * e - 3 \times X \times e - 02t + 8.24 \times e - 02Xt - 8.72 \times e - 2$$
$$R_{\text{Replacement}} = 1 - 5.60 \times e - 3 \times X \times e - 02t + 1.31 \times e - 01Xt - 2.14 \times e - 1 \qquad (5.5)$$

where X is the time of performance of integrity management practices, and t is whether integrity management practices are performed or not (0 or 1). To obtain equation (5.5), the system's reliability using BN according to each performance is evaluated, and the best function is fitted to the pit depth growth path.

Step 4: Obtaining cost functions for the integrity management actions

To obtain the cost functions for all mentioned integrity management practices, it considered the input from industries' experts by highlighting only and only direct costs [11].Given unit costs to all integrity management practices (provided in Table 5.2) and annual inflation rate as 0.61 % in Canada, 2020 (www.statista.com), the cost functions can be defined as a summation of all integrity management practices their single performance.

Table 5.2. The approximated integrity management actions cost for a single cycle

Reference name	Integrity management practices	Cost (US)
C_{MP_1}	Periodic inspection *	3,840
C_{MP_2}	Inhibitors treatment **	900000 per year
C_{MP_3}	Biocide treatment **	185000 million per year
C_{MP_4}	Biological treatment **	380000 million per year
C_{MP_5}	Manipulating operational parameters (Temperature) ***	15,000 per year
C_{MP_6}	Manipulating operational parameters (pH) ***	20,000 per year
C_{MP_7}	Manipulating operational parameters (Velocity) ***	35,000 per year
C_{MP_8}	Pigging	35,000 per mile
C_{MP_9}	Repair	2,400
$C_{MP_{10}}$	Replace	6,800
C_f	Failure cost ****	543,407
C_A	Annual budget	1,000,000

* Periodic inspection includes (i) Gaining access, (ii) Surface preparation, (iii) Inspection: UT, (iv) Inspection: RI, (v) Technical support, and (vi) Logistics [55].

** To compute the cost of these treatments, with consideration of pipeline (APL 5L grade X42) features (i.e., diameter, and length) and operation condition (flow rate), one standard cubic meter in the pipeline is assumed to obtain how many Kg of chemical treatments is required per one cubic meter. We then compute how many seconds with a constant flow rate are required for 1 standard cubic meter with an exact amount of chemical treatment. Subsequently, this is computed for kg/year, and finally considering the price value of 1 kg (Inhibitors, Biocide, and Biological) treatments. The total cost for a single year is therefore determined for each treatment.

*** It is estimated based on experts' opinions who have relevant expertise and background, and this study is conducted as partial study.

**** Failure cost includes (i) Loss because of breakdown, (ii) Loss because of shutdown, (iii) Spill cleaning, (iv) Environment damage, and (v) Liability charges [55].

Therefore, considering two sets: $I\{MP1, \dots, MP7\}$,$J\{\ MP8, MP9, MP10\}$, and K: I U J the cost function can be defined as the following:

$$\sum_{i=1}^{7} C_{MP_i} \left(\frac{X2_i}{(1+IR)^i} - \frac{X1_i}{(1+IR)^i}\right) + \sum_{j=8}^{10} \sum_{t=1}^{40} \frac{Y_{jt} C_{MP_i}}{(1+IR)^t} \tag{5.6}$$

where, C_{MP_i} is the cost of integrity management practice i in one-year, C_{MP_j} is the cost of integrity management practice j in each performance, IR is the annual inflation rate, $X1_i$ is start year of integrity management practice i, $X2_i$ is end year of integrity management practice i, Y_{jt} integrity management practice j is performed on time t ($t = 1$), otherwise ($t = 0$).

Step 5: Driving multi-objective functions based on maximizing reliability and minimizing cost

In the above model, the multi-optimization function can be defined with and without considering annual cost in the following and subject to the provided constraints. The completed form of models is provided in Appendix A. It should be added that constant terms in the equations are determined based on reliability function determinations.

Model 1 without consideration of annual cost:

$$\text{Max}\left[\text{Min}\left[\sum_{i=1}^{7} R_{MP_i} + \sum_{j=8}^{10} \sum_{t=1}^{40} R_{MP_j}(Y_{jt})t\right]\right] \tag{5.6}$$

$$\text{Min} \sum_{i=1}^{7} C_i (X2_i - X1_i) + \sum_{j=8}^{10} \sum_{t=1}^{40} Y_{jt} C_j + r \times C_f \tag{5.7}$$

Subject to.

$$R_{MP_i} \tag{5.8}$$

$$1 \leq X2_i \leq 40 \qquad \forall i \in I \tag{5.9a}$$

$$1 \leq X1_i \leq 40 \qquad \forall i \in I \tag{5.9b}$$

$$1 \leq X2_i - X1_i \leq 39 \qquad \forall i \in I \tag{5.9c}$$

$$C_{MP_i} \tag{5.10}$$

Model 2 with consideration of annual cost:

$$\text{Max}\left[\text{Min}\left[\sum_{i=1}^{7} R_{MP_i} + \sum_{j=8}^{10} \sum_{t=1}^{40} R_{MP_j}(Y_{jt})t\right]\right] \tag{5.11}$$

$$\text{Min} \sum_{t=1}^{40} \sum_{k=1}^{10} (C_i Y_{kt} / (1 + IR)^{t}) + (r \times C_f) / (1 + IR)^{t} \tag{5.12}$$

Subject to.

$$C_{MP_i} \tag{5.13}$$

$$R_{MP_i} \tag{5.14}$$

$$1 \leq Y_k \leq 40 \qquad \forall k \in K \tag{5.15}$$

$$C_f = 543407 \tag{5.16}$$

In the above model, Equations (5.6) and (5.7) in model 1 and Equations (5.11) and (5.12) in model 2 are objective functions, Equations (5.10) and (5.13) are costs in model 1 and 2, respectively. Equations (5.8) in model 1 and (5.14) in model 2 are reliability functions for each integrity management practice. Equation (5.16) is the annual budget. Finally, Equations (5.9) and 15 are additional restrictions for the time of integrity management practices performed.

Step 6: Finding all optimal integrity management actions

In this step, the program code for performing GA is provided in MATLAB software. A similar code of Pseudocode of GA to obtain the optimum solutions are depicted in the state of arts, such as [56–58]. The optimum solutions to schedule the MIC integrity management practices are conducted based on Models 1 and 2. The chromosome codification of performing integrity management practices time can also find out in the literature. The population size is considered 40 based on the recommendation from literature, and the values of the three other parameters in GA generation, crossover fraction, and mutation are 60, 0.75, and 0.3. respectively.

The employed computer has an Intel Core i7(5500) CPU @ 2.4 GHz with 8 GB RAM. Similar to all GA-based studies, the reproduced performing times are wildly fluctuating the whole lifetime of the pipeline. These performing times then steadily converge to the optimal solution values. Due to the influence of such fluctuation, the computation of fitness value is also challenging and would differ from the best fitness value. It should be added that the GA can only find the local optimal solution most of the time for integer programming models. However, the initial steps in GA cover nearly the pipeline lifetime, which guarantees global optimization rather than local optimization. Thus, it provides an advantage for decision-makers to make reliable decisions. The mean fitness value is also steadily going to the best fitness value equal to 52.658. The Pareto optimal solutions, with consideration of annul budget, are depicted in Figure 5.7.

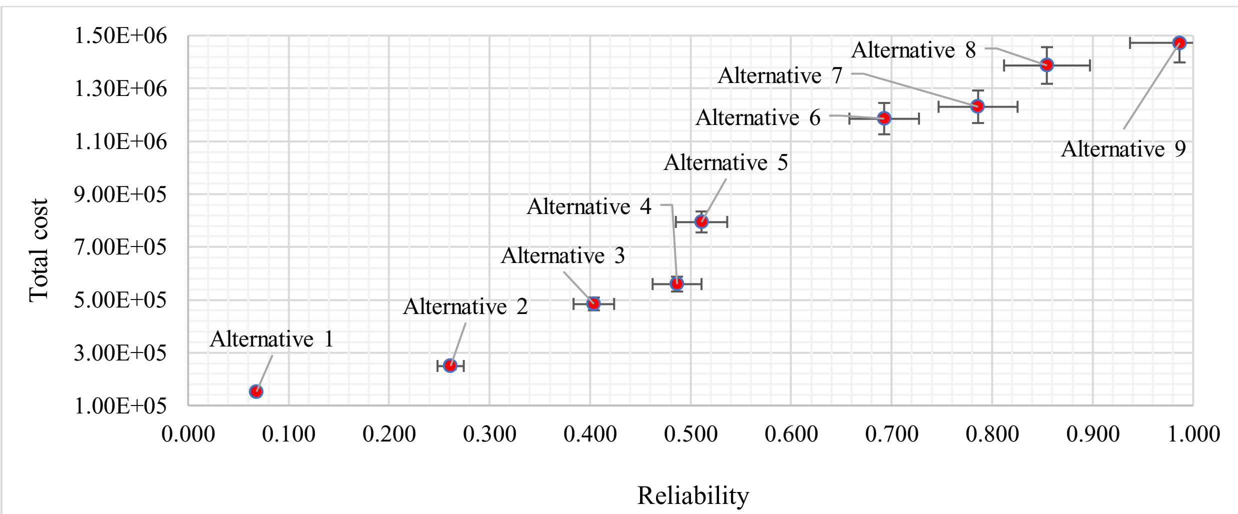

Figure 5.7. The optimal solutions with consideration of the annual budget

As illustrated in Figure 5.7, the two objectives, reliability and cost, are targeting differently. Once program runtime was finished, there were 36 optimal solutions, which by analyzing only 9 of them can be adequate or somehow acceptable since the others have close results, not a representation of our problems or not feasible. Similarly, the Pareto optimal solutions without consideration of the annual budget are depicted in Figure 5.8.

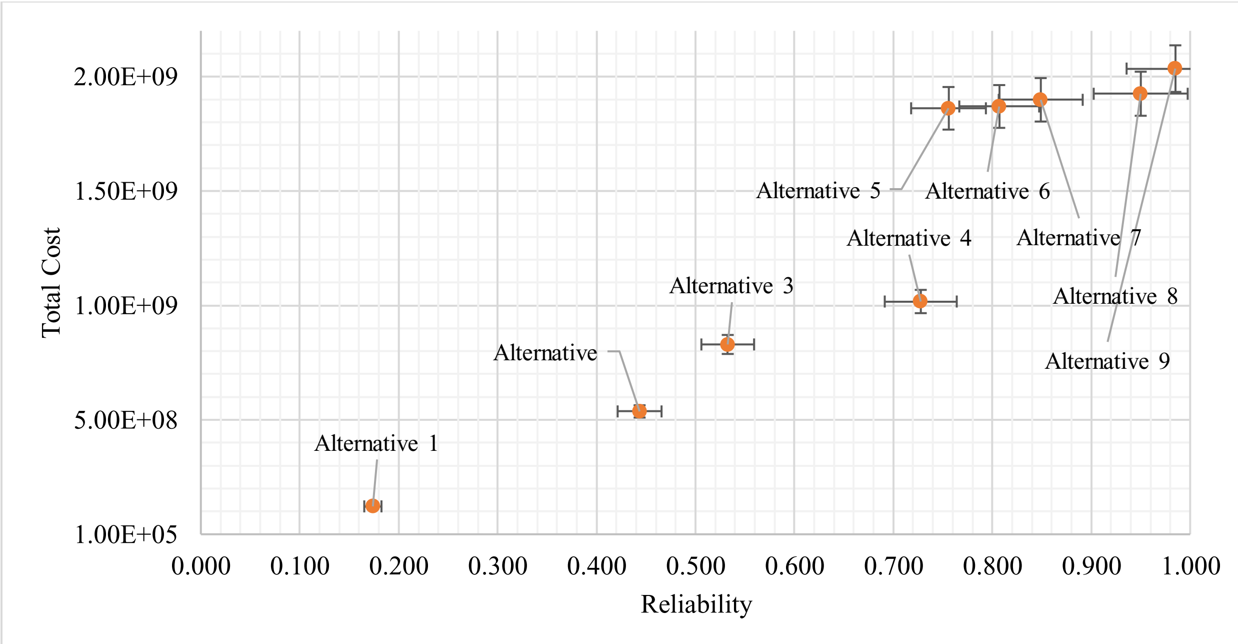

Figure 5.8. The optimal solutions without consideration of the annual budget

In the next step, decision-makers can decide on scheduling integrity management practices over a period.

Step 7: Identification and Implementing the optimal decision

According to the Pareto optimal solutions obtained in step 6, the optimal scheduling plan for performing the integrity management practices with several time inspections can be evaluated. There are nine alternatives for decision-makers to retain and maintain the pipeline for the set target of 40 years. For example, alternatives 5, 8, and 9 were evaluated for optimal solutions without considering the annual budget in detail, which is presented in Table 5.3. This table shows in which year the integrity management practices can be performed. For instance, in alternative 5, the integrity management practices MP5 (Manipulating operational parameters (Temperature)), MP 6 (Manipulating operational parameters (pH)), and MP 7 ((Manipulating operational parameters

(Velocity)) are performed in years 1 and 3 - 38. Also, Figure 5.9 illustrates how much MP 7 is performed every single year. To add more, a couple of management actions are performing concisely during a single year. This figure provides the information to see how many days the management action should be performed in a single year.

Table 5.3. Optimal solutions without consideration of annual budget

Integrity management practices	**Year**		
	Alternative 5	**Alternative 8**	**Alternative 9**
MP 1	4, 9, 13, 18, 22, 27, 30, 34, 38	5, 9, 16, 21, 28	2, 4, 6, 8,10,12,14 ,16,18, 20, 21 - 30
MP 2	1- 7, 9 - 16, 18-25, 28 - 34, 36 - 37	NA	NA
MP 3	2 - 6, 8 - 15, 17, 19, 22, 24 - 32, 35 - 37	NA	NA
MP 4	7, 8,17, 26, 27, 35	4 - 10, 15 - 19	2, 4 - 20
MP 5	1, 3 - 38	1- 2, 5 - 10	NA
MP 6	1, 3 - 38	1 - 2, 5 - 10	NA
MP 7	1, 3 - 38	1- 2, 5 -10	NA
MP 8	4, 7, 11, 15, 20, 26, 30, 34, 36, 37	5,10	4, 8, 15, 22, 28
MP 9	38	NA	NA
MP 10	NA	30	33

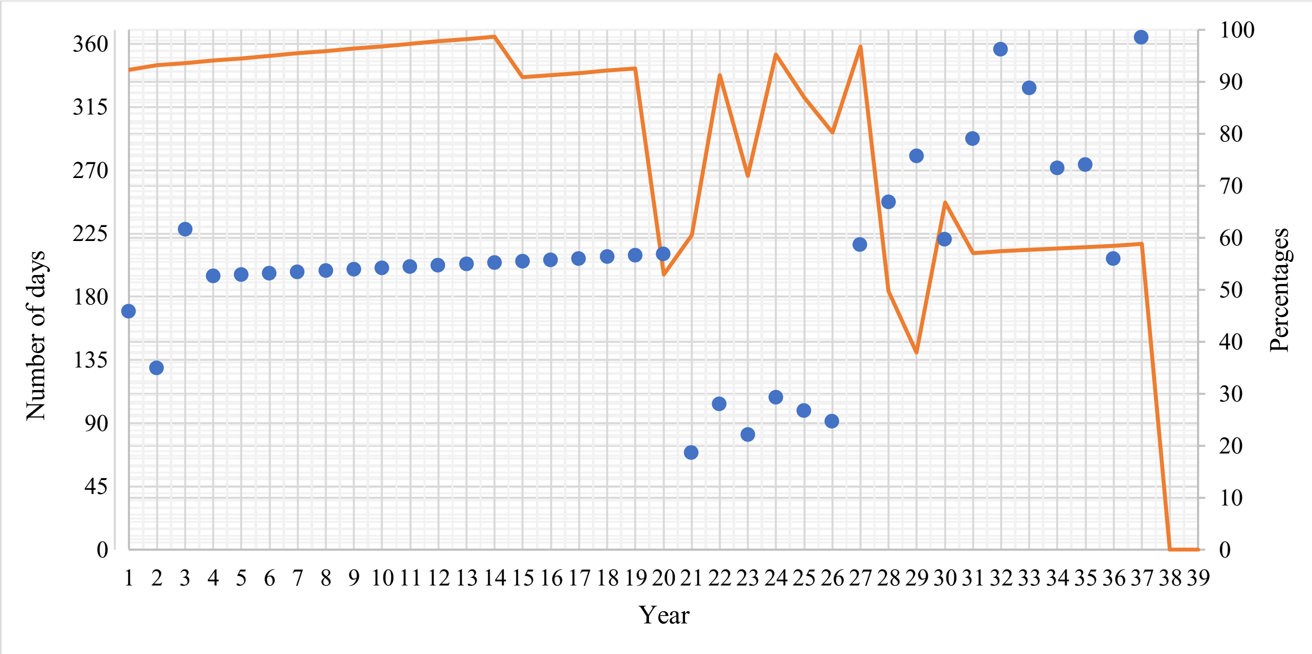

Figure 5.9. The percentages of the integrity management practice MP 7, which should be performed in 40 years

A similar procedure is also conducted to determine the optimal scheduling plan for performing the integrity management practices considering the annual budget. There are also nine alternatives for decision-makers to retain and maintain the pipeline for the set target of 40 years. For example, alternatives 5, 7, and 9 were evaluated for optimal solutions considering the annual budget in detail, which is presented in Table 5.4. Figure 5.10 illustrates how much MP6 can be performed every single year.

Table 5.4. Optimal solutions with consideration of the annual budget

Integrity management practices	**Year**		
	Alternative 5	**Alternative 7**	**Alternative 9**
MP 1	6, 14, 22, 28, 30, 32, 34	4, 8, 12, 16, 20, 24, 28, 30, 32, 34, 36	4, 8, 12, 16, 20, 24, 28, 30, 32, 34, 36
MP 2	1 - 35	1-38	1-38,

MP 3	3 - 5,7 - 10, 12 - 15, 17 - 20, 22 -26, 28 - 32, 35	1-38	1-38,
MP 4	NA	NA	2, 8, 14, 20, 26, 28, 30, 32, 34, 35, 36, 37, 38
MP 5	1- 30, 32, 36	1-38	1-38
MP 6	1- 30, 32, 36	1-38	1- 38
MP 7	1-30, 32, 36	1- 38	1-38
MP 8	4, 10, 16, 24, 31, 36	4, 10, 15, 20, 25, 30,36	4, 10, 15, 20, 25, 30, 36
MP 9	20, 28, 35	20, 30, 38	NA
MP 10	NA	NA	38

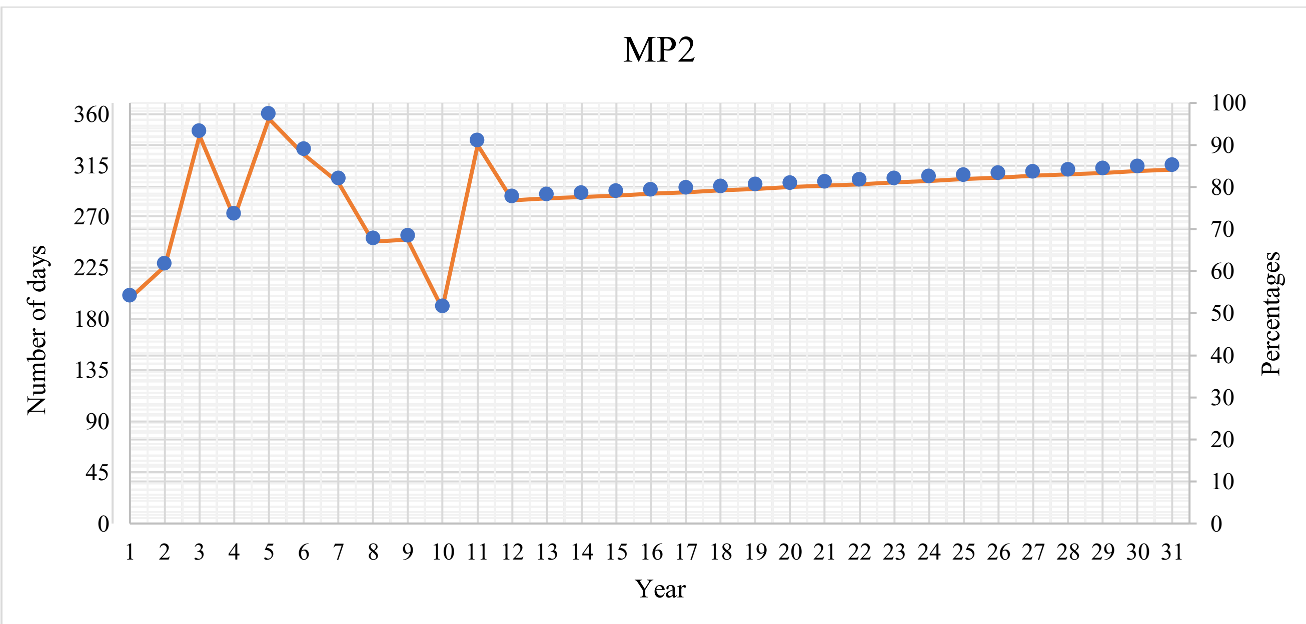

Figure 5.10. The percentages of the integrity management practice MP 7, which should be performed in 40 years

As was explained in Section 3, Pareto optimal solutions provide different types of answers, all of which are feasible and optimum. What can be understood is first is that the mentioned annual budget (1,000,000) has not impacted the optimal solutions. This means that the obtained optimal solutions with and without consideration of the annual budget are almost the same. Another interesting point is that in “Alternative 9”, Model 1 (with consideration of annual budget), decision-makers can decrease the number of integrity management practices by early replacing corroded parts of the pipelines. This means that reactive integrity management practice in some cases will have many more advantages and merits compared with proactive actions.

By updating input information based on data from in-line inspection tools, reliability functions and scheduling of integrity management practices would be updated, respectively, which would impact the outcomes of the decision-making processes.

5.4. Conclusions

In this study, a probabilistic framework is proposed to determine the optimum time interval for performing both reactive and proactive integrity management practices for the corroded subsea pipeline under the influence of MIC. For this purpose, multi-objective optimization is utilized based on all integrity management practices' reliability and cost functions. The dynamic structure of BN is used to obtain reliability functions. GA is then employed to search for all optimum solutions, in which the optimal solutions are non-dominated against each other with consideration of both objective functions. The analysis results show that the obtained diverse set of optimum solutions allows decision-makers to balance reliability and cost of integrity management actions. The annual budget is also added as a constraint to the model. It is indicated that the annual budget has no significant impact on the optimum solutions. Thus, the proposed framework in this study can be based on decision-making support tools for optimal maintenance for a corroded subsea pipeline subjected to risk, safety, and resource integrity management.

However, some critical challenges have arisen in current work that needs to be mentioned, which could be improved as directions for further research. Firstly, in this study, a single defect and other pit depth growth paths are considered for integrity management purposes. While in realistic cases, multiple defects, which may have counter effects, play a critical role in the reliability of the pipelines. As a direction for future study, the generation of new defects using stochastic models can be considered over a period. Secondly, the direct cost is only considered for failure cost in the optimization model. However, indirect costs such as salary/wages, transport, and rent, might be higher than the direct cost. Thus, a parametric study can examine the influence of indirect cost on the optimal solutions in future studies.

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Appendix A.

Model 1 without consideration of annual cost:

$$\text{Max}\left[\text{Min}\left[\sum_{i=1}^{7} R_{MP_i} + \sum_{j=8}^{10}\sum_{t=1}^{40} R_{MP_j}(Y_{jt})\, t\right]\right] \tag{A1}$$

$$\text{Min}\sum_{i=1}^{7} C_i\,(X2_i - X1_i) + \sum_{j=8}^{10}\sum_{t=1}^{40} Y_{jt}\, C_j + r \times C_f \tag{A2}$$

Subject to.

$$R_{MP_1} = 1 - 0.0005\left(X2_{MP_1} - X1_{MP_1}\right)^2 - \left(X2_{MP_1} - X1_{MP_1}\right) + 0.0077 \tag{A3}$$

$$R_{MP_2} = 1 - 2\text{e}-05\left(X2_{MP_2} - X1_{MP_2}\right)^2 - 0.0358\left(X2_{MP_2} - X1_{MP_2}\right) - 0.0018 \tag{A4}$$

$$R_{MP_3} = 1 - 0.0003\left(X2_{MP_3} - X1_{MP_3}\right)^2 - 0.034\left(X2_{MP_3} - X1_{MP_3}\right) + 0.009 \quad \text{(A5)}$$

$$R_{MP_4} = 1 - 0.0002\left(X2_{MP_4} - X1_{MP_4}\right)^2 - 0.0304\left(X2_{MP_4} - X1_{MP_4}\right) + 0.0029 \quad \text{(A6)}$$

$$R_{MP_5} = 1 - 0.0003\left(X2_{MP_5} - X1_{MP_5}\right)^2 - 0.0362\left(X2_{MP_5} - X1_{MP_5}\right) + 0.0029 \quad \text{(A7)}$$

$$R_{MP_6} = 1 - 0.0004\left(X2_{MP_6} - X1_{MP_6}\right)^2 - 0.0458\left(X2_{MP_6} - X1_{MP_6}\right) + 0.0111 \quad \text{(A8)}$$

$$R_{MP_7} = 1 - 0.0003\left(X2_{MP_7} - X1_{MP_7}\right)^2 - 0.0331\left(X2_{MP_7} - X1_{MP_7}\right) + 0.0038 \quad \text{(A9)}$$

$$R_{MP_8} = 1 - 0.0001\,(Y_{MP_8\,t})^2\,t - 0.0329\,(Y_{MP_8\,t})\,t - 0.0196 \quad \text{(A10)}$$

$$R_{MP_9} = 1 - 0.0024\,(Y_{MP_9\,t})^2\,t - 0.0824\,(Y_{MP_9\,t})\,t - 0.0872 \quad \text{(A11)}$$

$$R_{MP_{10}} = 1 - 0.0056\,(Y_{MP_{10}\,t})^2\,t - 0.1313\,(Y_{MP_{10}\,t})\,t - 0.2136 \quad \text{(A12)}$$

$$1 \le X2_i \le 40 \qquad \forall\, i \in I \quad \text{(A13)}$$

$$1 \le X1_i \le 40 \qquad \forall\, i \in I \quad \text{(A14)}$$

$$1 \le X2_i - X1_i \le 39 \qquad \forall\, i \in I \quad \text{(A15)}$$

$$Y_{MP_9} = 0 \text{ if } \left(\text{Max}\left[\text{ Min}\left[\textstyle\sum_{i=1}^{7} R_{MP_i} + \sum_{t=1}^{40} R_8\,(Y_{MP_8\,t})\,t\right]\right]\right) \le 0.2 \quad \text{(A16)}$$

$$Y_{MP_{10}} = 0 \text{ if } \left(\text{Max}\left[\text{ Min}\left[\textstyle\sum_{i=1}^{7} R_{MP_i} + \sum_{t=1}^{40} R_{MP_8}\,(Y_{MP_8\,t})\,t\right]\right]\right) \le 0.2 \quad \text{(A17)}$$

$$C_{MP_1} = 3840 \quad \text{(A18)}$$

$$C_{MP_2} = 9000000 \quad \text{(A19)}$$

$$C_{MP_3} = 18500000 \quad \text{(A20)}$$

$$C_{MP_4} = 38000000 \quad \text{(A21)}$$

$$C_{MP_5} = 15000 \quad \text{(A22)}$$

$$C_{MP_6} = 20000 \tag{A23}$$

$$C_{MP_7} = 35000 \tag{A24}$$

$$C_{MP_8} = 35000 \tag{A25}$$

$$C_{MP_9} = 2400 \tag{A26}$$

$$C_{MP_{10}} = 6800 \tag{A27}$$

$$C_f = 543407 \tag{A28}$$

$$1 \leq X2_i \tag{A29}$$

$$r > \text{Max}\left[\text{Min}\left[\sum_{i=1}^{7} R_{MP_i} + \sum_{j=8}^{10}\sum_{t=1}^{40} R_{MP_j}(Y_{jt})\, t\right]\right] \tag{A30}$$

Model 2 with consideration of annual cost:

$$\text{Max}\left[\text{Min}\left[\sum_{i=1}^{7} R_{MP_i} + \sum_{j=8}^{10}\sum_{t=1}^{40} R_{MP_j}(Y_{jt})\, t\right]\right] \tag{A31}$$

$$\text{Min}\sum_{t=1}^{40}\sum_{k=1}^{10}\left(C_i Y_{kt}/(1+IR)^t\right) + \left(r \times C_f\right)/(1+IR)^t \tag{A32}$$

Subject to.

$$Y_{MP_9} = 0 \text{ if } \left(\text{Max}\left[\text{Min}\left[\sum_{i=1}^{7} R_{MP_i} + \sum_{t=1}^{40} R_{MP_8}(Y_{MP_8 t})\, t\right]\right]\right) \leq 0.2 \tag{A33}$$

$$Y_{MP_{10}} = 0 \text{ if } \left(\text{Max}\left[\text{Min}\left[\sum_{i=1}^{7} R_{MP_i} + \sum_{t=1}^{40} R_{MP_8}(Y_{MP_8 t})\, t\right]\right]\right) \leq 0.2 \tag{A34}$$

$$C_{MP_1} = 3840 \tag{A35}$$

$$C_{MP_2} = 9000000 \tag{A36}$$

$$C_{MP_3} = 18500000 \tag{A37}$$

$$C_{MP_4} = 38000000 \tag{A38}$$

$$C_{MP_5} = 15000 \tag{A39}$$

$$C_{MP_6} = 20000 \tag{A40}$$

$$C_{MP_7} = 35000 \tag{A41}$$

$$C_{MP_8} = 35000 \tag{A42}$$

$$C_{MP_9} = 2400 \tag{A43}$$

$$C_{MP_{10}} = 6800 \tag{A44}$$

$$r > x\mathrm{Max}\left[\mathrm{Min}\left[\sum_{i=1}^{7} R_{MP_i} + \sum_{j=8}^{10}\sum_{t=1}^{40} R_{MP_j}(Y_{jt})\, t\right]\right] \tag{A45}$$

$$R_{MP_1} = 1 - 0.0005\left(Y_{MP_1 t}\right)^2 - \left(Y_{MP_1 t}\right) - 0.0077 \tag{A46}$$

$$R_{MP_2} = 1 - 2\mathrm{e}-05\left(Y_{MP_2 t}\right)^2 - 0.0358\left(Y_{MP_2 t}\right) - 0.0018 \tag{A47}$$

$$R_{MP_3} = 1 - 0.0003\left(Y_{MP_3 t}\right)^2 - 0.034\left(Y_{MP_3 t}\right) + 0.009 \tag{A48}$$

$$R_{MP_4} = 1 - 0.0002\left(Y_{MP_4 t}\right)^2 - 0.0304\left(Y_{MP_4 t}\right) + 0.0029 \tag{A49}$$

$$R_{MP_5} = 1 - 0.0003\left(Y_{MP_5 t}\right)^2 - 0.0362\left(Y_{MP_5 t}\right) + 0.0029 \tag{A50}$$

$$R_{MP_6} = 1 - 0.0004\left(Y_{MP_6 t}\right)^2 - 0.0458\left(Y_{MP_6 t}\right) + 0.0111 \tag{A51}$$

$$R_{MP_7} = 1 - 0.0003\left(Y_{MP_7 t}\right)^2 - 0.0331\left(Y_{MP_7 t}\right) + 0.0038 \tag{A52}$$

$$R_{MP_8} = 1 - 0.0001\left(Y_{MP_8 t}\right)^2 t - 0.0329\left(Y_{MP_8 t}\right) t * 0.0196 \tag{A53}$$

$$R_{MP_9} = 1 - 0.0024\,(Y_{MP_9 t})^2\, t - 0.0824\,(Y_{MP_9 t})\, t + 0.0872 \tag{A54}$$

$$R_{MP_{10}} = 1 - 0.0056\,(Y_{MP_{10} t})^2\, t + 0.1313\,(Y_{MP_{10} t})\, t - 0.2136 \tag{A55}$$

$1 \leq Y_k \leq 40 \qquad \forall\ k \in K$ (A56)

$C_f = 543407$ (A57)

$C_A = 1000000$

(A58)

References

[1] P. Kannan, S.P. Kotu, H. Pasman, S. Vaddiraju, A. Jayaraman, M.S. Mannan, A systems-based approach for modeling of microbiologically influenced corrosion implemented using static and dynamic Bayesian networks, J. Loss Prev. Process Ind. 65 (2020) 104108. https://doi.org/10.1016/j.jlp.2020.104108.

[2] T.L. Skovhus, V.I.A. Building, E.S. Andersen, Management of Microbiologically Influenced Corrosion in Risk Based Short introduction to MIC, Soc. Pet. Eng. (2016).

[3] M. Taleb-Berrouane, F. Khan, K. Hawboldt, R. Eckert, T.L. Skovhus, Model for microbiologically influenced corrosion potential assessment for the oil and gas industry, Corros. Eng. Sci. Technol. 53 (2018) 378–392. https://doi.org/10.1080/1478422X.2018.1483221.

[4] A.-W. Dawuda, M. Taleb-berrouane, F. Khan, A probabilistic model to estimate microbiologically influenced corrosion rate, Process Saf. Environ. Prot. 148 (2021) 908–926. https://doi.org/https://doi.org/10.1016/j.psep.2021.02.006.

[5] T.L. Skovhus, D. Enning, J.S. Lee, Microbiologically Influenced Corrosion in the Upstream Oil and Gas Industry, Taylor & Francis, 2017.

[6] CEPA, Committed to safety, committed to Canadians, Calgary, 2017.

[7] S. Kariyawasam, W. Peterson, Effective improvements to reliability based corrosion management, in: IPC, ASME, Calgary, 2010: pp. IPC2010-31425.

[8] H.P. Hong, Inspection and maintenance planning under external corrosion considering generation of new defects, Struct Saf. 21 (1999) 203–22.

[9] W.J.S. Gomes, A.T. Beck, T. Haukaas, Optimal inspection planning for onshore pipelines subject to external corrosion, Reliab. Eng. Syst. Saf. 118 (2013) 18–27. https://doi.org/10.1016/j.ress.2013.04.011.

[10] W.J.S. Gomes, A.T. Beck, Optimal inspection and design of onshore pipelines under external corrosion process, Struct. Saf. 47 (2014) 48–58. https://doi.org/10.1016/j.strusafe.2013.11.001.

[11] S. Zhang, W. Zhou, Cost-based optimal maintenance decisions for corroding natural gas pipelines based on stochastic degradation models, Eng. Struct. 74 (2014) 74–85. https://doi.org/10.1016/j.engstruct.2014.05.018.

[12] C. Gong, W. Zhou, Multi-objective maintenance strategy for in-service corroding pipelines using genetic algorithms, Struct. Infrastruct. Eng. 14 (2018) 1561–1571. https://doi.org/10.1080/15732479.2018.1459744.

[13] J. Latif, Z.A. Khan, M.H. Nazir, K. Stokes, R. Smith, An optimal condition based maintenance scheduling for metal structures based on a multidisciplinary research approach, Struct. Infrastruct. Eng. 15 (2019) 1366–1381. https://doi.org/10.1080/15732479.2019.1621908.

[14] K. Park, G. Lee, C. Kim, J. Kim, K. Rhie, W.B. Lee, Comprehensive framework for underground pipeline management with reliability and cost factors using Monte Carlo simulation, J. Loss Prev. Process Ind. 63 (2020) 104035. https://doi.org/10.1016/j.jlp.2019.104035.

[15] S. Ghimire, M. Flury, E.J. Scheenstra, C.A. Miles, Optimal location of gas network maintenance centres: A case study from Poland, Sci. Total Environ. (2020) 135577. https://doi.org/10.1016/j.scitotenv.2019.135577.

[16] X. Liu, J. Zheng, J. Fu, Z. Nie, G. Chen, Optimal inspection planning of corroded pipelines using BN and GA, J. Pet. Sci. Eng. 163 (2018) 546–555. https://doi.org/10.1016/j.petrol.2018.01.030.

[17] Z. Yuan, N. Khakzad, F. Khan, P. Amyotte, Risk-based optimal safety measure allocation for dust explosions, Saf. Sci. 74 (2015) 79–92. https://doi.org/10.1016/j.ssci.2014.12.002.

[18] N. Khakzad, F. Khan, P. Amyotte, Dynamic safety analysis of process systems by mapping bow-tie into Bayesian network, Process Saf. Environ. Prot. 91 (2013) 46–53. https://doi.org/10.1016/j.psep.2012.01.005.

[19] S. Adumene, S. Adedigba, F. Khan, S. Zendehboudi, An integrated dynamic failure assessment model for offshore components under microbiologically influenced corrosion, Ocean Eng. 218 (2020) 108082. https://doi.org/10.1016/j.oceaneng.2020.108082.

[20] E. Zarei, F. Khan, M. Yazdi, A dynamic risk model to analyze hydrogen infrastructure, Int. J. Hydrogen Energy. 46 (2021) 4626–4643. https://doi.org/https://doi.org/10.1016/j.ijhydene.2020.10.191.

[21] X. Li, Y.-F. Li, H. Li, H.-Z. Huang, An algorithm of discrete-time Bayesian network for reliability analysis of multilevel system with warm spare gate, Qual. Reliab. Eng. Int. 37 (2021) 1116–1134. https://doi.org/https://doi.org/10.1002/qre.2784.

[22] S. Adumene, F. Khan, S. Adedigba, Operational safety assessment of offshore pipeline with multiple MIC defects, Comput. Chem. Eng. (2020) 106819. https://doi.org/10.1016/j.compchemeng.2020.106819.

[23] M. Yazdi, S. Kabir, M. Walker, Uncertainty handling in fault tree based risk assessment: State of the art and future perspectives, Process Saf. Environ. Prot. 131 (2019). https://doi.org/10.1016/j.psep.2019.09.003.

[24] M. Yazdi, F. Khan, R. Abbassi, R. Rusli, Improved DEMATEL methodology for effective safety management decision-making, Saf. Sci. 127 (2020) 104705. https://doi.org/https://doi.org/10.1016/j.ssci.2020.104705.

[25] M.M. Abaei, R. Abbassi, V. Garaniya, E. Arzaghi, A. Bahoo Toroody, A dynamic human reliability model for marine and offshore operations in harsh environments, Ocean Eng. 173 (2019) 90–97. https://doi.org/10.1016/j.oceaneng.2018.12.032.

[26] A.-A. Baksh, R. Abbassi, V. Garaniya, F. Khan, Marine transportation risk assessment using Bayesian Network: Application to Arctic waters, Ocean Eng. 159 (2018) 422–436. https://doi.org/https://doi.org/10.1016/j.oceaneng.2018.04.024.

[27] E. Arzaghi, R. Abbassi, V. Garaniya, J. Binns, C. Chin, N. Khakzad, G. Reniers, Developing a dynamic model for pitting and corrosion-fatigue damage of subsea pipelines, Ocean Eng. 150 (2018) 391–396. https://doi.org/10.1016/j.oceaneng.2017.12.014.

[28] J. Fu, F. Khan, Monitoring and modeling of environmental load considering dependence and its impact on the failure probability, Ocean Eng. 199 (2020) 107008. https://doi.org/https://doi.org/10.1016/j.oceaneng.2020.107008.

[29] H. Qin, W. Zhou, S. Zhang, Bayesian inferences of generation and growth of corrosion defects on energy pipelines based on imperfect inspection data, Reliab. Eng. Syst. Saf. 144 (2015) 334–342. https://doi.org/10.1016/j.ress.2015.08.007.

[30] D.L. Kelly, C.L. Smith, Bayesian inference in probabilistic risk assessment-The current state of the art, Reliab. Eng. Syst. Saf. 94 (2009) 628–643. https://doi.org/10.1016/j.ress.2008.07.002.

[31] S. Faghih-Roohi, M. Xie, K.M. Ng, Accident risk assessment in marine transportation via Markov modelling and Markov Chain Monte Carlo simulation, Ocean Eng. 91 (2014) 363–370. https://doi.org/https://doi.org/10.1016/j.oceaneng.2014.09.029.

[32] W.R. Gilks, Markov Chain Monte Carlo in Practice, Chapman & Hall, London, 1996. https://doi.org/10.1007/978-1-4899-4485-6.

[33] M. Rausand, S. Haugen, Risk Assessment: Theory, Methods, and Applications, Wiley, 2020.

[34] ISO 31000: Risk Management, Int. Stand. Organ. (2009).

[35] S.M. Lynch, Bayesian Theory, History, Applications, and Contemporary Directions, Int. Encycl. Soc. Behav. Sci. (2015) 378–382. https://doi.org/10.1016/B978-0-08-097086-8.43013-8.

[36] N.E. Fenton, M. (Martin D.. Neil, Risk assessment and decision analysis with Bayesian networks, 2013.

[37] E. Zarei, M. Yazdi, R. Abbassi, F. Khan, A hybrid model for human factor analysis in process accidents: FBN-HFACS, J. Loss Prev. Process Ind. (2019) 142–155. https://doi.org/10.1016/j.jlp.2018.11.015.

[38] M. Taleb-Berrouane, F. Khan, P. Amyotte, Bayesian Stochastic Petri Nets (BSPN) - A new modelling tool for dynamic safety and reliability analysis, Reliab. Eng. Syst. Saf. 193 (2020) 106587. https://doi.org/https://doi.org/10.1016/j.ress.2019.106587.

[39] A. Nedjati, G. Izbirak, B. Vizvari, J. Arkat, Complete coverage path planning for a multi-UAV response system in post-earthquake assessment, Robotics. 5 (2016). https://doi.org/10.3390/robotics5040026.

[40] H.A. Taha, Operations Research: An Introduction, 10th Edition, 10th ed., Pearson, 2017.

[41] L. Bianchi, M. Dorigo, L.M. Gambardella, W.J. Gutjahr, A survey on metaheuristics for stochastic combinatorial optimization, Nat. Comput. 8 (2009) 239–287. https://doi.org/10.1007/s11047-008-9098-4.

[42] R. Balamurugan, A.M. Natarajan, K. Premalatha, Stellar-mass black hole optimization for biclustering microarray gene expression data, Appl. Artif. Intell. 29 (2015) 353–381. https://doi.org/10.1080/08839514.2015.1016391.

[43] A. Nedjati, B. Vizvari, G. Izbirak, Post-earthquake response by small UAV helicopters, Nat. Hazards. 80 (2016) 1669–1688. https://doi.org/10.1007/s11069-015-2046-6.

[44] A. Nedjati, G. Izbirak, J. Arkat, Bi-objective covering tour location routing problem with replenishment at intermediate depots: Formulation and meta-heuristics, Comput. Ind. Eng. 110 (2017) 191–206. https://doi.org/10.1016/j.cie.2017.06.004.

[45] M.D.C. Moura, I.D. Lins, E.L. Droguett, R.F. Soares, R. Pascual, A multi-objective genetic algorithm for determining efficient risk-based inspection programs, Reliab. Eng. Syst. Saf. 133 (2015) 253–265. https://doi.org/10.1016/j.ress.2014.09.018.

[46] A.A. Motlagh, N. Shabakhty, A. Kaveh, Design optimization of jacket offshore platform considering fatigue damage using Genetic Algorithm, Ocean Eng. 227 (2021) 108869. https://doi.org/https://doi.org/10.1016/j.oceaneng.2021.108869.

[47] A. Mahrooghi, E. Lakzian, Optimization of Wells turbine performance using a hybrid artificial neural fuzzy inference system (ANFIS) - Genetic algorithm (GA), Ocean Eng. 226 (2021) 108861. https://doi.org/https://doi.org/10.1016/j.oceaneng.2021.108861.

[48] Y. Wang, Z. Yin, Y. Liu, Predicting the bulk drag coefficient of flexible vegetation in wave flows based on a genetic programming algorithm, Ocean Eng. 223 (2021) 108694. https://doi.org/https://doi.org/10.1016/j.oceaneng.2021.108694.

[49] L. Zhou, P. Huang, S. Chi, M. Li, H. Zhou, H. Yu, H. Cao, K. Chen, Structural health monitoring of offshore wind power structures based on genetic algorithm optimization and uncertain analytic hierarchy process, Ocean Eng. 218 (2020) 108201. https://doi.org/https://doi.org/10.1016/j.oceaneng.2020.108201.

[50] D. Dubois, Representation, propagation, and decision issues in risk analysis under incomplete probabilistic information: Commentary, Risk Anal. 30 (2010) 361–368. https://doi.org/10.1111/j.1539-6924.2010.01359.x.

[51] J. Bhandari, R. Abbassi, V. Garaniya, F. Khan, Risk analysis of deepwater drilling operations using Bayesian network, J. Loss Prev. Process Ind. 38 (2015) 11–23. https://doi.org/10.1016/J.JLP.2015.08.004.

[52] S. Adumene, F. Khan, S. Adedigba, S. Zendehboudi, Offshore system safety and reliability considering microbial influenced multiple failure modes and their interdependencies, Reliab. Eng. Syst. Saf. (2021) 107862. https://doi.org/https://doi.org/10.1016/j.ress.2021.107862.

[53] R. Javaherdashti, K. Alasvand, Biological Treatment of Microbial Corrosion Opportunities and Challenges, Elsevier Inc, 2019. https://doi.org/10.1016/C2017-0-04219-2.

[54] M. Yazdi, F. Khan, R. Abbassi, Microbiologically influenced corrosion (MIC) management using Bayesian inference, Ocean Eng. (2021). https://doi.org/10.1016/j.oceaneng.2021.108852.

[55] P. Thodi, F. Khan, M. Haddara, Risk based integrity modeling of offshore process components suffering stochastic degradation, J. Qual. Maint. Eng. 19 (2013) 157–180. https://doi.org/10.1108/13552511311315968.

[56] S. Mirjalili, J. Song Dong, A.S. Sadiq, H. Faris, Genetic Algorithm: Theory, Literature Review, and Application in Image Reconstruction BT - Nature-Inspired Optimizers: Theories, Literature Reviews and Applications, in: S. Mirjalili, J. Song Dong, A. Lewis

(Eds.), Springer International Publishing, Cham, 2020: pp. 69–85. https://doi.org/10.1007/978-3-030-12127-3_5.

[57] S. Mirjalili, Genetic Algorithm BT - Evolutionary Algorithms and Neural Networks: Theory and Applications, in: S. Mirjalili (Ed.), Springer International Publishing, Cham, 2019: pp. 43–55. https://doi.org/10.1007/978-3-319-93025-1_4.

[58] S. Mirjalili, J.S. Dong, Non-dominated Sorting Genetic Algorithm BT - Multi-Objective Optimization using Artificial Intelligence Techniques, in: S. Mirjalili, J.S. Dong (Eds.), Springer International Publishing, Cham, 2020: pp. 37–45. https://doi.org/10.1007/978-3-030-24835-2_4.

Chapter 6

Resilience assessment of a subsea pipeline using dynamic Bayesian network

Preface

A version of this chapter has been submitted to the journal of ***Journal of Pipeline Science and Engineering, 2022: 100053****. I am the primary author along with the Co-authors, Faisal Khan, Rouzbeh Abbassi, and Noor Quddus. I developed the conceptual framework for the resilience assessment of a subsea pipeline model and carried out the literature review. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' feedbacks. Co-author Faisal Khan helped in the concept development and testing the model, reviewing, and revising the manuscript. Co-author Rouzbeh Abbassi provided support in implementing the concept and testing the model. Co-author Noor Quddus provided support in reviewing and correcting the manuscript. The co-authors also contributed to the review and revision of the manuscript.*

Abstract

Microbiologically influenced corrosion (MIC) is a serious concern and plays a significant role in the marine and subsea industry's infrastructure failure. A probabilistic methodology is introduced in the present study to assess the subsea system's resilience under MIC. Conventionally, the risk-based models are constructed using the system's characteristic features. This helps decision-makers understand how a system operates and how the failed system can be recovered. The subsea system needs to be designed with sufficient resilience to maintain the performance under the time-varying interdependent stochastic conditions. This paper presents the dynamic Bayesian Network-based approach to model the subsea system's resilience as a function of time. An industry-based

application study of the subsea pipeline is studied to demonstrate the efficiency and effectiveness of the proposed methodology for the resilience assessment. The proposed methodology will assist decision-makers in considering the resilience in the system design and operation.

Keywords: Pipeline, Offshore, Bayesian Network, Engineering resilience, MIC, Subsea system

6.1. Introduction

The main engineering-based infrastructures in the oil and gas industrial sectors have the potential to have a high material degradation rate. Different types of catastrophic failures in ocean environmental conditions have been recognized due to undesired corrosion [1,2]. The mechanisms of corrosion and their complexities in subsea and marine technologies depend on varieties of parameters, including material properties, operating, and environmental circumstances [3–7]. The mentioned parameters fall into temperature, salinity, metal composition, pressure, seawater flow velocity, carbon dioxide, and more. These are prone to the stochastic and uncertain nature of microbially influenced corrosion (MIC). There is a limited understanding of MIC formation and propagation, causing risky operational decisions, which leads to system failure and direct/indirect consequences [1,8,9]. This would continue to face a severe degradation, particularly in microorganism groups (i.e., sulphate-reducing bacteria (SRB), exopolymers, manganese-oxidizing, acid-producing bacteria, sulphate-oxidizing bacteria, and the iron-oxidizing bacteria in marine environments) [10]. These factors are commonly stochastic in nature and time dependent. Thus, designing a reliable system suspected of the MIC occurrence under such uncertain circumstances is challenging for engineering decision-makers.

MIC formation and its propagation as a mechanistic model have been studied by numerous researchers [11]. For example, Gu et al. [12] introduced the bioenergetic theory by describing the thermodynamic-based mechanism for MIC formation within SRB. The MIC formation depends on the microbes' respiration process. This process contains an extracellular electron transferring the ions (e.g., nitrate, or sulphate) to the microbial cytoplasm. The conclusion is derived as an integrated mechanistic model including mass transfer, electrochemical and biochemical reactions, and kinetics could deliver a reliable tool to predict the MIC formation and propagation. A limited number of models for MIC risk assessment are accessible in the existing state of the art [13–17]. In addition, risk-based models have been utilized to support decision-making in the system design period [18,19]. For example, Al-Darbi et al. [20] developed a mathematics-based polarization model. In that work, the authors explained cathodic SRB mediated polarization and its corresponding effects of MIC rate in different pit depth growth dynamically. Sørensen et al. [14] identified the worst MIC rate and risk factors by proposing a risk-based model according to the sulphate reducing archaea (SRA), methanogens, and SRB. The study highlighted that the colony of the bacteria could increase the wastage rate and suggested having a proactive plan to control the MIC rate. Marciales et al. [11] made a comprehensive review of the MIC mechanistic model, its prediction rate, and the shortages.

There are a few limitations of the studies as mentioned above. First, the approaches are not dynamic-based and could not reflect the non-linearity and complexity of dependency with MIC influential parameters in-service time of the system. Second, the available risk-based models are defined by permanent failure and assessing the scenarios reaching into the failures. Instead, the system can be assessed based on its states once the disruption has occurred. In the present work, it is assumed that these disruptions are caused by the MIC rate and its corresponding pit depth growth path and effect on structural safety. The states of the system are changing in a dynamic manner after the disruption. Therefore, resilience, instead of risk assessment, should develop risk-based models. This means that resilience assessment of marine and subsea systems under the influence of MIC would be a much more desirable task.

Numerous resilience metrics and relevant evaluation-based approaches have been improved to assess and develop engineering resilience of the system, such as but not limited to the following references [21–30]. In the next section, a review of resilience assessment has been done in safety engineering system domains. There is still room for further development among the existing state of the art. According to this point, the dynamic Bayesian network is considered a reliable tool in the field of probabilistic assessment approaches within reasoning and knowledge representation. Dynamic Bayesian network has the capability of system failure modeling, where the system has interdependency between the factors with consideration of conditional probabilities. Thus, this study has three contributions to the safety and scientific communities. The first contribution is developing a new influence diagram for the resilience assessment of the subsea system. Therefore, the introduced methodology considers two uncertainties called data and model. The second contribution is to assess the system's resilience under the influence of internal MIC using a dynamic Bayesian network. The third is developing a framework to design a MIC-based subsea system with high resilience.

The organization of this study is provided as the following. In Section 2, the resilience in the safety engineering system and pipeline domains is discussed. In Section 3, the new methodology is proposed to assess and further evaluate the engineering system's resilience. In Section 4, an application case study is studied. Finally, a conclusion, further remarks, and directions for future studies are provided in Section 5.

6.2. Reviewing resilience in safety engineering system domains

In this section, a literature reviewing process has been conducted with three main steps, as depicted in Figure 6.1. First, the published studies from several primary databases were collected considering the proper keywords such as “resilience” AND “system” AND “safety”. Subsequently, a decision is made about each paper, whether it has been indexed by WOS (Web of Science) or Scopus. Otherwise, they are excluded. Search has been conducted from January 2000 to the end of April 2021 and gathered about 1005 papers. Timeline selection is because most research studies on resilience areas have been released in the last 20 years. Afterward, the related studies' keywords, titles, and abstracts are reviewed. In the next step, 148 studies are excluded with consideration of title, abstract, and keywords, in which the ignored papers were not application-based or did not have a considerable development of the resilience concept in the engineering system domains. Then, 112 studies are retrieved by reviewing the full text of the manuscript.

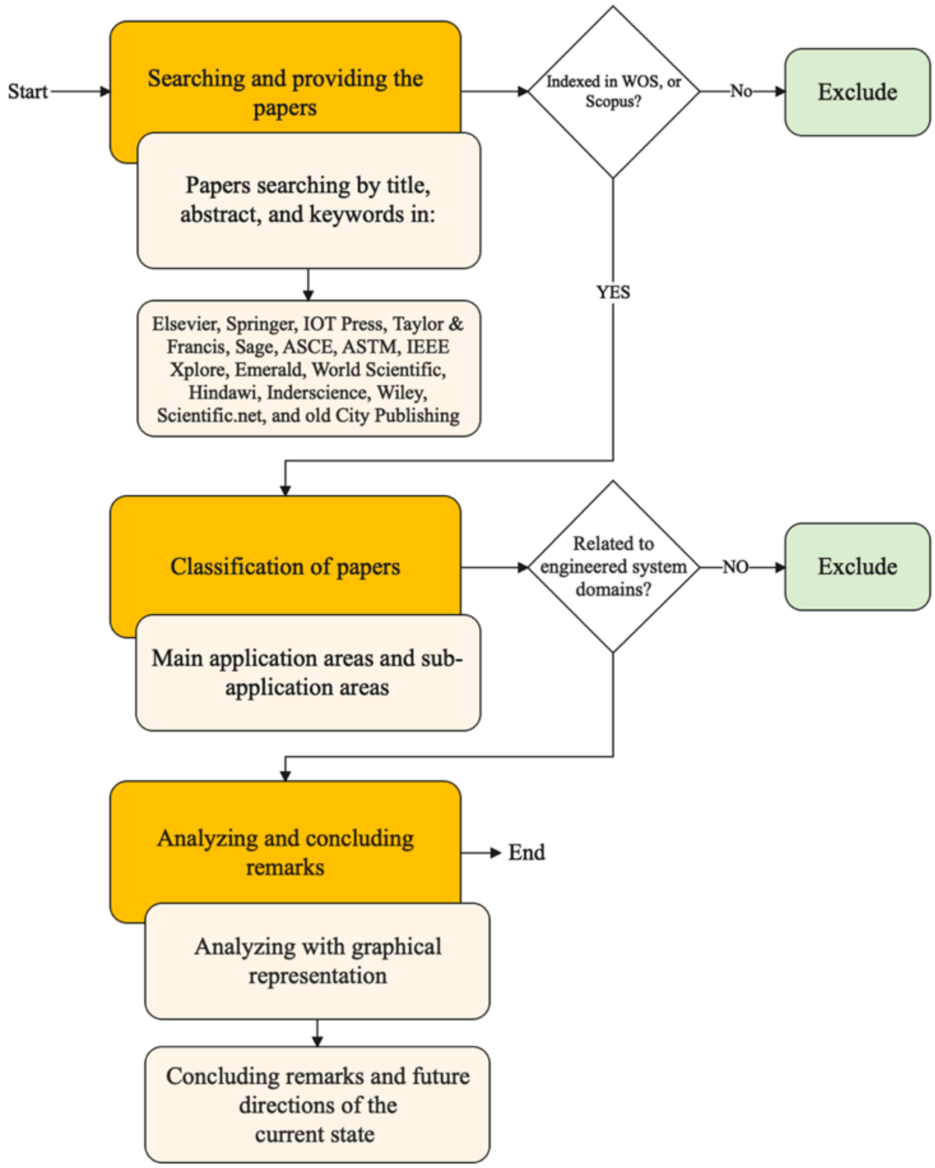


Figure 6.1. Steps of methodology to review resilience in engineering system domains

Recently, there has been considerable growth in resilience topics in addressing the main research question of how an engineering system can restore its performance after a disruption occurs [31,32]. Holling [33] defined the term "resilience" as an ecological system property, in which this can measure its resistance to disruption and its capability to absorb changes and stabilize to its original form. Since its first explicit definition by Holling, resilience has been extensively utilized in numerous applications areas, including chemical process industries [34–39], infrastructure resilience [40–43], Engineering electrical electronic [44–46], Operations research management science [47–50], Engineering civil [51–53], and Environmental Sciences [54–57]. The resilience studies in the state of the art present the latest concept of resilience assessment for the design of the engineering system. Many scholars have been attempted to introduce new methodologies by assessing and measuring the resilience in different engineering system attributes. As an example, a two-state Markov chain framework is utilized for the resilience assessment of supply systems, in which the system probability from failure to full-recovery state is studied [58]. In another study, a time-dependent method is proposed to quantify the system resilience [22]. Baroud et al. [59] quantified the resilience of the system, considering the recovered performance loss over time. In two studies, Hosseini et al. [60] and Yodo and Wang [61] quantified the complex system resilience of industry application-based such as production process and supply chain. Hosseini and Barker [62] used an approach underlying the idea of Bayesian networks for resilience quantification and assessment of a water-way network. Yodo et al. [63] proposed a dynamic Bayesian network approach to model and predict the resilience of complex engineered electricity distribution systems over time. According to the WOS database, Table 6.1 provides the studies in engineering domains within high contributions in resilience-based methodologies.

Table 6.1. The published works in engineering domains within high contributions in resilience-based methodologies

Number	Reference	Keywords
#1	Madni and Jackson (2009) [64]	Defining resilience from different perspectives and learning lessons could design resilient systems.
#2	Ouyang and Dueñas-Osorio (2014) [65]	Developing a probabilistic technique for resilience assessment of power systems.

#3	Aven (2011) [66]	Discussing and looking more closely into the risk concepts and risk assessment and resilience and vulnerability.
#4	Barker et al. (2013) [67]	Providing two different importance measures to assess the resilience of the components.
#5	Patriarca et al. (2018) [68]	Reviewing the methodology based on resilience engineering
#6	de Carvalho (2011) [69]	Using Functional Resonance Analysis Model (FRAM) to understand the main resilience attributes for the case study managing the air traffic system.
#7	Azadeh et al. (2014a) [34]	Assessing the factors playing an essential role in the resilience assessment process, with a case study of highly risky circumstances of the chemical complex plant.
#8	Azadeh et al. (2014b) [35]	Evaluating the performance of factors plays an essential role in the resilience assessment process, with a case study of highly risky circumstances of the chemical complex plant.
#9	Gomes et al. (2009) [70]	Assessing the resilience engineering of a complex socio-technical system as a subsea helicopter transportation system.
#10	Shirali et al. (2012) [71]	Studying the shortages and limitations of structuring resilience in a petrochemical complex unit.

What can be concluded by reviewing the resilience in the existing literature falls into two points (i) resilience is an uncertain and time-dependent feature of an engineering system, and (ii) resilience may sound similar to the availability of the system. However, this is the system's distinctive property and should be distinguished by the engineering system's reliability and maintainability. The resilience assessment of an engineering system depends on the system's performance loss in the state of the art. While there is a lack of probability consideration, the system could recover or restore to its normal state after the disruption. Taking the vehicle tire with the self-sealant central tire inflation system as an example [72], there is a vehicle with tire punctuation at the moment. Conventionally, the vehicle should be stopped to change the tire and then continue the road. However, the car may still work with deficient performance (i.e., disruption occurrence) when there is no chance to change a flat tire (e.g., there is no spare tire, and there is no garage service nearby). In simple words, there is a very low probability of the system being restored to its normal performance level or desired functionality. Therefore, this vehicle cannot be called a resilient vehicle.

Nevertheless, in case the flat tire has the capability to quickly be restored to the desired functionality with a self-sealant central tire inflation system, the system would have a high probability of being at a normal performance level. Therefore, the probabilistic perspective of resilience definition and assessment can better reflect engineering system performance over time.

6.2.1. Resilience assessment in engineering application domains

The resilience of the engineering system includes four characteristics named as (i) absorption, (ii) adaption, (iii) restoration, and (iv) learning, which represents the engineering system's ability to absorb, adapt, restore, and learn after disruptions occurrence over service lifetime. The resilience characteristics are the inherent properties of engineering systems, and it is an essential task to be evaluated. Therefore, resilience characteristics can be abstracted with system functionalities' states. Once the system faces a disruption, absorption as a capability of system resistance prepares and adjusts itself to prevent the disruption impact and minimize the undesired consequences. Subsequently, two scenarios can be implied as (i) the engineering system can adequately be prepared and self-adjusted to prevent any disruptions, and (ii) in case of disruption, the engineering system has enough potential to reduce the change of functionality rate (i.e., decreasing functionality) [73,74]. Another resilience characteristic is the adaption referring to the system's ability to recover the performance loss of the engineering system after disruption occurrence without any external intervention actions from the restoration. In addition, restoration is the system's ability to receive external intervention actions to repair the performance loss initiated by disruption into the normal operation state. It should be highlighted that the new state should not essentially be exactly equal to the last state, either less or more than the state before disruption (i.e., normal operation state). However, the new state has to be at an acceptable level of functionalities satisfying the system operating regulations. Finally, learning is the system's ability to study the past disruptions and then assist the system in obtaining reliable knowledge for its performance improvement. According to this point, the system would respond better to future disruptions. The learning ability of the system can improve the system with the operational procedure, safety, and technical guidelines.

According to the definitions mentioned above of resilience characteristics, resilience can be refined using functionalities' states [31]. As shown in Figure 6.2, the functionality curve of the system is depicted to show the quantification of resilience performance. In this figure, $F(t)$ signifies the system's functionality (system performance) in normal operating state at time t. F_0 denotes the initial functionality of the system, and F_2 is the functionality of the system after disruption occurrence. In addition, t_0 is the initial time, t_1 denotes the disruption time, t_2 signifies the time when the system has the lowest functionality, and t_3 is a time when system functionality is recovered (adaption and restoration) to the normal operating state. By analyzing the performance curve, one can measure the system's ability to anticipate the absorb, adapt to, and restore from disruptions.

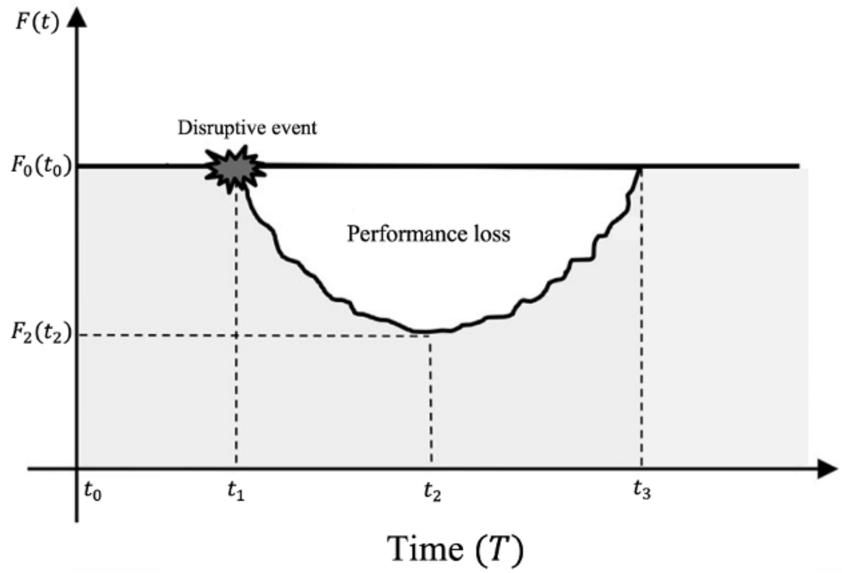


Figure 6.2. Simple representation of time-dependent performance loss (functionality curve) within a disruptive event (modified after [74])

6.3. The proposed methodology

In this section, a methodology is proposed to dynamically assess the subsea system's resilience under the influence of MIC. Conventionally, assessing and further managing the engineering systems under the influence of MIC consider merely failure scenarios. However, MIC formation and propagation are debatable topics in existing literature and complex in the incredibly uncertain and potentially harsh environmental operating conditions. Therefore, the resilience assessment of the suspected system with MIC would be a much more desirable task, in which the impact of MIC on the engineering system needs to be adequately understood, and the system requires to be designed such that the system should be able to develop an early response before the system reaches to complete failure. Thus, as demonstrated in Figure 6.3, the five steps methodology is proposed to assess the resilience of a subsea system under the influence of MIC. This framework enables decision-makers to understand the engineering system properly and save it long. In step one, the system is defined by highlighting the environmental condition, which fluid is carried, and system prosperities. In addition, the influence diagram of MIC and all required information for developing the models will be obtained. In step two, the four functionalities (absorption, adaptation, restoration, and disruptions) of the subsea system under the influence of MIC are identified. Besides, a Markov chain is developed to present the functionality states of the system. In step three, the transition rates are computed in the developed Markov chain in step two. Moreover, the Markov chain is translated into the dynamic Bayesian network explained in section Preliminary 1, in which transition rates in the Markov chain process define the relevant conditional probabilities in the corresponding Bayesian Network. In step four, the probabilities of functionality states of the system are computed, and the probability summation of all functionality states representing resilience is then obtained. Finally, in step five, the sensitivity analysis is studied to recognize the critical parameters in the subsea system, in which the contributions of parameters into the resilience variation are evaluated.

The details of the steps are provided in the following sections.

Step one: Defining the system and obtaining the influence diagram of MIC, and all required information

In this step, the system is defined by highlighting the environmental condition, which fluid is carried, and the system prosperities. For example, the system is defined as APL 5L grade X42 subsea pipeline. In this case, it carries the hydrocarbon material like co-mingled fluids and would highly be suspected to internal MIC. The subsea pipeline needs to operate for more than 30 years.

In addition, the influence diagram (mechanistic model) of MIC is established. This model reflects the corrosion type (which in this case is MIC), chemical compositions of internal fluid, type of material, material composition, characteristics features of the pipeline, and operating and environmental circumstances. At the end of the day, MIC leads to pipeline failure by increasing the pit depth growth path and reducing the wall thickness.

The related data is collected from various sources, such as industries, operating circumstances, or decision-makers judgment which has a relevant background in the field.

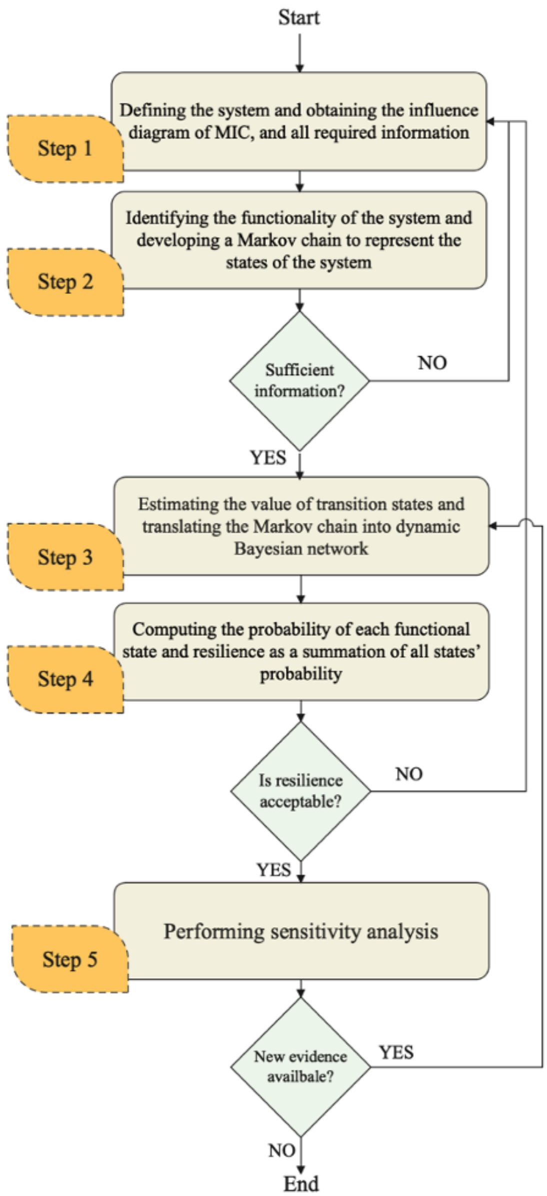


Figure 6.3. The developed methodology for resilience assessment of the subsea system under the influence of MIC

Step two: Identifying the functionality of the system and developing a Markov chain to represent the states of the system

In this step, the four functionalities state (absorption, adaptation, restoration, and disruptions) of the understudy system are defined, in which all states are decomposed into the substates. As an example, the functionality state of absorption can be broken top-down into redundancy, preventive measure, and robustness. The functionality state of adaptation can be decomposed into flexibility, protection measures, and learning. This process continues until the system's detailed structural resilience is derived.

Step three: Estimating the value of transition states of the Markov chain and translating the Markov chain into the dynamic Bayesian network

Preliminary 1. Dynamic Bayesian Network

This part presents the theoretical context of the dynamic Bayesian Network. Dynamic Bayesian Network is a directed acyclic graph (DAG), including edges and vertices, which are named as arcs and nodes, respectively, in the constructed network. In a Bayesian Network, nodes signify the variables, and arcs denote the relations between two different nodes. This is properly known as a practical method with enough potential to consider the uncertainty and variability over time. In this accordance, this assists decision-makers in predicting the decisions connected with complicated decision-making problems [75–78]. The dynamic Bayesian Network also used the prior knowledge of the main event, which further could execute a rational-based statistical inference.

In contrast, the circumstances are correct. According to this point, the prior knowledge can be derived from decision-makers opinions or frequentist approaches within observed data [79–82]. The term dynamic means dynamic system modeling.

The probabilities of X and Y as two variables can occur when the production of X and Y given X in terms of probability. The expression, as mentioned earlier, can be stated as the following Equation:

$$P(X\ ,Y) = P(X) \times P(Y|X) \tag{6.1}$$

where $P(X, Y)$ represents the probability of both variables X and Y which can occur.

With consideration of symmetry law, Equation (6.1) can be modified into Equation (6.2) as:

$$P(X|Y) = \frac{P(Y|X) \times P(X)}{P(Y)} \tag{6.2}$$

where $P(Y|X)$ represents the evidence probability of Y when the hypothesis of X true holds, $P(X)$ is denoted as the prior probability of variable X, $P(Y)$ is equal to the prior probability that the evidence Y has occurred (true), and $P(Y|X)$ is equal to the posterior probability of X given the evidence of variable Y. To get more details of the transformation of Equation (6.1) into Equation (6.2), one can refer to the previous literature [83].

The joint probability distribution of the variables is decomposed as Equation (6.3):

$$P(X_1, X_2, X_3, \ldots, X_n) = P(X_1|\ X_2, X_3, \ldots, X_n) \times P(X_2|X_3, \ldots, X_n) \ldots \times P(X_{n-1}|X_n) \tag{6.3}$$

Subsequently, by simplification Equation (6.3) can be streamlined into Equation (6.4):

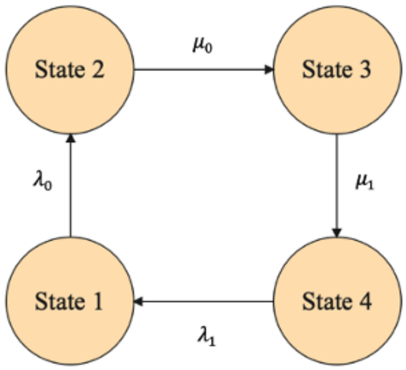
$$P(X_1, X_2, X_3, \ldots, X_n) = \prod_{i=1}^{n} P(X_i|X_{i+1}, X_{i+2}, \ldots, X_n) = \prod_{i=1}^{n} P(X_i|\ \text{Parents}\ (X_i)) \tag{6.4}$$

in which X_i, X_{i+1} and X_n are standing for the parent nodes at different time slices $t = 0$, $t = 1$, and $t = n$.

Dynamic Bayesian Network presents the relationships between causes and effects nodes in probabilistic manners. Two types of analysis are introduced to show that the proposed model can be effectively used in the decision-making problems as in each time slice: (i) forward propagation analysis and (ii) backward propagation analysis.

A dynamic Bayesian network is developed to quantify resilience in the present work. In addition, it is assumed that resilience is independent of exterior factors such as harsh environment and human error. That is while the exterior factors influence the system performance and system resilience. However, they are not considered in this study. ■

Then, a Markov chain is developed by obtaining the transition probabilities of four functionalities' state (absorption, adaptation, restoration, and disruptions) as λ_0, μ_0, λ_1, and μ_1. The value of λ_0, μ_0, λ_1, and $\mu_1$are affected by four attributes as mentioned above. The computation process would be much more complicated by decomposing the absorption, adaptation, restoration, and disruptions into the substates. In step three, there are a couple of assumptions as (i) the rates of adaptation and restoration are considered constant value as μ_0 Furthermore, μ_1, respectively, and (ii) an exponential representation is utilized for time slices between $t = 0$ and $t = 1$ as λ_0. At the end of the day, the understudy system would be reached the new state 4. After that, the new chain begins. Thus, the third assumption is defined as (iii) the rate of failure for the understudy system in normal operational circumstance is assumed to be constant value as λ_1. Figure 6.4 presents a simplified version of the Markov chain model illustrating the functionalities' state of resilience as well as their corresponding rates. It should be added that terms λ, and μ are assumed that there are parameters of a negative exponential distribution based on domain experts. The explanation of mathematical terms in which how λ, and μ would be converted into probabilities are available in the existing literature [84].



Transition rates of the Markov chain				
Transition rate	**State 1**	**State 2**	**State 3**	**State 4**
State 1	1-λ_0	λ_1	0	0
State 2	0	1-μ_0	μ_0	0
State 3	0	0	1-μ_1	μ_1
State 4	λ_1	0	0	1-λ_1

Figure 6.4. Markov chain model illustrating the functionalities' state resilience

In past steps, the defined Markov chain was translated into the dynamic Bayesian network. As depicted in Figure 6.5, the probability of each transition state in the Markov chain model is translated into the conditional probabilities, in which four functionalities' state (absorption, adaptation, restoration, and disruptions). For example, the transition probability of state 3 to state 4 in the defined Markov chain is transformed into the conditional probabilities' functionality state from state 3 to state 4 given restoration in the structured Bayesian network. To obtain more information, one can refer to transferring the Markov chain model to the Bayesian network [84], and the Markov chain into the dynamic Bayesian network [85].

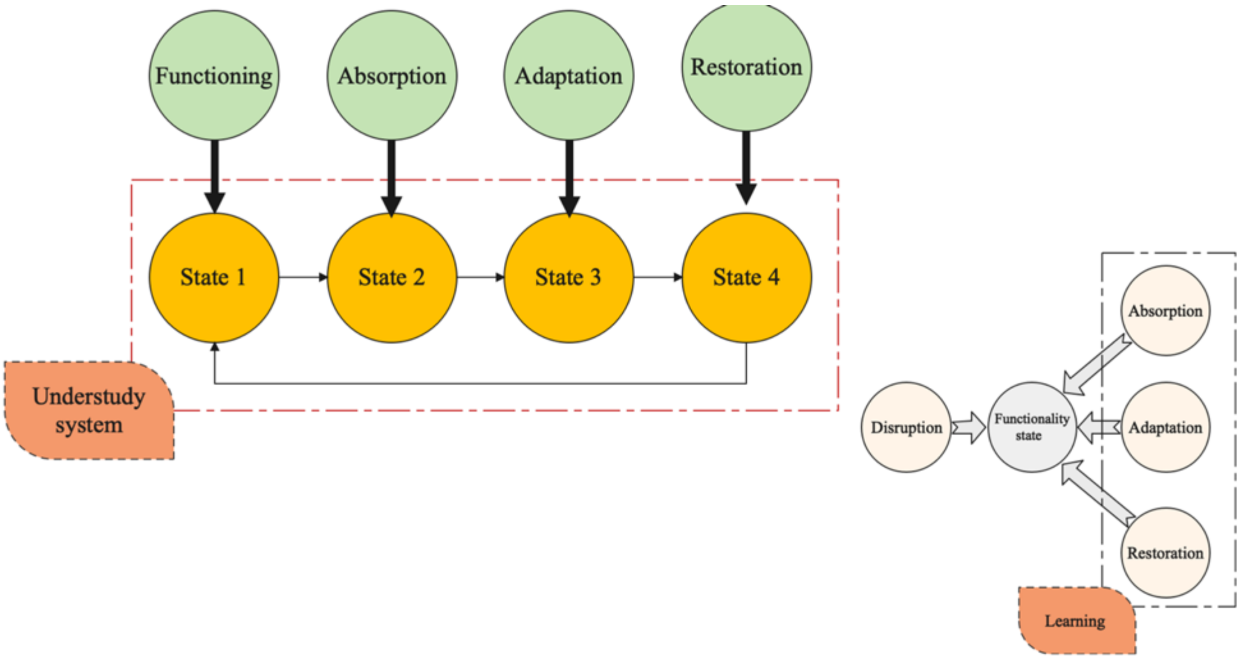


Figure 6.5. Translation of Markov chain (part a) model to the dynamic Bayesian network (part b)

Step four: Computing the probability of each functional state and resilience as a summation of all states' probability

In this step, a dynamic Bayesian network can dynamically assess the understudy system's resilience. Forward and backward propagation analysis can be conducted in a dynamic Bayesian network. This enables decision-makers to update the latest evidence and model the system according to real-time conditions. The dynamic Bayesian network representation of resilience includes six nodes as states of functionalities, four functionalities' states, and learning. The first mentioned node presents the child node, and the rest represent the parent nodes in this structured Bayesian network. All probabilities regarding the corresponding functional state are computed to obtain the system resilience quantification. For example, the four states have a relationship for the child node according to the identified functionalities' state in the Markov chain model (see Figure 6.5). The time dependency of system resilience is taken into account with the model of the functionalities' state in different time slices such as time $t = 0$ to $t = 1$. It is assumed that the parent nodes, including absorption, adaptation, and restoration, are constructed within three states High, Moderate, and Low. In addition, it is considered that the disruption node has two states as Yes and No, meaning the occurrence of disruption over time. It is also considered that the first disruption appears at time $t = 0$ since it is the time system starting to work. Therefore, the functioning state of disruption would be set as "Yes". It is worth noting that to our best understanding from the problem as well as having support from the literature [39,60,61,63], resilience is intrinsically standing for the system properly except for human errors; this should be independent of an exterior parameter such as disruption. That is, the exterior parameters can considerably affect the functionality of the engineering system and the corresponding performance. Subsequently, it has an impact on system resilience. For instance, the environmental conditions as an exterior parameter can affect system resilience under normal operating, in which temperate environmental circumstances have higher resilience than harsh environmental conditions. Therefore, the exterior parameters can change the functionalities' state (resilience) of the system within two aspects (i) human reliability and (ii) system performance. According to this point, the disruption in the present study only refers to system performance (i.e., MIC impacts system performance).

The dynamic Bayesian network in the present work illustrates three different processes over time (i) influence of state absorption, adaptation, restoration, and disruptions on the system resilience, (ii) exterior disruptions, and (iii) system resilience in the period. It can be concluded that if the system is working without any disruptions, the functionalities' state depends on the last states. This means that the disruption would occur based on the degradation of the system in its normal time. Looking at the dynamic Bayesian network representing the system resilience over time, the disruption occurs at time $t = 1$, and the functioning state (state 1) depends on its corresponding state at time $t = 0$. This includes the resilience nodes containing absorption, adaptation, and restoration, and they are assessed at both time $t = 1$ and $t = 0$. The only node repressing disruption is assessed at time $t = 1$. According to this point, the functionalities' state is changing from state 1 to state 4, and vice versa. Considering the concept of resilience, the system resilience can be obtained using probabilities of the system to be sustained in the normal operating state or restored into the normal operating state from an abnormal state in two periods after and before the time of disruption. It should be added that inference analysis in dynamic Bayesian Network such as filtering, prediction, and smoothing based on the times of shreds of evidence and the times of queries does not with the scope of present work.

Two cases can be derived as scenarios to assess the resilience probabilities: (i) the high ability of the engineering system for disruption absorption is strong and properly handled the upfront damages. This system's capability can increase the probabilities of the system being sustained in the normal operating state. Therefore, the probability of the system absorbing the damages is state 1 in the resilience functionality curve (Figure 6.2). (ii) the system can be restored by receiving external intervention actions (i.e., repair action) to the acceptable functional state. The probability of the system reaching the probability of system restored from disruption state is the probability of state 4 in resilience functionality curve (Figure 6.2).

In addition, the resilience is quantified by probability summation of all functionalities' states from state 1 to state 4 in different time slices. In this way, resilience can be presented as a probabilistic term. Using a dynamic Bayesian network enables decision-makers to properly represent the temporal term's resilience within different time slices. This would help assessors determine the recovery time (as an example, 85%) of the resilience loss after a disruption.

Step five: Sensitivity analysis

In this step, sensitivity analysis is executed to determine the main and critical factors in the resilience system. All the functionalities' state and resilience attributes can be marked as targets for sensitivity analysis. For example, all of the factors can be varied to the High, Moderate, and Low probability of operating state, and then assess the system resilience in the temporal term.

6.4. Application of the proposed methodology

The proposed methodology is applied to an "APL 5L" with an "X42 grade" subsea pipeline. In this case, it carries the hydrocarbon material like co-mingled fluids and would highly be suspected to MIC. The subsea pipeline needs to operate for more than 30 years [86–88]. The detailed descriptions of the computation process assessing the resilience of the subsea system are provided as the following.

Step one: Defining the system and obtaining the influence diagram of MIC, and all required information

In this step, a mechanistic model of MIC rate is provided. The mechanistic model of MIC rate includes (i) environmental circumstances such as CO_2 partial pressure, O_2, temperature, and Sulphides, (ii) operating circumstances such as pressure and velocity, (iii) material circumstances such as steel Carbon content, (iv) exposure duration. The rate of MIC has a direct contribution to the maximum pit depth, and the subsea pipeline would further fail. Therefore, it is essential to design the pipeline with the capability of accepting a certain level of failure. According to this point, the disruption attribute of resilience is defined based on the rate of MIC as Sever or High.

The mechanistic model of MIC rate and relevant data based on literature [87,89–91], and operational and chemical analysis from a subsea facility off the East Coast of

Canada is presented in Figure 6.6 (i.e., the observed variables). In addition, a chemical examination of produced water shows the overall microorganisms through the qPCR (quantitative Polymerase Chain Reaction) technique (3.20e+06 (16S rRNA copies/mL for the sample)), different types of microorganisms' percentage (Methermicoccus 4.79 %, Desulfovibrio 8.72 %, Dethiosulfatibacter 10.14 %, Archaeoglobus 38.36 %, Thermoanaerobacter 1.349 %, Thermococcus 9.88 %, Thermosipho 3.6 %, Methermicoccus 4.79 %), and sulfate reduction rate (SRR) (umolS/mL/day 0.52 in situ). In order to have insights developing a mechanistic model of MIC, the relevant MIC-based guidelines are taken into account [92–98].

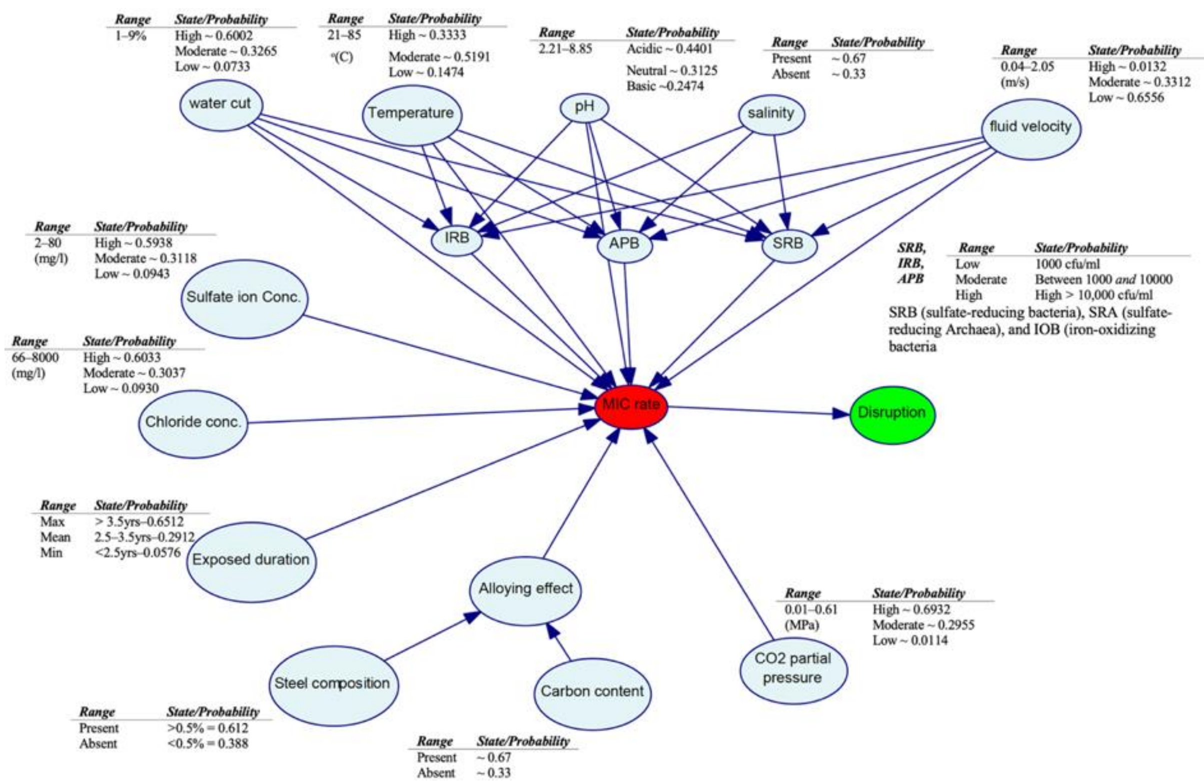


Figure 6.6. The influence diagram representing the mechanistic model of MIC rate and relevant data

Step two: Identifying the functionality of the system and developing a Markov chain to represent the states of the system

In this step, the four functionality states (absorption, adaptation, restoration, and disruption) of the subsea pipeline are defined, in which all states are decomposed into the substates (e.g., the Markov chain presented in Figure 6.5). Besides main resilience attributes, this is influenced by more parameters such as learning and external factors. Thus, to assess the resilience of the subsea pipeline under the influence of MIC, a new model is developed by identifying key contributing factors of the system, as illustrated in Figure 6.7.

Three factors are identified that effecting the absorption ability of the system as (i) preventive actions (these measures prevent the occurrence of disruptions), (ii) redundancy (this ability of the system provides an additional component that is not required to function and reduces the impact of disruption), and (iii) robustness (this is the system ability, in which the system resist any changes caused by the disruption) [39,63,72]. Thus, different preventive actions are taken into account in the pipeline design to prevent the MIC occurrence, such as (i) assuring cleanness, (ii) coating, (iii) cathodic protection, and (iv) periodic inspection. Two factors are identified that effecting the adaptation ability of the system as (i) mitigative actions (these measures reduce the consequences of undesired disruptions and can maintain the system to operate), and (ii) flexibility (this is the ability of the system by adapting the deviations and perversions without effecting to the functionality of the system). In addition, different mitigative actions are considered in the system, including (i) Inhibitors treatment, (ii) Biocide treatment, (iii) Biological treatment, (iv) Manipulating operational parameters, and (v) Pigging [86]. Finally, three factors are identified that effecting the restoration ability of the system (i) mitigative actions (mentioned earlier) and (ii) maintenance actions (repair or replace).

The resilience of the system would be enhanced by improving the resilience attributes (absorption, adaptation, restoration, and disruption) [32,72]. The above contributors' factors into the system resilience are connected within the normal arcs. The reason is that the factors establish the resilience attributes simultaneously at the same time slice.

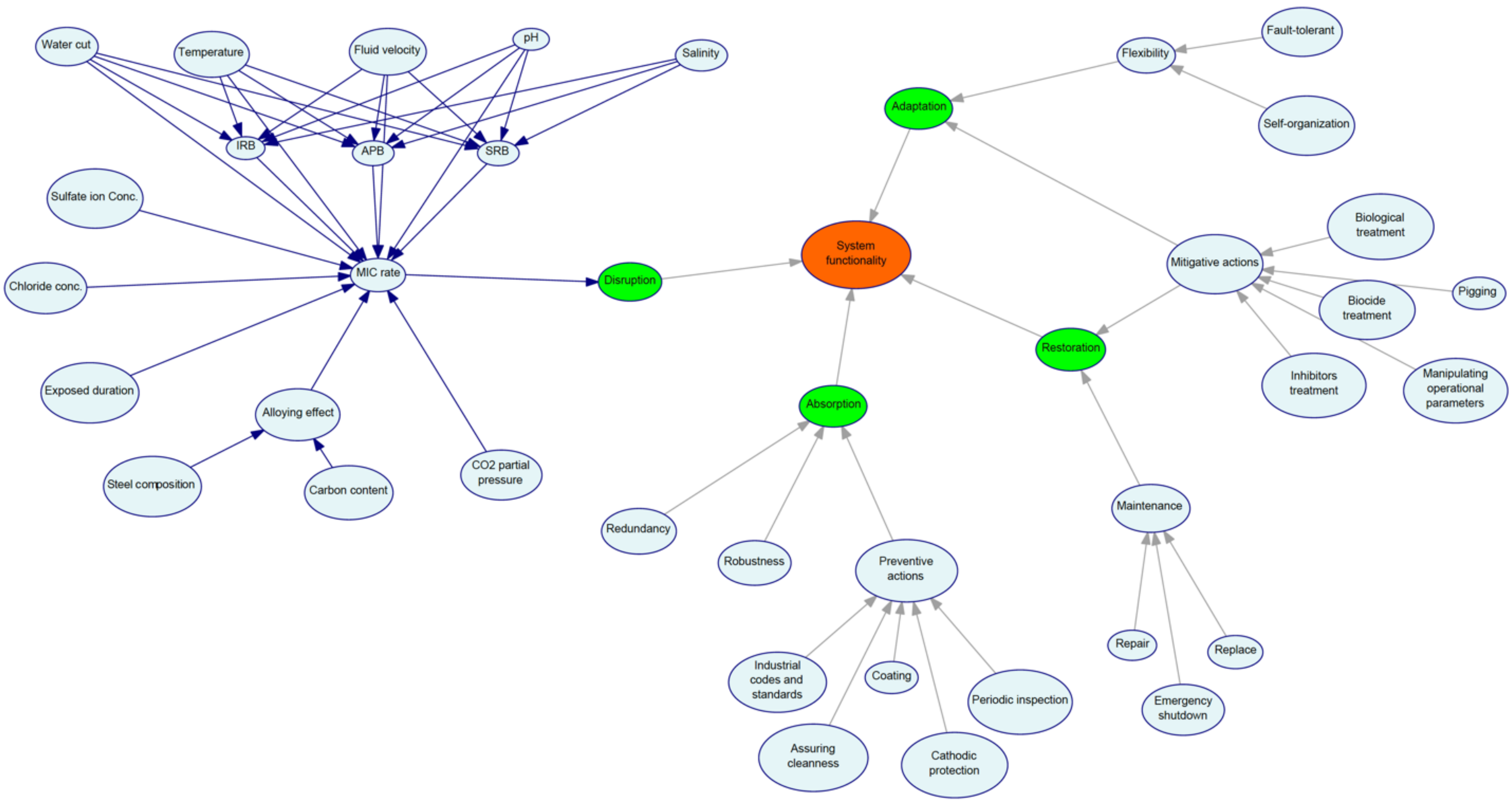


Figure 6.7. The influence diagram presents the system resilience of the subsea pipeline

As shown in Figure 6.7, a schematic representation influence diagram is provided for the resilience assessment of the subsea system under the influence of MIC. The system functionality is assessed for measuring system resilience of subsea pipelines, considering the rate of MIC. In the following, we studied the substates of resilience attributes, in which all influential parameters are evaluated.

(i) Disruption

In this study, the disruption is defined as the rate of MIC, and the rate of MIC for an individual corrosion defect is influenced by different parameters, including bacteria colonies (SRB, APB, and IRB), material properties, exposure duration, and the environmental parameters. Different environmental factors in MIC rate play an important role in temperature, pressure, pH, fluid velocity, oil and gas-phase composition, and solids [99]. It should be highlighted that the IRB, SRB, and APB activities are a function of the nearby environmental parameters. For example, the fluid velocity would induce a MIC defect due to boosted turbulence and mass transfer of fluid velocity on the surface [100]. The temperature would double the rate of MIC in the interval 283.15–288.15 ^{o}K and would rise in the interval 273.15–348.15 ^{o}K. In addition, the MIC rate would be accelerated in an acidic medium due to mentioned temperature ranges [4,100,101]. The high value of pressure can enhance the rate of MIC by increasing the protective surface dissolution from the metal surface. Microbial activities can tolerate a wide variety of pressure, such as SRB standing up to ~51 Megapascal pressure [4,102]. The value of pH depends on many factors such as temperature, organic acids, buffering species' concentrations, pressures of H2S and CO2 [103]. The final example, the rate of MIC depends on water conductivity function. The higher value of Cl^- concentration would increase the water conductivity. The MIC rate would grow by increasing the Cl^- concentration with a range of 10,000 – 120,000 ppm [104]. In addition, the influence diagram of the mechanistic model of MIC rate and relevant data are depicted in Figure 6.7.

(ii) Absorption

In this study, absorption is decomposed into three parameters. The subsea pipeline is assumed to be strong and healthy in the constitution. Besides, the system has a high ability to tolerate disruptions, and therefore the system would be much more robust. Redundancy in pipeline design is taken into account using High Integrity Pressure Protection Systems (HIPPS) in case of pressure drop caused by disruptions. The preventive actions are presumed to be already in the pipeline design and installation. The cathodic protection and coatings have the lowest installation difficulty and cost, which proficiently prevents MIC occurrence [105]. This study assumes that Fusion-bonded epoxy (FBE) and sacrificial anode techniques are used for the mentioned coating and cathodic protection, respectively [86,106].

(iii) Adaption

This study decomposes adaption into two parameters: flexibility and mitigation actions. The latter will be explained in the restoration part (iv: restoration). In addition, the flexibility of the pipeline is evaluated by providing the answer to the following question. First, regarding fault-tolerant, "*Could the total subsea system continue to operate in case of disruptions for the critical components, machinery, servers, and software?*". Second, regarding self-organization, "*Does the onsite decision-maker(s) have enough authority to make an adequate decision?*". In this study, it is considered that the system has a high ability of flexibility, and the system has a high capability of fault-tolerant and decision-maker(s) have enough authority to make a viable decision.

(iv) Restoration

This study decomposes restoration in detail by performing two different sets of actions. First, mitigative actions are explained as follows: (i) MIC inhibitors are referred to chemicals that influence anodic part such as chromates CrO_4^{2-}, and NO_2^- [107]. A value of 80 % efficiency is considered for inhibitors in the system and assumed that the inhibitors have a required dosage through the system [86,108]. (ii) Biocides are defined as living things (microbes) killers such as chlorine dioxide, Metronidazole, Formaldehyde, and Glutaraldehyde [109–111]. A 60 % value for laboratory-results (Formaldehyde) efficiency is used in this study [86,111]. Periodical pigging is a mechanical strategy that is used to mitigate MIC. A value of 65 % pigging efficiency based on laboratory results is considered in this study [112]. Periodical pigging would help to remove the piece of the biofilm and solid particles [113]. The biological treatment is another mitigative action that uses bacteria against the MIC responsible for primary bacteria [114]. For example, persevering the system with Nitrate induces the heterotrophic to reduce the rate of MIC up to 40 % [115]. The manipulation parameters which can treat the MIC effectively are explained earlier.

Regarding maintenance actions, replacement and repair are considered in case of disruption. Selecting replacement or repair depends on the pipeline's age, budget, and efficiency over the expected service life of the pipeline, as discussed in previous authors' study [86]. Finally, the emergency shutdown may be used to reduce the consequences of the emergency disruption occurrence.

Step three: Estimating the value of transition states of the Markov chain and translating the Markov chain into the dynamic Bayesian network

As presented in Figures 6.4 and 6.5, the transition states of four resilience attributes (absorption, adaptation, restoration, and disruptions) from state one to state four are characterized with relevant transitional probabilities λ_0, μ_0, λ_1, and μ_1. This should be added that the transitional probabilities would better be obtained from historical data in case of availability. To obtain the values of state one to state four, the conditional probability tables for the corresponding nodes are utilized afterward, directing the node state of functionality [85].

For simplicity, it is assumed that the nodes representing absorption, adaptation, and restoration have only states "High" and "Low". As an example, the state "High" for the node restoration means that how much is the probability of the system to have an ability of restoration, in which the system could restore itself from the state disruption into the state normal. Figure 6.8 shows the translation of the Markov chain into the Bayesian network, presenting all potential contributing factors. In the present work, the importance weights present the impact of parental nodes on their corresponding child nodes, in which the weights represent the relevant conditional probabilities. In this work, the Best worst method (BWM) is utilized to assist in obtaining conditional probabilities. BWM, proposed by Rezaei (2015) [116] applied in different application domains [117–122], requires fewer comparison data than existing methods and provides much more viable and consistent results based on its unique comparison procedure. BWM handles a subjective judgment caused by uncertainty in this decision-making process. It should be noted that the BWM is developed based on the opinions coming from decision-makers within relevant backgrounds about the understudy system. Therefore, the weights of contributing factors highly depend on the specific features of the system and its operational condition and environmental circumstances. The importance weights of the causal factors are presented in Table 6.2. In addition, the contributing parameters' effects of parental nodes are assumed to be neutral and independent. Thus, the Leaky Noisy-OR gate functions are used to model all parent nodes' impact on the corresponding child nodes [123,124]. Besides, the subsea pipeline is assumed that the system is functioning appropriately with consideration of all industrial safety precautions.

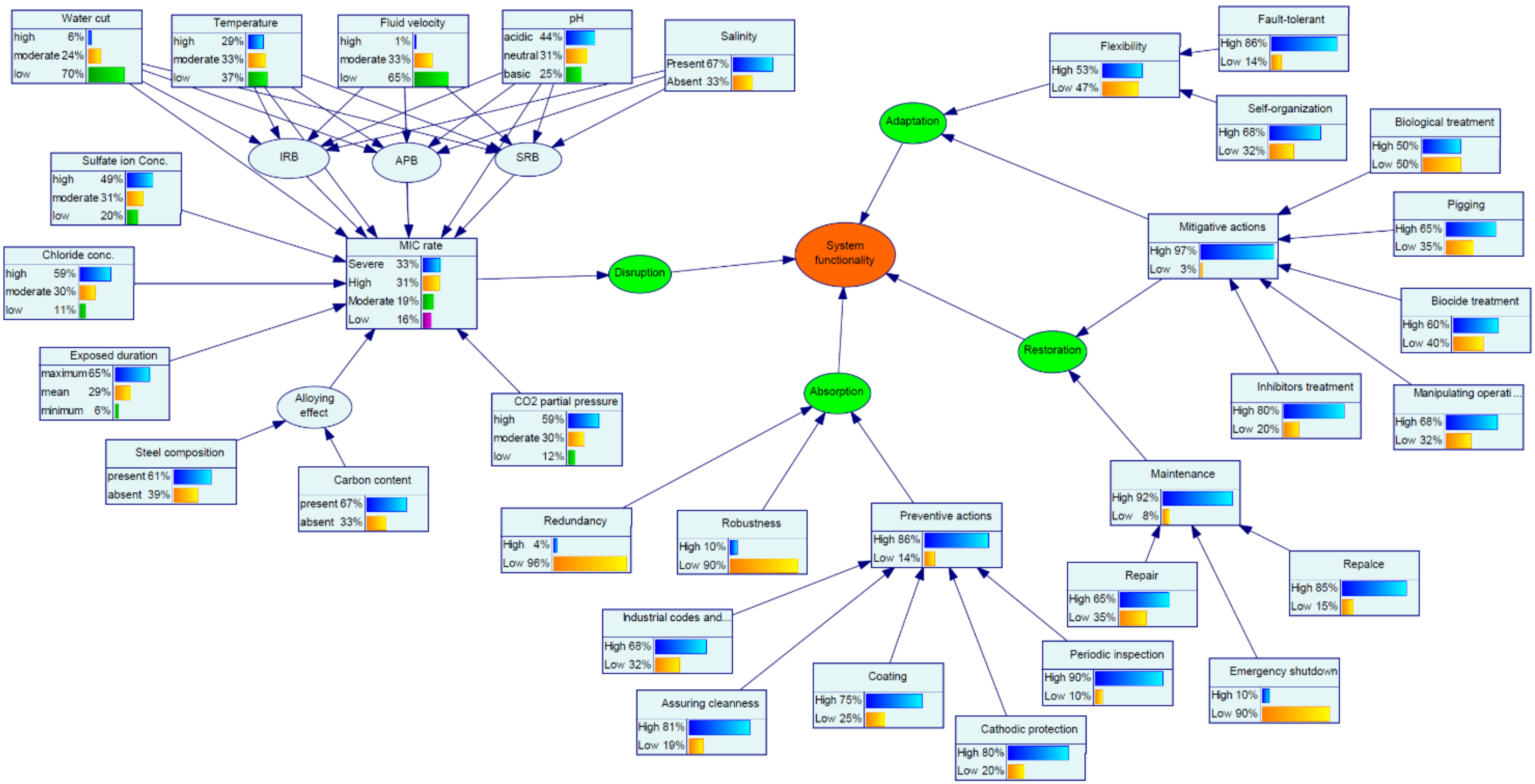


Figure 6.8. The Bayesian network structure for resilience assessment of the subsea pipeline influenced by MIC

Table 6.2. The importance weights of the contributing parameters for the three resilience attributes (absorption, adaption, and restoration) in the identified Bayesian network structure

Child nodes	Node tag	Node descriptions	Importance weights*, state "High"
Absorption	N1	Redundancy	~ 0.04
	N2	Robustness	~ 0.10
	N3	Preventive measures	~ 0.86
Preventive measures	N4	Industrial codes and standards	~ 0.68
	N5	Assuring cleanness	~ 0.81
	N6	Coating	~ 0.75
	N7	Cathodic protection	~ 0.80
	N8	Periodic inspection	~ 0.90
Adaption	N9	Flexibility	~ 0.53
Adaption / Restoration	N10	Mitigative actions	~ 0.97
Restoration	N11	Maintenance actions	~ 0.92
Maintenance actions	N13	Repair	~ 0.65
	N13	Replace	~ 0.85
	N14	Emergency shutdown	~ 0.10
Mitigative actions	N15	Inhibitor treatment	~ 0.80
	N16	Manipulating parameters	~ 0.68
	N17	Biocide treatment	~ 0.60
	N18	Pigging	~ 0.65

	N19	Biological treatment	~ 0.50
Flexibility	N21	Fault-tolerant	~ 0.86
	N22	Self-organization	~ 0.68
* It considered as conditional probability			

Step four: Computing the probability of each functional state and resilience as a summation of all states' probability

In this step, a dynamic model of the Bayesian network is developed to obtain the resilience of the subsea system over time. The structural dynamic Bayesian network within 70-time slices is depicted in Figure 6.9. It is considered the time slice indicating month; however, it can be a second, minute, an hour, a day, a week, or a year. The results show that the four attributes, disruption, absorption, adaption, and restoration at $t = 0$ are 0.78, 0.81, 0.75, and 0.91, respectively. To assess the resilience in the period of $t = 1$ to $t = 70$, the state of node disruption is set to be "High". As shown in Figure 6.10, the resilience of the system decreases gradually until it reaches the lowest point as 0.091 at time $t = 6$. According to Figure 6.10, it is concluded that the 90 % recovery of performance loss from the lowest point is equal to 0.9091 (i.e., 0.90 * (1 - 0.091) + 0.091) in 30 time slices (i.e., 36 – 6 = 30). In addition, the lower absorption system ability results in a more important reduction in system performance loss (resilience), and the performance loss would be greater in the case of higher absorption ability of the system. After a rapid decrease of performance loss, the adaption and restoration abilities of the system are going to be recovered till the state four probability is stabilized at 0.9091. Another observation is that the system continues to improve even after 90 % recovery of performance lost and is stabilized at time $t = 46$ and afterward (see Figure 6.11).

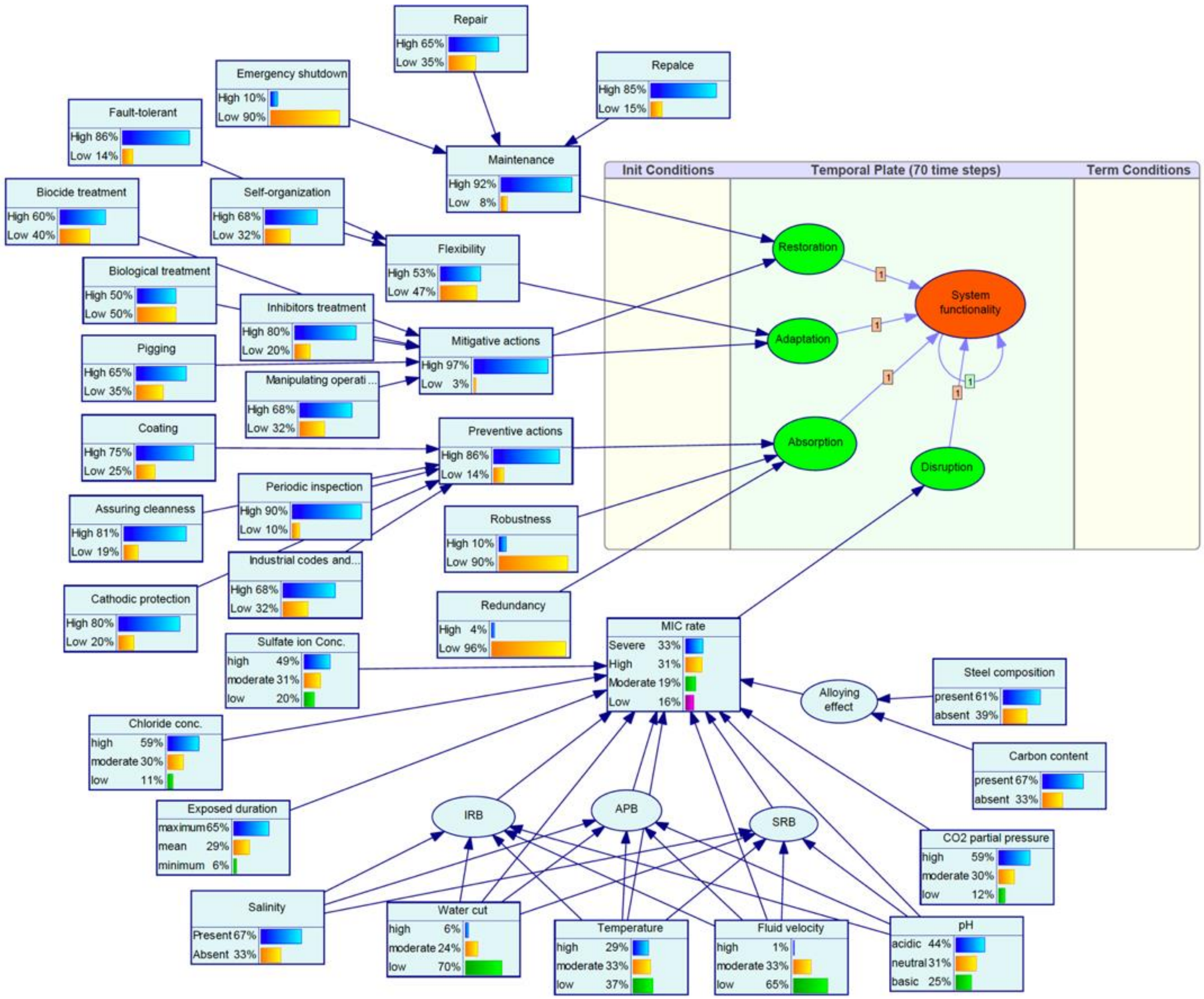


Figure 6.9. The structural dynamic Bayesian network for assessing the resilience of the subsea pipeline over time

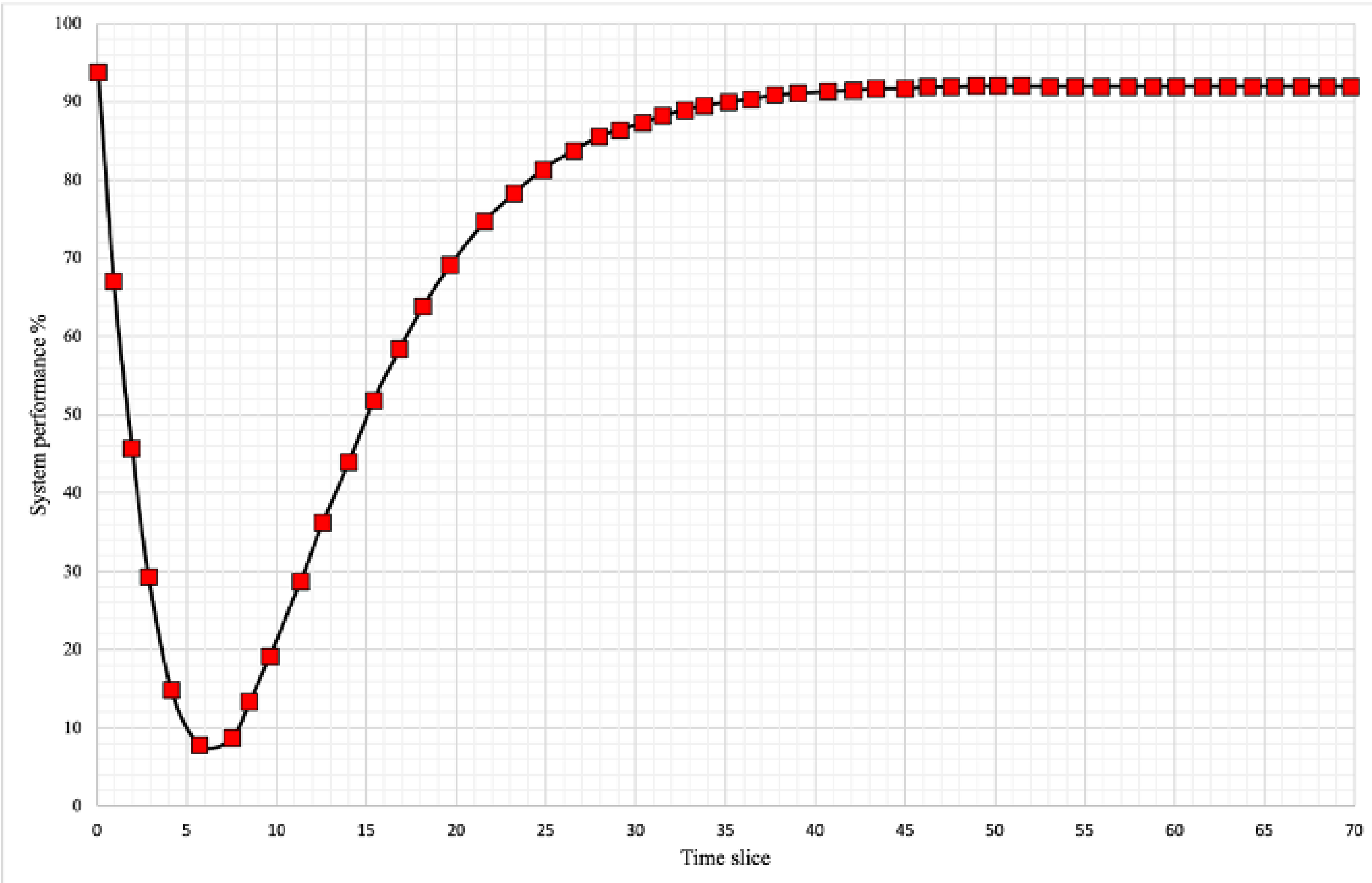


Figure 6.10. The resilience assessment of subsea pipeline over time

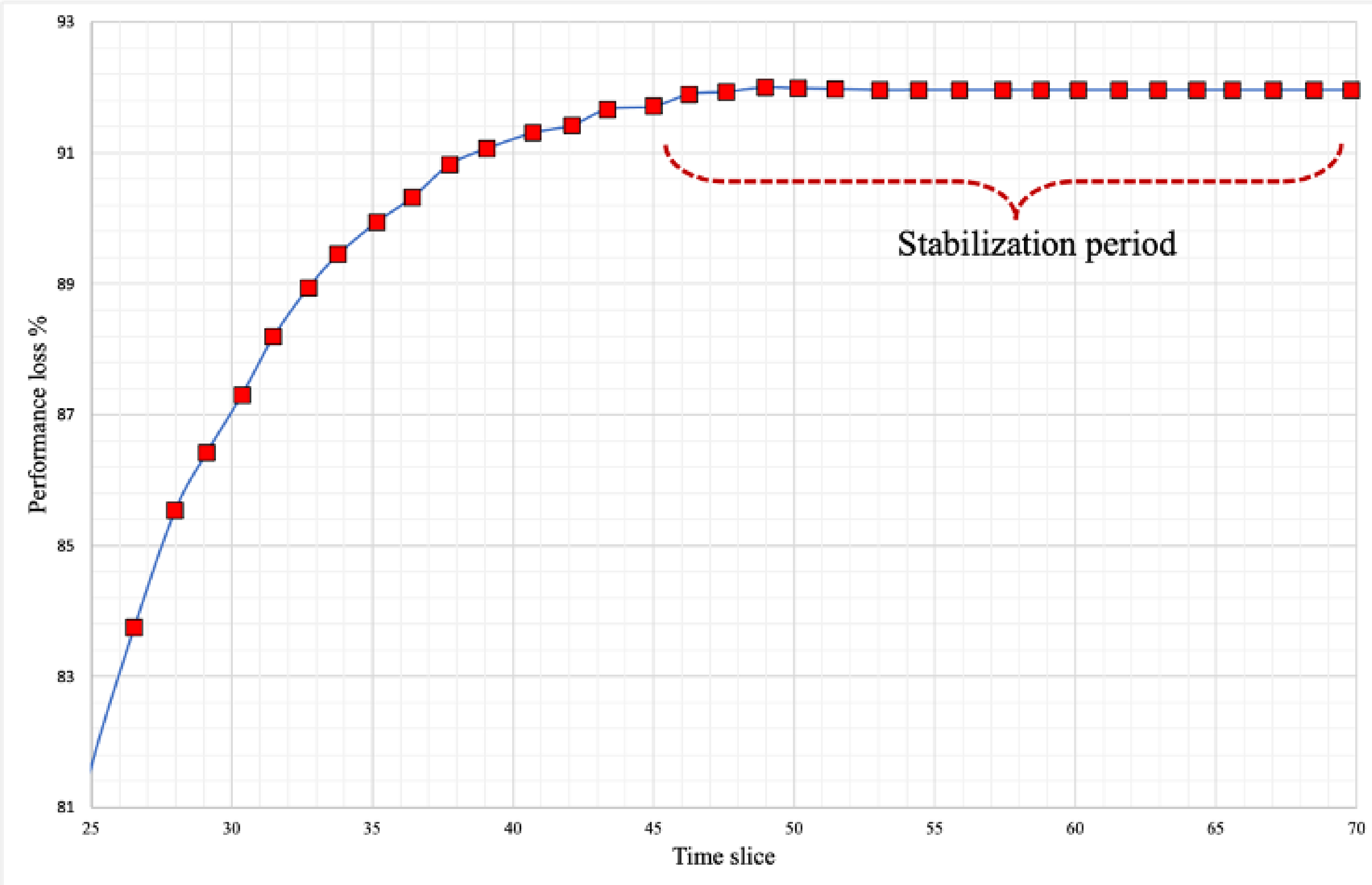


Figure 6.11. The resilience of subsea pipeline after 90 % recovery of performance lost (stabilization period)

Step five: Sensitivity analysis

In this step, the sensitivity analysis is conducted in two ways. First, the node "Learning," as explained in Section 3 ("*The ability of a system to learn from past experiences, knowledge, and previous disruption. This helps practitioners in predicting and avoiding disruptions.*") is added to the dynamic Bayesian network model, in which this plays as an external factor to consider the experience in the past and use to predict the future disruptions. The second is identifying the primary contributing resilience factors. This would help decision-makers identify the most critical factors in the system and provide some intervention actions for improvement.

First, the node "Learning" is added to the dynamic Bayesian network model, as depicted in Figure 6.12. It is assumed that the learning node has three states "High", "Moderate", and "Low". The results of system resilience for different states of node learning are illustrated in Figure 6.13. It can be concluded that subsea pipeline with higher learning ability typically has a sharper recovery rate. In this case, the system resilience with state "High" learning ability is improved much more than the system resilience with "Low" learning ability. The 90 % recovery of performance loss from the lowest point equals 0.9091, and the time for the state High, Moderate, and Low are 19, 21, and 25 time slices, respectively. Learning from the experiences helps decision-makers improve the system's resilience attributes for the following possible disruptions in the future. In addition, learning ability would offer constructive response from knowledge achieved from occurred disruptions. This also helps system resilience generating new knowledge to better respond to the disruptions. This new knowledge can be performed to correct inappropriate technical guidelines, assist the specialists in predicting the undesired disruptions, and make the appropriate adjustments in the subsea pipeline.

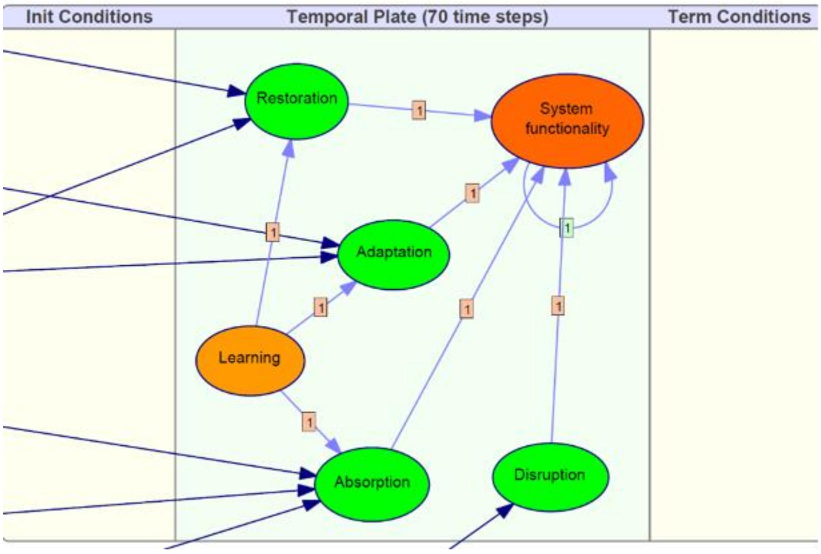


Figure 6.12. Performing sensitivity analysis by adding the node “Learning” to the dynamic Bayesian network

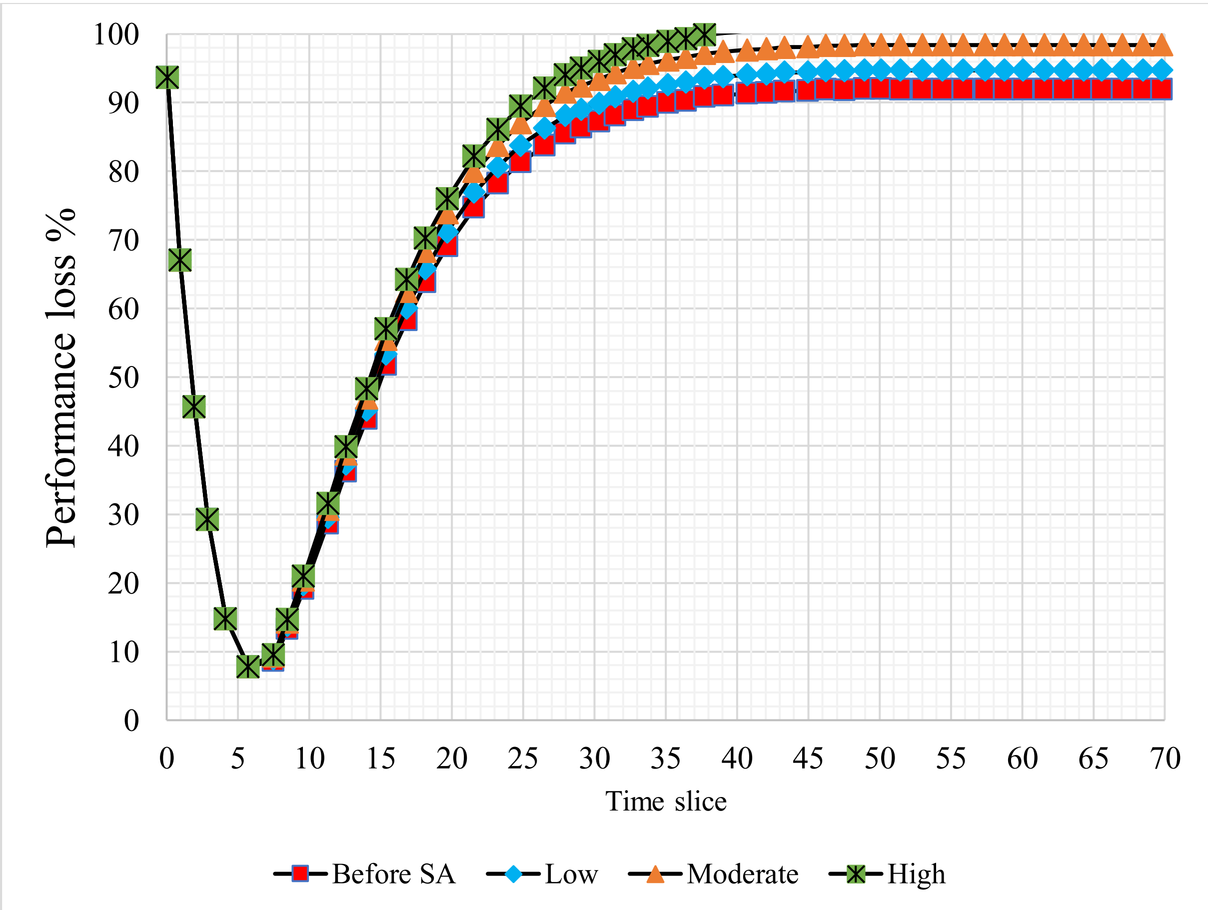


Figure 6.13. The sensitivity analysis of resilience assessment for subsea pipeline considering node “Learning” with different states

The second is performing sensitivity analysis by changing the contributing factors (i.e., resilience attributes), in which the time to 90 % recovery is evaluated. The results are illustrated in Figure 6.14, in which the factor disruption based on reliability has more variation. The factors adaption, restoration, and absorption are relatively consistent over time. In Figure 6.15, two lines represent the desired system resilience when all nodes in the Bayesian network are set to be "High", and system resilience fails since a node has the state "Low", and the rest of the nods are set to state "High". According to this point, the system resilience becomes the lowest in ascending order when the nodes are not functioning: N3 (Preventive measures), N16 (Manipulating parameters), N10 (Mitigative actions), and N17 (Biocide treatment). Finally, in Figure 6.16, the variation of states' probability is time dependent.

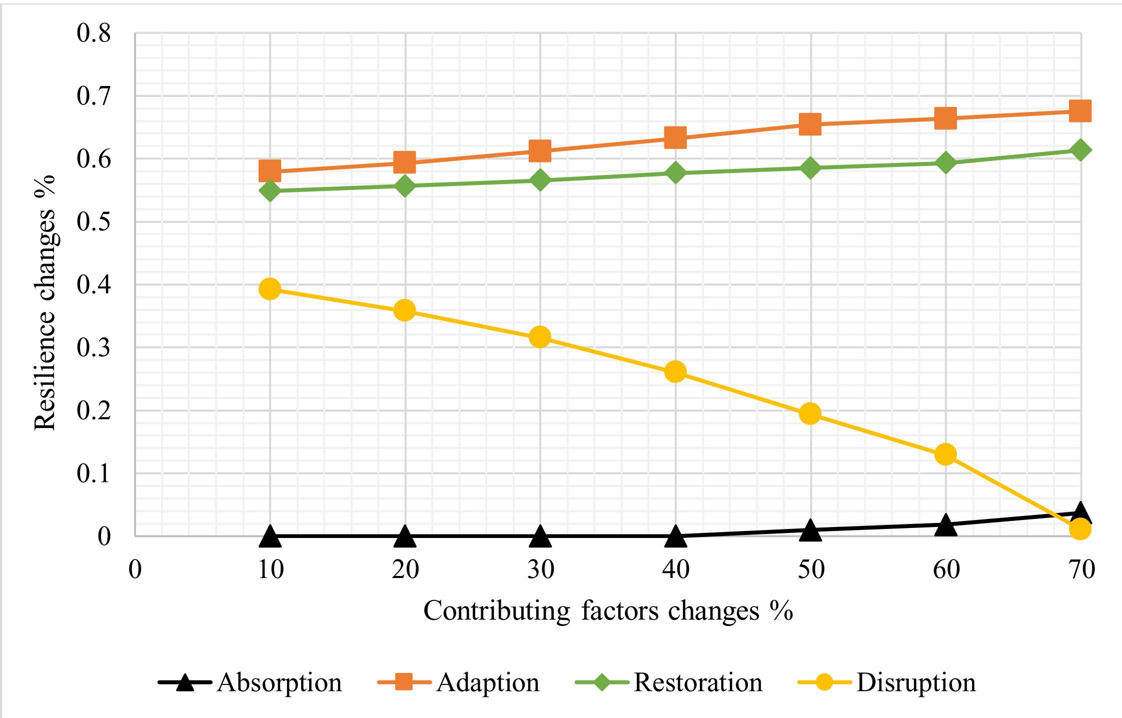


Figure 6.14. Assessing the variation of contributing factors on system resilience changes

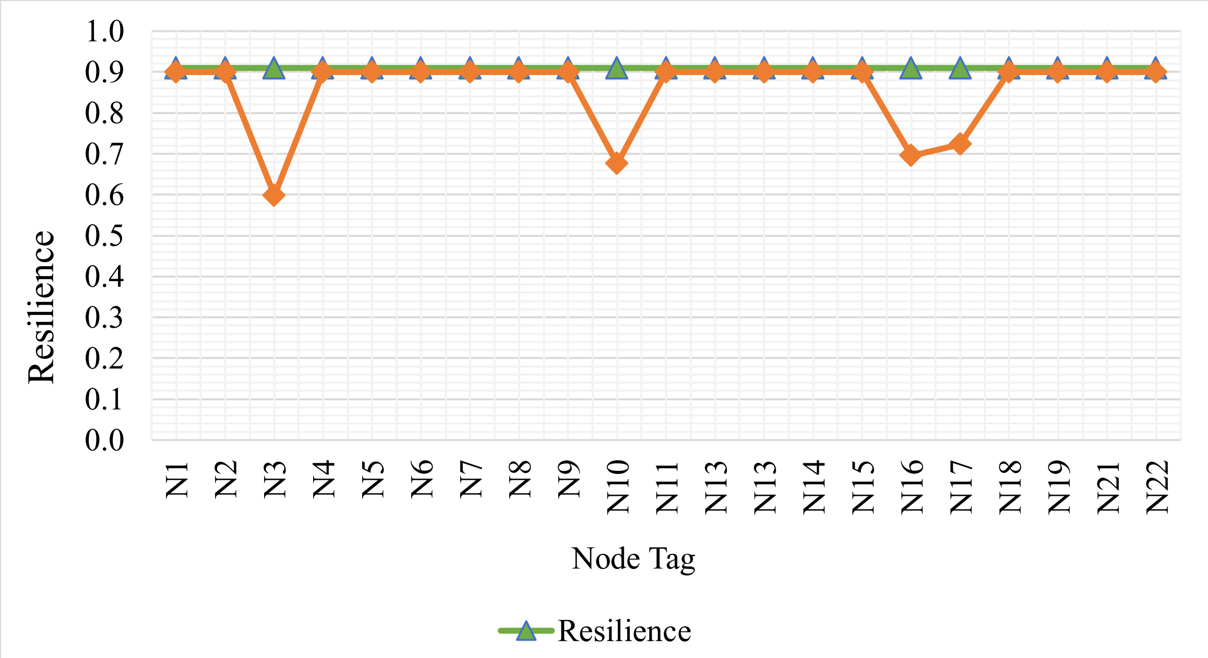


Figure 6.15. Assessing the variation of contributing factors (child nodes) on system resilience changes

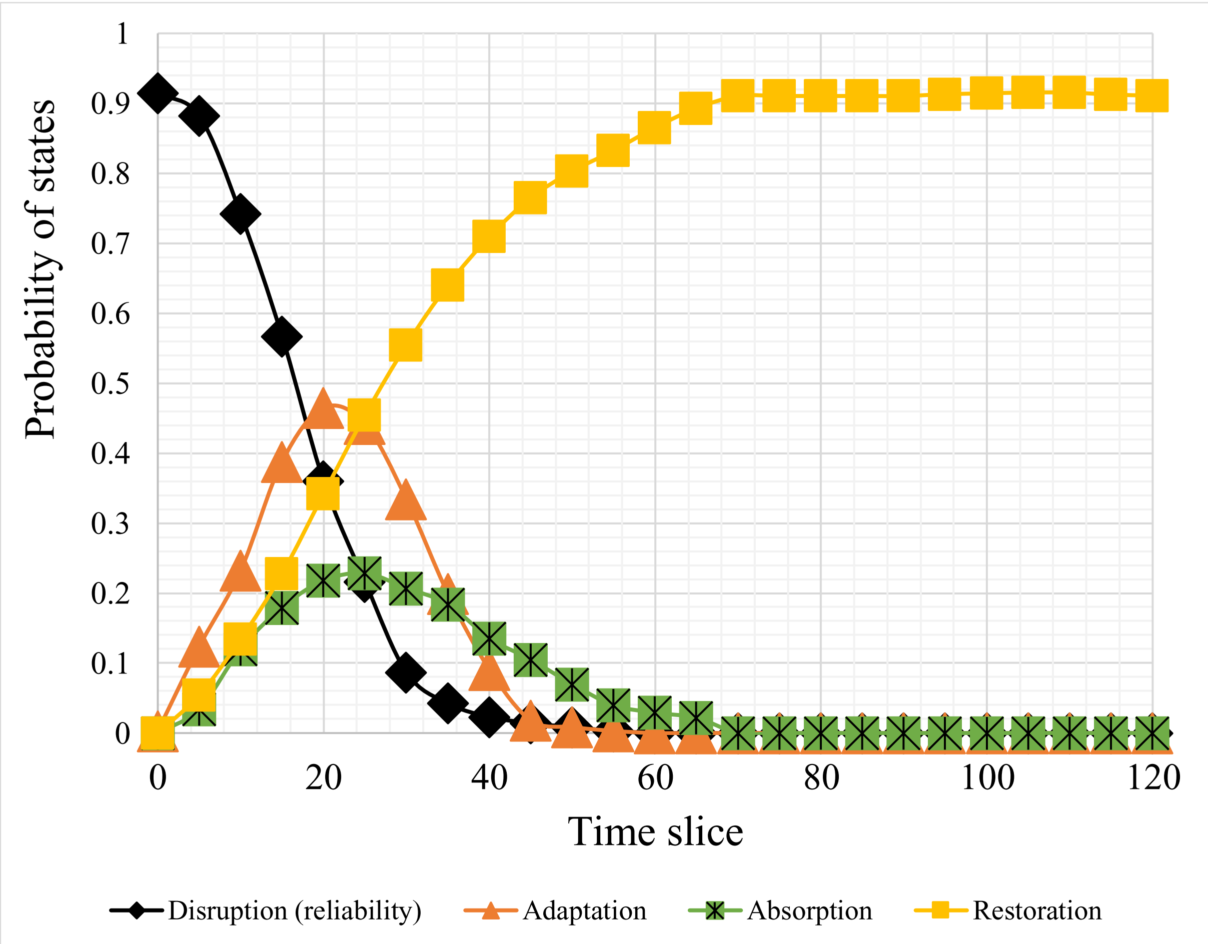


Figure 6.16. Assessing the variation of states' probability in a time-dependent manner

To validate the resilience assessment of the model, it requires information and data for the states' functionalities as well as inherent features of the system. First, considering the dynamic Bayesian network, analyzing the posterior needs to be performed for model verification. In this case, the system functionalities of restoration are 70 time slices (stabilization period). As shown in Figure 6.16, the time-dependent states' functionalities are provided. The probability of disruption drops to nearly 0.2 at $t = 25$. States' probabilities of adaption and absorption touch their peak of 0.45 and 0.2 at 20 and 25 time slices, respectively. In addition, the system resilience goes to the lowest point around 0.1 at $t = 10$ time slices and surges till it stabilizes at 0.91 at $t = 70$ time slices. This information has enough potential to validate the proposed model partially. The reason is the that the changes of system resilience variation are exactly based on the expectations. Therefore, it can be concluded that the obtained evidence is expected to result in rapid restoration for the resilience of the system.

6.5. Conclusions

In this study, a new methodology is proposed using a dynamic Bayesian network to assess the subsea pipeline's resilience dynamically. There are limited attempts to quantify the system's restoration probability with the sustained operation, which defines resilience. Lack of data, uncertainty in the data, and the impact of harsh environmental conditions make MIC management of the subsea pipeline further challenging. The dynamic Bayesian network approach provides a mechanism to model and manage the resilience of such a system. It addresses most of the challenges mentioned above. In addition, i) it utilizes both types of subjective and objective input information, ii) it performs the network updating once the new information becomes available, and iii) it assesses the resilience of the system over time.

This work proposes a new methodology to assess resilience as a function of time. Applying the methodology to a practical case study confirms that the proposed framework could provide a dynamic resilience profile. The dynamic resilience profile helps decision-makers better understand the subsea pipeline's resilience capability, monitor its performance, evaluate the safety-critical actions', prevent undesired disruptions, and identify the viable operational system improvement. In addition, the robustness and applicability of the proposed approach assert that it can be performed in other types of pipeline derogations and different engineering application domains. Such investigation is recommended to can be conducted for future study.

Two challenges have been faced during the study, which require further consideration. Firstly, while the current study has focused on discrete time-dependent operations, the actual operation is continued. This means discrete states characterize the Bayesian network's child nodes. A dynamic continuous Bayesian network can address this challenge. It is not considered in the present study to maintain the simplicity of the approach and establish the foundational base that a dynamic Bayesian network can model system resilience. Secondly, the transition states and the probabilities of the child nodes could be determined using historical data rather than logic (used in the current study). A data-driven approach can define the conditional probability tables and assist in addressing the epistemic uncertainty of the model. Authors hope other research will pick on these challenges and comprehensively address them.

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References

[1] T.L. Skovhus, D. Enning, J.S. Lee, Microbiologically Influenced Corrosion in the Upstream Oil and Gas Industry, Taylor & Francis, 2017.

[2] M.E.A. Ben Seghier, D. Höche, M. Zheludkevich, Prediction of the internal corrosion rate for oil and gas pipeline: Implementation of ensemble learning techniques, J. Nat. Gas Sci. Eng. 99 (2022) 104425. https://doi.org/https://doi.org/10.1016/j.jngse.2022.104425.

[3] S. Chandrasekaran, Advanced Marine Structures, 1th ed., CRC Press, 2015. https://doi.org/10.1201/b18792.

[4] A. Ibrahim, K. Hawboldt, C. Bottaro, F. Khan, A. Ibrahim, K. Hawboldt, C. Bottaro, Review and analysis of microbiologically influenced corrosion : the chemical environment in oil and gas facilities environment in oil and gas facilities, Corros. Eng. Sci. Technol. 2782 (2018). https://doi.org/10.1080/1478422X.2018.1511326.

[5] M. Yazdi, F. Khan, R. Abbassi, Operational subsea pipeline assessment affected by multiple defects of microbiologically influenced corrosion, Process Saf. Environ. Prot. 158 (2021) 159–171. https://doi.org/10.1016/j.psep.2021.11.032.

[6] M.E.A. Ben Seghier, B. Keshtegar, M. Taleb-Berrouane, R. Abbassi, N.-T. Trung, Advanced intelligence frameworks for predicting maximum pitting corrosion depth in oil and gas pipelines, Process Saf. Environ. Prot. 147 (2021) 818–833. https://doi.org/https://doi.org/10.1016/j.psep.2021.01.008.

[7] A. Guillal, M.E.A. Ben Seghier, A. Nourddine, J.A.F.O. Correia, Z. Bt Mustaffa, N.-T. Trung, Probabilistic investigation on the reliability assessment of mid- and high-strength pipelines under corrosion and fracture conditions, Eng. Fail. Anal. 118 (2020) 104891. https://doi.org/https://doi.org/10.1016/j.engfailanal.2020.104891.

[8] R.B. Eckert, T.L. Skovhus, Failure Analysis of Microbiologically Influenced Corrosion, 1th ed., CRC Press, 2021. https://doi.org/10.1201/9780429355479.

[9] M. Yazdi, F. Khan, R. Abbassi, N. Quddus, H. Castaneda-Lopez, A review of risk-based decision-making models for microbiologically influenced corrosion (MIC) in offshore pipelines, Reliab. Eng. Syst. Saf. (2022) 108474. https://doi.org/https://doi.org/10.1016/j.ress.2022.108474.

[10] I.B. Beech, C.C. Gaylarde, Recent advances in the study of biocorrosion: an overview , Rev. Microbiol. . 30 (1999) 117–190.

[11] A. Marciales, Y. Peralta, T. Haile, T. Crosby, J. Wolodko, Mechanistic microbiologically influenced corrosion modeling — A review, Corros. Sci. 146 (2019) 99–111. https://doi.org/10.1016/j.corsci.2018.10.004.

[12] T. Gu, K. Zhao, S. Nesic, A new mechanistic model for MIC based on a biocatalytic cathodic sulfate reduction theory, Corrosion. (2009) 1–12.

[13] J. Kaduková, E. Škvareková, V. Mikloš, R. Marcinčáková, Assessment of microbially influenced corrosion risk in slovak pipeline transmission network, J. Fail. Anal. Prev. 14 (2014) 191–196. https://doi.org/10.1007/s11668-014-9782-x.

[14] K.B. Sørensen, U.S. Thomsen, S. Juhler, J. Larsen, Cost Efficient MIC Management System based on Molecular Microbiological Methods, in: NACE Int. Conf. Expo, 2012.

[15] S. Maxwell, S. Campbell, Monitoring the Mitigaation of MIC Risk in Pipelines, in: Corros. NACExpo; 61st Annu. Conf. &E Expo., 2006: pp. 1–10.

[16] A. Vigneron, I.M. Head, N. Tsesmetzis, Damage to offshore production facilities by corrosive microbial biofilms, Appl. Microbiol. Biotechnol. 102 (2018) 2525–2533. https://doi.org/10.1007/s00253-018-8808-9.

[17] T.L. Skovhus, E.S. Andersen, E. Hillier, D.N. V Gl, Management of Microbiologically Influenced Corrosion in Risk-Based Inspection Analysis, in: Int. Oilf. Corros. Conf. Exhib., 2018: pp. 9–10.

[18] T. Aven, M. Ylönen, How the risk science can help us establish a good safety culture, J. Risk Res. (2021) 1–19. https://doi.org/10.1080/13669877.2020.1871056.

[19] T. Aven, E. Zio, Some considerations on the treatment of uncertainties in risk assessment for practical decision making, Reliab. Eng. Syst. Saf. 96 (2011) 64–74. https://doi.org/https://doi.org/10.1016/j.ress.2010.06.001.

[20] M.M. Al-Darbi, K. Agha, M.R. Islam, Comprehensive Modelling of the Pitting Biocorrosion of Steel, Can. J. Chem. Eng. 83 (2005) 872–881. https://doi.org/https://doi.org/10.1002/cjce.5450830509.

[21] M. Abimbola, F. Khan, Resilience modeling of engineering systems using dynamic object-oriented Bayesian network approach, Comput. Ind. Eng. 130 (2019) 108–118. https://doi.org/https://doi.org/10.1016/j.cie.2019.02.022.

[22] D. Henry, J. Emmanuel Ramirez-Marquez, Generic metrics and quantitative approaches for system resilience as a function of time, Reliab. Eng. Syst. Saf. 99 (2012) 114–122. https://doi.org/https://doi.org/10.1016/j.ress.2011.09.002.

[23] S. Yalda, A.B. M., Z. Yanjie, Z. Dongming, H. Hongwei, Resilience-Based Strategies for Topology Enhancement and Recovery of Metrorail Transit Networks, ASCE-ASME J. Risk Uncertain. Eng. Syst. Part A Civ. Eng. 6 (2020) 4020017. https://doi.org/10.1061/AJRUA6.0001057.

[24] D. Zhang, F. Du, H. Huang, F. Zhang, B.M. Ayyub, M. Beer, Resiliency assessment of urban rail transit networks: Shanghai metro as an example, Saf. Sci. 106 (2018) 230–243. https://doi.org/https://doi.org/10.1016/j.ssci.2018.03.023.

[25] Q. Feng, X. Zhao, D. Fan, B. Cai, Y. Liu, Y. Ren, Resilience design method based on meta-structure: A case study of offshore wind farm, Reliab. Eng. Syst. Saf. 186 (2019) 232–244. https://doi.org/https://doi.org/10.1016/j.ress.2019.02.024.

[26] A. Mentes, O. Turan, A new resilient risk management model for Offshore Wind Turbine maintenance, Saf. Sci. 119 (2019) 360–374. https://doi.org/https://doi.org/10.1016/j.ssci.2018.06.022.

[27] B. Cai, Y. Zhang, X. Yuan, C. Gao, Y. Liu, G. Chen, Z. Liu, R. Ji, A Dynamic-Bayesian-Networks-Based Resilience Assessment Approach of Structure Systems: Subsea Oil and Gas Pipelines as A Case Study, China Ocean Eng. 34 (2020) 597–607. https://doi.org/10.1007/s13344-020-0054-0.

[28] B. Cai, Y. Zhang, H. Wang, Y. Liu, R. Ji, C. Gao, X. Kong, J. Liu, Resilience evaluation methodology of engineering systems with dynamic-Bayesian-network-based degradation and maintenance, Reliab. Eng. Syst. Saf. 209 (2021) 107464. https://doi.org/https://doi.org/10.1016/j.ress.2021.107464.

[29] Y. Abebe, S. Tesfamariam, Storm sewer pipe renewal planning considering deterioration, climate change, and urbanization: a dynamic Bayesian network and GIS framework,

Sustain. Resilient Infrastruct. (2020) 1–16. https://doi.org/10.1080/23789689.2020.1740865.

[30] F. Khan, R. Yarveisy, R. Abbassi, Risk-based pipeline integrity management: A road map for the resilient pipelines, J. Pipeline Sci. Eng. 1 (2021) 74–87. https://doi.org/https://doi.org/10.1016/j.jpse.2021.02.001.

[31] S. Hosseini, K. Barker, J.E. Ramirez-Marquez, A review of definitions and measures of system resilience, Reliab. Eng. Syst. Saf. 145 (2016) 47–61. https://doi.org/10.1016/j.ress.2015.08.006.

[32] E.D. Vugrin, D.E. Warren, M.A. Ehlen, R.C. Camphouse, A Framework for Assessing the Resilience of Infrastructure and Economic Systems BT - Sustainable and Resilient Critical Infrastructure Systems: Simulation, Modeling, and Intelligent Engineering, in: K. Gopalakrishnan, S. Peeta (Eds.), Springer Berlin Heidelberg, Berlin, Heidelberg, 2010: pp. 77–116. https://doi.org/10.1007/978-3-642-11405-2_3.

[33] C.S. Holling, Resilience and Stability of Ecological Systems, Annu. Rev. Ecol. Syst. 4 (1973) 1–23. https://doi.org/10.1146/annurev.es.04.110173.000245.

[34] A. Azadeh, V. Salehi, M. Arvan, M. Dolatkhah, Assessment of resilience engineering factors in high-risk environments by fuzzy cognitive maps: A petrochemical plant, Saf. Sci. 68 (2014) 99–107. https://doi.org/https://doi.org/10.1016/j.ssci.2014.03.004.

[35] A. Azadeh, V. Salehi, B. Ashjari, M. Saberi, Performance evaluation of integrated resilience engineering factors by data envelopment analysis: The case of a petrochemical plant, Process Saf. Environ. Prot. 92 (2014) 231–241. https://doi.org/https://doi.org/10.1016/j.psep.2013.03.002.

[36] G.A. Shirali, I. Mohammadfam, V. Ebrahimipour, A new method for quantitative assessment of resilience engineering by PCA and NT approach: A case study in a process industry, Reliab. Eng. Syst. Saf. 119 (2013) 88–94. https://doi.org/https://doi.org/10.1016/j.ress.2013.05.003.

[37] A. Zinetullina, M. Yang, N. Khakzad, B. Golman, Dynamic resilience assessment for process units operating in Arctic environments, Saf. Extrem. Environ. (2019).

[38] J. Hu, F. Khan, L. Zhang, Dynamic resilience assessment of the Marine LNG offloading system, Reliab. Eng. Syst. Saf. 208 (2021) 107368. https://doi.org/10.1016/j.ress.2020.107368.

[39] A. Zinetullina, M. Yang, N. Khakzad, B. Golman, X. Li, Quantitative resilience assessment of chemical process systems using functional resonance analysis method and Dynamic Bayesian network, Reliab. Eng. Syst. Saf. 205 (2021) 107232. https://doi.org/10.1016/j.ress.2020.107232.

[40] M.K. Sen, S. Dutta, G. Kabir, Flood Resilience of Housing Infrastructure Modeling and Quantification Using a Bayesian Belief Network, Sustainability. 13 (2021) 1026. https://doi.org/10.3390/su13031026.

[41] T.K. Singhal, O.-S. Kwon, E.C. Bentz, C. Christopoulos, Development of a civil infrastructure resilience assessment framework and its application to a nuclear power plant, Struct. Infrastruct. Eng. (2020) 1–14. https://doi.org/10.1080/15732479.2020.1832538.

[42] R. Bjarte, L. David, T. Marianthi, P. Christer, From Risk Management to Resilience Management in Critical Infrastructure, J. Manag. Eng. 36 (2020) 4020039. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000795.

[43] L. Petersen, D. Lange, M. Theocharidou, Who cares what it means? Practical reasons for using the word resilience with critical infrastructure operators, Reliab. Eng. Syst. Saf. 199 (2020) 106872. https://doi.org/https://doi.org/10.1016/j.ress.2020.106872.

[44] R. Amin, P. Lohani, M. Ekka, S. Chourasia, S. Vollala, An enhanced anonymity resilience security protocol for vehicular ad-hoc network with Scyther simulation, Comput. Electr. Eng. 82 (2020) 106554. https://doi.org/https://doi.org/10.1016/j.compeleceng.2020.106554.

[45] E. Ozen, A. Orailoglu, Boosting Bit-Error Resilience of DNN Accelerators Through Median Feature Selection, IEEE Trans. Comput. Des. Integr. Circuits Syst. 39 (2020) 3250–3262. https://doi.org/10.1109/TCAD.2020.3012209.

[46] R. Gupta, S. Tanwar, N. Kumar, S. Tyagi, Blockchain-based security attack resilience schemes for autonomous vehicles in industry 4.0: A systematic review, Comput. Electr.

Eng. 86 (2020) 106717. https://doi.org/https://doi.org/10.1016/j.compeleceng.2020.106717.

[47] M.C.W. Saldanha, R.J.M. de Carvalho, R. Arcuri, A.G. Amorim, M.C.R. Vidal, P.V.R. de Carvalho, Understanding and improving safety in artisanal fishing: A safety-II approach in raft fishing, Saf. Sci. 122 (2020) 104522. https://doi.org/https://doi.org/10.1016/j.ssci.2019.104522.

[48] Q. Guo, S. Amin, Q. Hao, O. Haas, Resilience assessment of safety system at subway construction sites applying analytic network process and extension cloud models, Reliab. Eng. Syst. Saf. 201 (2020) 106956. https://doi.org/https://doi.org/10.1016/j.ress.2020.106956.

[49] G.K. Kaya, M.F. Hocaoglu, Semi-quantitative application to the Functional Resonance Analysis Method for supporting safety management in a complex health-care process, Reliab. Eng. Syst. Saf. 202 (2020) 106970. https://doi.org/https://doi.org/10.1016/j.ress.2020.106970.

[50] F. Bento, L. Garotti, M.P. Mercado, Organizational resilience in the oil and gas industry: A scoping review, Saf. Sci. 133 (2021) 105036. https://doi.org/https://doi.org/10.1016/j.ssci.2020.105036.

[51] S. Doug, V. Brian, K. Faisal, T. Rocky, Integration of Resilience and FRAM for Safety Management, ASCE-ASME J. Risk Uncertain. Eng. Syst. Part A Civ. Eng. 6 (2020) 4020008. https://doi.org/10.1061/AJRUA6.0001044.

[52] H. Ashkan, B. Hamed, Y.-B.S.M. Mahdi, D.F. Mohammadi, V. Armin, Z. Pouyan, Q. Pierre, Enhanced Seismic Performance of Timber Structures Using Resilient Connections: Full-Scale Testing and Design Procedure, J. Struct. Eng. 146 (2020) 4020180. https://doi.org/10.1061/(ASCE)ST.1943-541X.0002749.

[53] S. Li, T. Zhao, M.S. Alam, Z. Cheng, J. Wang, Probabilistic seismic vulnerability and loss assessment of a seismic resistance bridge system with post-tensioning precast segmental ultra-high performance concrete bridge columns, Eng. Struct. 225 (2020) 111321. https://doi.org/https://doi.org/10.1016/j.engstruct.2020.111321.

[54] B. Accou, G. Reniers, Introducing the Extended Safety Fractal: Reusing the Concept of Safety Management Systems to Organize Resilient Organizations, Int. J. Environ. Res. Public Heal. . 17 (2020). https://doi.org/10.3390/ijerph17155478.

[55] M. Zurek, G. Garbutt, T. Lieb, T. Hess, J. Ingram, Increasing Resilience of the UK Fresh Fruit and Vegetable System to Water-Related Risks, Sustain. . 12 (2020). https://doi.org/10.3390/su12187519.

[56] M.K. Sen, S. Dutta, G. Kabir, Flood Resilience of Housing Infrastructure Modeling and Quantification Using a Bayesian Belief Network, Sustain. . 13 (2021). https://doi.org/10.3390/su13031026.

[57] H. Sun, F. Zhen, Z. Xie, Urban resilience assessment based on contradiction between supply and demand of the daily activity–environment system: A case study on Nanjing, China, Sci. Total Environ. 765 (2021) 144567. https://doi.org/https://doi.org/10.1016/j.scitotenv.2020.144567.

[58] R.M. Vogel, R.A. Bolognese, Storage-Reliability-Resilience-Yield Relations for Over-Year Water Supply Systems, Water Resour. Res. 31 (1995) 645–654. https://doi.org/https://doi.org/10.1029/94WR02972.

[59] H. Baroud, J.E. Ramirez-Marquez, K. Barker, C.M. Rocco, Stochastic Measures of Network Resilience: Applications to Waterway Commodity Flows, Risk Anal. 34 (2014) 1317–1335. https://doi.org/https://doi.org/10.1111/risa.12175.

[60] S. Hosseini, N. Yodo, P. Wang, Resilience Modeling and Quantification for Design of Complex Engineered Systems Using Bayesian Networks, (2014). https://doi.org/10.1115/DETC2014-34558.

[61] N. Yodo, P. Wang, Resilience Modeling and Quantification for Engineered Systems Using Bayesian Networks, J. Mech. Des. 138 (2016). https://doi.org/10.1115/1.4032399.

[62] S. Hosseini, K. Barker, Modeling infrastructure resilience using Bayesian networks: A case study of inland waterway ports, Comput. Ind. Eng. 93 (2016) 252–266. https://doi.org/https://doi.org/10.1016/j.cie.2016.01.007.

[63] N. Yodo, P. Wang, Z. Zhou, Predictive Resilience Analysis of Complex Systems Using Dynamic Bayesian Networks, IEEE Trans. Reliab. 66 (2017) 761–770. https://doi.org/10.1109/TR.2017.2722471.

[64] A.M. Madni, S. Jackson, Towards a Conceptual Framework for Resilience Engineering, IEEE Syst. J. 3 (2009) 181–191. https://doi.org/10.1109/JSYST.2009.2017397.

[65] M. Ouyang, L. Dueñas-Osorio, Multi-dimensional hurricane resilience assessment of electric power systems, Struct. Saf. 48 (2014) 15–24. https://doi.org/https://doi.org/10.1016/j.strusafe.2014.01.001.

[66] T. Aven, On Some Recent Definitions and Analysis Frameworks for Risk, Vulnerability, and Resilience, Risk Anal. 31 (2011) 515–522. https://doi.org/https://doi.org/10.1111/j.1539-6924.2010.01528.x.

[67] K. Barker, J.E. Ramirez-Marquez, C.M. Rocco, Resilience-based network component importance measures, Reliab. Eng. Syst. Saf. 117 (2013) 89–97. https://doi.org/https://doi.org/10.1016/j.ress.2013.03.012.

[68] R. Patriarca, J. Bergström, G. Di Gravio, F. Costantino, Resilience engineering: Current status of the research and future challenges, Saf. Sci. 102 (2018) 79–100. https://doi.org/https://doi.org/10.1016/j.ssci.2017.10.005.

[69] P.V.R. de Carvalho, The use of Functional Resonance Analysis Method (FRAM) in a mid-air collision to understand some characteristics of the air traffic management system resilience, Reliab. Eng. Syst. Saf. 96 (2011) 1482–1498. https://doi.org/https://doi.org/10.1016/j.ress.2011.05.009.

[70] J.O. Gomes, D.D. Woods, P.V.R. Carvalho, G.J. Huber, M.R.S. Borges, Resilience and brittleness in the offshore helicopter transportation system: The identification of constraints and sacrifice decisions in pilots' work, Reliab. Eng. Syst. Saf. 94 (2009) 311–319. https://doi.org/https://doi.org/10.1016/j.ress.2008.03.026.

[71] G.H.A. Shirali, M. Motamedzade, I. Mohammadfam, V. Ebrahimipour, A. Moghimbeigi, Challenges in building resilience engineering (RE) and adaptive capacity: A field study in a chemical plant, Process Saf. Environ. Prot. 90 (2012) 83–90. https://doi.org/https://doi.org/10.1016/j.psep.2011.08.003.

[72] R. Yarveisy, C. Gao, F. Khan, A simple yet robust resilience assessment metrics, Reliab. Eng. Syst. Saf. 197 (2020) 106810. https://doi.org/10.1016/j.ress.2020.106810.

[73] N. Yodo, P. Wang, Engineering Resilience Quantification and System Design Implications: A Literature Survey, J. Mech. Des. 138 (2016). https://doi.org/10.1115/1.4034223.

[74] N. Yodo, P. Wang, Z. Zhou, Using Dynamic Bayesian Networks, 66 (2017) 1–10.

[75] H. Li, C. Guedes Soares, H.-Z. Huang, Reliability analysis of a floating offshore wind turbine using Bayesian Networks, Ocean Eng. 217 (2020) 107827. https://doi.org/https://doi.org/10.1016/j.oceaneng.2020.107827.

[76] A.-A. Baksh, R. Abbassi, V. Garaniya, F. Khan, Marine transportation risk assessment using Bayesian Network: Application to Arctic waters, Ocean Eng. 159 (2018) 422–436. https://doi.org/https://doi.org/10.1016/j.oceaneng.2018.04.024.

[77] A. Nedjati, M. Yazdi, R. Abbassi, A sustainable perspective of optimal site selection of giant air - purifiers in large metropolitan areas, Springer Netherlands, 2021. https://doi.org/10.1007/s10668-021-01807-0.

[78] M. Yazdi, F. Khan, R. Abbassi, R. Rusli, Improved DEMATEL methodology for effective safety management decision-making, Saf. Sci. 127 (2020) 104705. https://doi.org/https://doi.org/10.1016/j.ssci.2020.104705.

[79] H. Li, H. Díaz, C. Guedes Soares, A failure analysis of floating offshore wind turbines using AHP-FMEA methodology, Ocean Eng. 234 (2021) 109261. https://doi.org/https://doi.org/10.1016/j.oceaneng.2021.109261.

[80] S. Adumene, M. Okwu, M. Yazdi, M. Afenyo, R. Islam, C.U. Orji, F. Obeng, F. Goerlandt, Dynamic logistics disruption risk model for offshore supply vessel operations in Arctic waters, Marit. Transp. Res. 2 (2021) 100039. https://doi.org/https://doi.org/10.1016/j.martra.2021.100039.

[81] M. Yazdi, Ignorance-aware safety and reliability analysis : A heuristic approach, Qual. Reliab. Eng. Int. 36 (2019) 652–674. https://doi.org/10.1002/qre.2597.

[82] M. Yazdi, N.A. Golilarz, K.A. Adesina, A. Nedjati, Probabilistic Risk Analysis of Process Systems Considering Epistemic and Aleatory Uncertainties: A Comparison Study, Int. J. Uncertainty, Fuzziness Knowledge-Based Syst. 29 (2021) 181–207. https://doi.org/10.1142/S0218488521500098.

[83] N.E. Fenton, M. (Martin D.. Neil, Risk assessment and decision analysis with Bayesian networks, 2013.

[84] M. Rausand, S. Haugen, Risk Assessment: Theory, Methods, and Applications, Wiley, 2020.

[85] N. Khakzad, Application of dynamic Bayesian network to risk analysis of domino effects in chemical infrastructures, Reliab. Eng. Syst. Saf. 138 (2015) 263–272. https://doi.org/10.1016/j.ress.2015.02.007.

[86] M. Yazdi, F. Khan, R. Abbassi, Microbiologically influenced corrosion (MIC) management using Bayesian inference, Ocean Eng. (2021). https://doi.org/10.1016/j.oceaneng.2021.108852.

[87] S. Adumene, F. Khan, S. Adedigba, Operational safety assessment of offshore pipeline with multiple MIC defects, Comput. Chem. Eng. (2020) 106819. https://doi.org/10.1016/j.compchemeng.2020.106819.

[88] S. Adumene, F. Khan, S. Adedigba, S. Zendehboudi, H. Shiri, Offshore pipeline integrity assessment considering material and parametric uncertainty, J. Pipeline Sci. Eng. (2021). https://doi.org/https://doi.org/10.1016/j.jpse.2021.09.005.

[89] S. Adumene, S. Adedigba, F. Khan, S. Zendehboudi, An integrated dynamic failure assessment model for offshore components under microbiologically influenced corrosion, Ocean Eng. 218 (2020) 108082. https://doi.org/10.1016/j.oceaneng.2020.108082.

[90] T. Lund, R.B. Eckert, E. Rodrigues, Management and control of microbiologically in fl uenced corrosion (MIC) in the oil and gas industry — Overview and a North Sea case study, 256 (2017) 31–45.

[91] R. Eckert, Field guide for investigating internal corrosion of pipelines, NACE International, Houston, 2003.

[92] ASTM E3-2017. Standard guide for preparation of metallographic specimens, West Conshohocken, 2017. https://doi.org/10.1520/E0003-11R17.

[93] ASTM A370. Standard test methods and definitions for mechanical testing of steel products., West Conshohocken, 2020. https://doi.org/10.1520/ A0370-20.

[94] ASTM D-93. Standard test methods for flash point by Pensky- Martens closed cup tester, West Conshohocken, 2020. https://doi.org/2020. 10.1520/ D0093-20.

[95] ASTM D422-63-Standard test method for particle-size analysis of soils., West Conshohocken, 2007. 10.1520/ D0422-63R07E02.

[96] SP0775-Preparation, installation, analysis, and interpretation of corrosion coupons in oilfield operations, Houston, TX, 2018.

[97] ASTM E1404. Standard specification for laboratory glass conical flasks, West Conshohocken, 2019. 10.1520/E1404-94R19.

[98] TM0194-Field monitoring of bacterial growth in oil and gas systems, Houston, TX, 2014.

[99] S. Papavinasam, Corrosion Control in the Oil and Gas Industry, 1th ed., Gulf Professional Publishing Elsevier, London, 2013.

[100] K.D. Efird, E.J. Wright, J.A. Boros, T.G. Hailey, Correlation of Steel Corrosion in Pipe Flow with Jet Impingement and Rotating Cylinder Tests, Corrosion. 49 (1993) 992–1003. https://doi.org/10.5006/1.3316026.

[101] R. McConnell, Volatile corrosion inhibitors offer effective protection for processing and shipment of metal-based products, Met. Finish. 106 (2008) 23–27. https://doi.org/https://doi.org/10.1016/S0026-0576(08)80283-8.

[102] T. Li, G. Wang, P. Yin, Z. Li, L. Zhang, J. Liu, M. Li, L. Zhang, L. Han, P. Tang, Effect of negative pressure on growth, secretion and biofilm formation of Staphylococcus aureus, Antonie Van Leeuwenhoek. 108 (2015) 907–917. https://doi.org/10.1007/s10482-015-0545-9.

[103] R. Javaherdashti, C. Nwaoha, Henry Tan, Corrosion and Materials in the Oil and Gas Industries, CRC Press, 2013.

[104] S. Papavinasam, A. Doiron, R.W. Revie, Model to Predict Internal Pitting Corrosion of Oil and Gas Pipelines, Corrosion. 66 (2010) 35006–35011. https://doi.org/10.5006/1.3360912.

[105] T.L. Skovhus, R.B. Eckert, E. Rodrigues, Management and control of microbiologically influenced corrosion (MIC) in the oil and gas industry—Overview and a North Sea case study, J. Biotechnol. 256 (2017) 31–45. https://doi.org/10.1016/j.jbiotec.2017.07.003.

[106] E.M. Orazem, Underground pipeline corrosion, Detection, analysis and prevention, Elsevier, Woodhead Publishing, 2014.

[107] B. Chugh, S. Thakur, A.K. Singh, Microbiologically Influenced Corrosion Inhibition in Oil and Gas Industry, Corros. Inhib. Oil Gas Ind. (2020) 321–338. https://doi.org/10.1002/9783527822140.ch13.

[108] Y. Bai, Q. Bai, Subsea Engineering Handbook, 2010.

[109] NACE, Selection, Application, and Evaluation of Biocides in the Oil and Gas Industry, Houston, 2006. https://doi.org/TR 31205.

[110] C.W.S. Cheung, I.B. Beech, The use of biocides to control sulphate-reducing bacteria in biofilms on mild steel surfaces, Biofouling. 9 (1996) 231–249. https://doi.org/10.1080/08927019609378305.

[111] J.L. Dawson, Chemical treating in oil and gas production, Shreir's Corros. (2010) 2900–2929. https://doi.org/10.1016/B978-044452787-5.00160-8.

[112] J. Mand, J. Longwell, D. Enning, Observations on the Effect of Simulated Pigging and Corrosion Inhibitor Exposure on Microbiologically Influenced Corrosion of Carbon Steel, in: NACE Int., Houston, 2019. https://doi.org/Paper No. 13103.

[113] R. Javaherdashti, How is MIC treated, in: Microbiol. Influ. Corros. An Eng. Insight, Springer, London, 2008.

[114] R. Javaherdashti, K. Alasvand, Biological Treatment of Microbial Corrosion Opportunities and Challenges, Elsevier Inc, 2019. https://doi.org/10.1016/C2017-0-04219-2.

[115] G. Bødtker, T. Thorstenson, B.L.P. Lillebø, B.E. Thorbjørnsen, R.H. Ulvøen, E. Sunde, T. Torsvik, The effect of long-term nitrate treatment on SRB activity, corrosion rate and bacterial community composition in offshore water injection systems, J. Ind. Microbiol. Biotechnol. 35 (2008) 1625–1636. https://doi.org/10.1007/s10295-008-0406-x.

[116] J. Rezaei, Best-worst multi-criteria decision-making method, Omega (United Kingdom). 53 (2015) 49–57. https://doi.org/10.1016/j.omega.2014.11.009.

[117] G. Yadav, S.K. Mangla, S. Luthra, S. Jakhar, Hybrid BWM-ELECTRE-based decision framework for effective offshore outsourcing adoption: a case study, Int. J. Prod. Res. 56 (2018) 6259–6278. https://doi.org/10.1080/00207543.2018.1472406.

[118] H. Aboutorab, M. Saberi, M.R. Asadabadi, O. Hussain, E. Chang, ZBWM: The Z-number extension of Best Worst Method and its application for supplier development, Expert Syst. Appl. 107 (2018) 115–125. https://doi.org/10.1016/j.eswa.2018.04.015.

[119] M. Yazdi, A. Nedjati, E. Zarei, R. Abbassi, A reliable risk analysis approach using an extension of best-worst method based on democratic-autocratic decision-making style, J. Clean. Prod. (2020) 120418. https://doi.org/10.1016/j.jclepro.2020.120418.

[120] M. Yazdi, T. Saner, M. Darvishmotevali, Application of an Artificial Intelligence Decision-Making Method for the Selection of Maintenance Strategy, in: 10th Int. Conf. Theory Appl. Soft Comput. Comput. with Words Perceptions - ICSCCW-2019. ICSCCW 2019. Adv. Intell. Syst. Comput., Springer, Cham, 2020: pp. 246–253. https://doi.org/doi.org/10.1007/978-3-030-35249-3_31.

[121] E. Zarei, F. Khan, M. Yazdi, A dynamic risk model to analyze hydrogen infrastructure, Int. J. Hydrogen Energy. 46 (2021) 4626–4643. https://doi.org/https://doi.org/10.1016/j.ijhydene.2020.10.191.

[122] M. Pouyakian, A. Khatabakhsh, M. Yazdi, E. Zarei, Optimizing the Allocation of Risk Control Measures Using Fuzzy MCDM Approach: Review and Application BT - Linguistic Methods Under Fuzzy Information in System Safety and Reliability Analysis, in: M. Yazdi (Ed.), Springer International Publishing, Cham, 2022: pp. 53–89. https://doi.org/10.1007/978-3-030-93352-4_4.

[123] N. Khakzad, G. Reniers, R. Abbassi, F. Khan, Vulnerability analysis of process plants subject to domino effects, Reliab. Eng. Syst. Saf. 154 (2016) 127–136. https://doi.org/10.1016/j.ress.2016.06.004.

[124] N. Khakzad, F. Khan, P. Amyotte, Risk-based design of process systems using discrete-time Bayesian networks, Reliab. Eng. Syst. Saf. 109 (2013) 5–17. https://doi.org/10.1016/j.ress.2012.07.009.

Chapter 7

Summary, Conclusions and Recommendations

7.1. Summary

The present thesis reveals the original presentation of the Hierarchical Bayesian Analysis, Resilience assessment, Monte Carlo Markov Chain Simulation, non-homogeneous Markov processes, Meta-heuristic optimization algorithms, Bayesian inference, continuous Bayesian network, dynamic Bayesian network, and loss computations method for corrosion management of the marine and offshore systems under MIC. The existing MIC mechanistic models for failure estimations and further management are not structured in a dynamic manner, incapable of addressing the dynamic, unstable, and interdependency between the MIC contributing factors to estimate the system failure rate. The risk-based decision-making methodologies for MIC-based failures are established to address the significant MIC contributing factors and interdependencies. In addition, they can capture the lack of knowledge and assist microbial corrosion management of the offshore structure system.

The present thesis proposes integrated-based probabilistic models to manage the s offshore structure system suffering from MIC. The introduced model considers the interdependencies/interactions of contributing factors and their impacts on subsea systems' corrosion and failure rate. The stochastic behavior of microorganism metabolism in nature and failure estimation of corroding subsea systems are captured. A systematic literature review is conducted by highlighting the research shortages, requirements, and challenges of microbial corrosion in risk-based decision-making approaches. The results highlighted the potential and gaps in the present literature and explained the following research activities in the near future. Also, monitoring and management practices of the microbial corrosion are determined by engaging the "Continuous Bayesian Network technique with Hierarchical Bayesian Analysis". The integration helps overcome the Bayesian network's discrete value limitations and source-to-source uncertainty for each node. In addition, the non-homogeneous Markov processes and Poisson, homogeneous gamma is taken into account to model multiple defects generations, the average, and maximum pit depth growth. The outcomes help decision-makers choose an optimum and feasible maintenance plan for the offshore structure systems. Besides, the Meta-heuristic algorithm as Genetic Algorithm (GA) is used to obtain the optimum schedule for performing integrity management actions. The results identify a series of solutions allowing decision-makers to select the optimal combination of integrity management actions with the tradeoff between reliability and cost. Finally, the resilience of offshore structural systems impacted by MIC is assessed probabilistically. The aggregated results assisted decision-makers in consideration of the resilience in the design and operation period of the system.

7.2. Conclusions

The main remarks and conclusions obtained from the current thesis are summarized as the following.

7.2.1. Reviewing the risk-based decision-making models for microbiologically influenced corrosion

This research presents several observations in terms of microbial corrosion characteristics, detection, modeling, and management in the available state of the arts. A series of questions in terms of the sample, collecting data, assessments, and analysis are elaborated to represent the data integration in a risk-based decision-making model. In summary, the key finding is: the existence of microorganisms in the understudy system does not provide proof of microbial corrosion activities; many published model only depends on the off-site facilities and are limited to rapid assessment because of the high simulation cost and environmental conditions, the microbiological evaluation-based techniques (e.g., metagenomic and metabolomic) are the greatest reliable and robust methods to determine microbial corrosion, the data mining on the microbiological data set might offer a valued insight for the remarkable MIC impacts proliferation, and detecting MIC in a short time.

7.2.2. Development of an innovative MIC failure predication model

The present study predicts the rate of microbial corrosion and pit depth growth in the early stage of marine and offshore system development to derive an appropriate safety and integrity management plan(s) by preventing, mitigating, and controlling the system failure that occurs due to MIC. The modeling methods such as the Bayesian network can be utilized to estimate the rate of MIC and pit depth growth. The proposed methodology assists in accurately monitoring MIC activity and developing strategies to manage it. The MIC monitoring and management activities are achieved using the Continuous Bayesian Network technique with Hierarchical Bayesian Analysis. The integration of the Bayesian Network technique with Hierarchical Bayesian Analysis aids in dealing with the Bayesian network's discrete value drawbacks and "source-to-source uncertainty" for each node in the network. The approach could provide an accurate parameters value, including failure probability and MIC occurrence rate. The study provides a better understanding of the MIC rate contributing factors and failure probability. The outcomes help decision-makers to develop an effective microbial corrosion management plan.

7.2.3. Development of an integrated operational safety model considering multiple MIC defects

This research introduces a novel operational reliability analysis framework for subsea systems under multiple microbial corrosion defects. In the model, optimum maintenance scheduling of the subsea pipeline is evaluated. The non-homogeneous Poisson and Markov processes and homogeneous gamma are integrated to model the maximum and average pit depth and corrosion defects generations. The developed integrated operational safety model provides maintenance scheduling, detection probability, average and maximum pit depth, cost/benefit, and optimum maintenance plans. The current research task aids decision-makers in choosing conditional maintenance scheduling for offshore structures systems. In addition, the results indicated that with consideration applicability of the model, it could be applied to other processing systems.

7.2.4. Development of integrity risk management of subsea pipelines

This study has developed a multi-objective functional methodology involving dynamic continuous Bayesian network modeling to minimize the operational risk associated with the MIC. The Meta-heuristic algorithm as a Genetic Algorithm is used to obtain the optimum schedule for performing integrity management actions. The application of the proposed model is illustrated in a subsea pipeline under the influence of MIC. The analysis results highlighted that the obtained diverse set of optimum solutions allows decision-makers to balance reliability and cost of integrity management actions. The annual budget is also added as a constraint to the model. It is indicated that the annual budget has no significant impact on the optimum solutions. Thus, the proposed framework in this study can be based on decision-making support tools for optimal maintenance of a corroded subsea pipeline subjected to risk, safety, and resource integrity management.

7.2.5. Development of resilience risk assessment of subsea pipelines

This task model, the offshore structure system's resilience, uses a dynamic Bayesian network. The formation and propagation of microbial corrosion are debatable topics in the state of the arts and are uncertain and complex in harsh marine and environmental, operational situations. Thus, assessing the resilience of the marine and offshore systems under the influence of MIC is vital. According to this point, the microbial mechanism of corrosion should be adequately understood, and the understudy system needs to be designed in order to be able to develop an early response for the potential undesired event before the system collapse entirely. The actual application of the study indicated that the introduced methodology could reflect the resilience profile of the system dynamically. This approach assists decision-makers in having a comprehensive understanding of offshore structure system resilience capability, monitoring the corresponding performance, evaluating the safety and risk crucial intervention actions, preventing any potential undesired events (e.g., disruptions), and identifying system safety operational improvements. Besides, the applicability and robustness of the proposed dynamic resilience assessment asserted that it could be applied to other types of structural derogations in different application domains.

7.3. Recommendations

The present thesis aims in developing a practical approach to managing microbial corrosion management offshore structure systems. According to the conducted objectives, the following highlights are suggested for future research tasks and more investigations:

- The development of a progressive digitalization and data acquisition approach for MIC-based information needs to be deeply studied. Such work would systematically collect, assign, and analyze the related objective and subjective input information to have a robust and reliable microbial corrosion safety and integrity management strategy.

- The development of a dynamic cost-based MIC management optimization approach considering the best fitted machine learning algorithm for subsea systems can be a promising research work considering both direct and indirect costs.
- Advanced developments of probabilistic and fuzzy-based approaches could enhance the capabilities of marine and offshore systems by assessing and evaluating microbial corrosion treatments. Therefore, a human-machine intelligent system could further present an accurate timeline for operators and decision-makers to derive the risk levels.
- The development of an integrated dynamic continuous Bayesian network with resilience concepts needs to be investigated to minimize the subjective and objective uncertainties in MIC decision-making purposes.
- The development of a hybrid risk-based decision-making modeling approach for MIC management of subsea systems requires to be investigated dynamically. Such developments would enable decision-makers to separate the objective and subjective uncertainties adequately, considering the information sources to have robust and reliable safety and integrity decision-making system.