Failure Assessment of Pipelines Due to Microbiologically Influenced Corrosion

by

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Abstract

Microbiologically influenced corrosion (MIC) is a difficult degradation mechanism to diagnose in pipeline systems due to the complex interaction between biotic (i.e., microbial) and abiotic (e.g., fluid chemistry, pipe/vessel metallurgy/corrosion, and operating conditions) factors. This complexity often makes it difficult to accurately assess pipeline failures due to MIC. However, even with available data, failure investigators often face a number of challenges in diagnosing MIC such as how to properly integrate the available datasets, questions regarding data accuracy (e.g., confidence in the sampling and/or analysis method used) and lack of available information from operators (e.g., missing data). As a result, practical MIC failure assessments are most often performed by experts or specialists with significant knowledge and working experience in this topic. Based on these issues, the objectives of this thesis are three-fold: 1) to quantify the actual prevalence of MIC related pipeline failures in Alberta's oil and gas sector, 2) to perform a gap analysis of failure investigation methods used to assess these pipeline failures, and 3) to develop a novel expert system based on machine learning to assist both experts and non-experts in assessing potential MIC related pipeline failures. The first part of this study highlights a review and analysis of MIC related pipeline incidents in the province of Alberta, Canada over a three-year period (2017-2019). This review was used to quantify the occurrence of MIC failures relative to other corrosion mechanisms, and to conduct a gap analysis of MIC failure investigation techniques being used relative to the current state of the art. Over this three-year period, MIC was found to be responsible for 13.6% and 4.8% of all pipeline leak incidents due to internal and external corrosion, respectively (either as the main failure mechanism or as a contributing factor). Most of these failures were seen to occur in small

diameter upstream pipelines (with less than or equal to 220.3 mm outside diameter) carrying mainly multiphase fluids (oil-water emulsions) or produced water. In terms of the failure investigation methods currently being used, it was noted that there was some inconsistency among reports and a number of important gaps were identified. Various assessments lacked microbiological test data, in particular, tests which specifically identify microbial functional groups or speciation, which is critical to confirm observed corrosion mechanisms. Furthermore, a number of these assessments identified MIC primarily on the basis of corrosion morphology, which has been shown to be an incorrect assumption and approach without additional evidence. Details related to sampling methods were also lacking in these assessments, which created some uncertainty as to the quality of data obtained. Overall, most assessments did a reasonable job in characterizing and including chemical (solids, fluids, and corrosion products), metallurgical/ corrosion, and operating data. However, the integration of these various layers of evidence (i.e., connecting corrosion to microbiological activity, and eliminating possible abiotic corrosion mechanisms) was missing in many reports. The second part of this study highlights the modeling of an expert system for the classification of internal microbiologically influenced corrosion (MIC) failures related to pipelines in the upstream oil and gas industry. The model is based on machine learning (artificial neural network) and involves the participation of 15 MIC subject matter experts (SMEs). Each expert evaluated a number of model case studies representative of both MIC and non-MIC related upstream pipeline failures. The model accounts for variations in microbiological testing methods, microbiological sample types, degradation morphology, among others, and also incorporates cases with select missing datasets which is commonly found in actual failure assessments. The output classifications comprised elements of both potential for MIC and confidence in the data available. The results were

contrasted for 5- and 3-output classification models (5OC and 3OC, respectively). The 5OC model had an overall accuracy of 62.0% while the simpler 3OC model had a better accuracy of 74.8%. This modelling exercise has demonstrated that knowledge from subject matter experts can be captured in a reasonably effective model to screen for possible MIC failures. It is hoped that this study contributes to a better understanding of the prevalence of MIC in the oil and gas sector, and highlights the key areas necessary to improve the diagnosis of MIC failures in the future.

Preface

This thesis is an original work by Mr. Andre de Araujo Abilio and forms part of an international research collaboration, led by Dr. John David Wolodko at the University of Alberta, with Dr. Torben Lund Skovhus at VIA University College, Denmark, and with Mr. Richard Bruce Eckert at Microbial Corrosion Consulting, United States of America. This research is part of the geno-MIC Project, with funding from Genome Canada, the Government of Alberta, and Alberta Innovates through the Strategic Chair Program secured by Dr. John Wolodko and from the Alberta Innovates Graduate Student Scholarship awarded to Mr. Andre Abilio.

There are 6 chapters and 4 appendices in this thesis.

Chapter 1 contains introduction and the objectives of this research.

Chapter 2 presents literature review related to this thesis which includes elements of microbiologically influenced corrosion (MIC), failure analysis, integrity management, expert systems, and artificial neural networks (ANN).

Versions of **Chapter 3** and **Chapter 4** of this thesis have been published as A.A. Abilio, J. D. Wolodko, R. B. Eckert, and T. L. Skovhus, "Review and Gap Analysis of MIC Failure Investigation Methods in Alberta's Oil and Gas Sector", in *Failure Analysis of Microbiologically Influenced Corrosion*. Mr. A. A. Abilio was responsible for conceptualization, methodology, data collection, data analysis, manuscript composition, manuscript review and editing, and fund acquisition. Dr. J. D. Wolodko was responsible for conceptualization, methodology, resources, manuscript review and editing, and fund acquisition. Mr. R. B. Eckert was responsible for consultancy, manuscript review and editing. Dr. T. L. Skovhus was responsible for consultancy, manuscript review and editing. **Chapter 3**

speaks to the prevalence of microbiologically influenced corrosion (MIC) failures related to oil and gas upstream pipeline operations in Alberta. **Chapter 4** carries an extensive review and gap analysis to assess the current state of the art with respect to MIC failure investigation methods and techniques, and compare these to available best practices.

Chapter 5 develops an expert system based on artificial neural networks and offers a tool to assist both experts and non-experts in screening whether a failure is due to MIC or not and how reliant one can be in the output. It counts with the participation of 15 subject matter experts on MIC from industry and academia, accumulating 355 years of expertise in MIC assessments. A version of **Chapter 5** will be submitted to reputable journal for publication as A. A. Abilio, J. D. Wolodko, R. B. Eckert, and T. L. Skovhus, "Development of an Expert System for Assessing Failures in Oil and Gas Pipelines due to Microbiologically Influenced Corrosion (MIC)". Mr. A. A. Abilio was responsible for conceptualization, methodology, software implementation, data collection, data analysis, manuscript composition, manuscript review and editing, and fund acquisition. Dr. J. D. Wolodko was responsible for conceptualization, methodology, resources, manuscript review and editing, and fund acquisition. Mr. R. B. Eckert was responsible for resources, consultancy, manuscript review and editing. Dr. T. L. Skovhus was responsible for resources, consultancy, manuscript review and editing. This study received research ethics approval from the University of Alberta Human Research Ethics Board 2, project name "Development of an Expert System for Assessing MIC-Related Failures using Artificial Neural Networks", study ID 'Pro00109878', August 16, 2021.

Chapter 6 points out the novelty of the work, it summarizes the key findings of the research, and lists recommendations for future work.

Appendices A, **B**, **C**, and **D** are related to Chapter 5 and include the case studies provided to the subject matter experts who participated in the study, the inputs utilized to train the artificial neural network, the variations related to the experts' responses, and the calculations related to the sensitivity analysis carried out for the input parameters of the expert system.

Dedication

This work, I dedicate to my father, Alfredo, who dedicated his own life to provide for mine. To my mother, Zilnea, whose sacrifice and perseverance worked as driving example. To my brother, Artur, whose strength allowed me not to deviate from my path. To my sister, Adele, whose kindness has always been a refuge. And to my beloved partner, Carolina, whose devotion and affection kept me unswerving through hard times.

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Here I express my sincere gratitude and admiration to my supervisors and mentors Dr. John D. Wolodko, Dr. Torben Lund Skovhus, and Mr. Richard B. Eckert for their kind and ongoing support. Those without whom I would not be able to deliver my work.

I would like to thank the Alberta Energy Regulator for kindly hosting me at their facilities and for providing me with access to available data, files and personnel support.

Additionally, I would like to acknowledge the intellectual generosity of the 15 MIC subject matter experts that provided their time and expertise in evaluating the case studies utilized to train the artificial neural network developed in this research.

This work is part of a project entitled “Managing Microbial Corrosion in Canadian Offshore and Onshore Oil Production Operations” and for that I would like to acknowledge the funding contributions for this current study from Genome Canada, the Government of Alberta, Alberta Innovates, and DNV Corrosion Management Group, along with in-kind support from a number of industry partners.

I also would like to thank the Alberta Innovates, AMPP EMERG (Engage-Magnetize-Educate-Raise-Guide) Student Outreach Program (formerly NACE Foundation International), and the NACE Foundation of Canada for believing in my work and for granting me with the provided awards and scholarships.

I would like to thank my family, whose love, and kindness always fed me with the will to endure. Particularly to my aunt, Maria Ines, whose in-kind and financial support allowed me to accomplish this Master thesis.

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List of Abbreviations

Abbreviation	Description
3OC	3 output classification
5OC	5 output classification
ACE	Acetogens
AER	Alberta Energy Regulator
AERO	Aerobic
AMPP	Association for Materials Protection and Performance
ANA	Anaerobic
ANN	Artificial neural network
APB	Acid producing bacteria
API	American Petroleum Institute
APM	Acid producing microorganisms
ASM	American Society of Materials
ASTM	American Society for Testing and Materials
ATP	Adenosine triphosphate assay
BART	Biological activity reaction tests
CER	Canadian Energy Regulator
CMIC	Chemical microbially influenced corrosion
CSA	Standard Council of Canada
CST	Chemical spot testing
DNV	Det Norske Veritas

DNVGL	Det Norske Veritas Germanischer Lloyd
EDS	Energy-dispersive X-ray spectroscopy
EI	Energy Institute
EMERG	Engage-Magnetize-Educate-Raise-Guide
EMIC	Electrical microbially influenced corrosion
EOR	Enhanced oil recovery
ERW	Electric resistance welding
ES	Expert system
FER	Fermenters
GSPT	Gaskets, seals, packing glands, or threaded fittings
HAB	Heterotrophic anaerobic bacteria
HAZ	Heat affected zone
IOB	Iron-oxidizing bacteria
IRB	Iron-reducing bacteria
IReB	Iron-related bacteria
LNB	Low nutrient bacteria
M.E.	Microbial equivalent
MA	Methanogenic archaea
MFG	Microbial functional group
MH	MIC high – likely potential for MIC, high data confidence
MIC	Microbiologically influenced corrosion
ML	MIC low – likely potential for MIC, low data confidence
MMM	Molecular microbiological method

MnOB	Manganese-oxidizing bacteria
MPN	Most probable number
NACE	National Association of Corrosion Engineers – International
ND	Need more data – neither likely nor unlikely potential for MIC, negligible data confidence
NGS	Next generation sequencing
NH	No MIC low – unlikely potential for MIC, high data confidence
NL	No MIC low – unlikely potential for MIC, low data confidence
NRB	Nitrate-reducing bacteria
O.D.	Outside diameter
qPCR	Quantitative polymerase chain reaction
RBI	Risk-based inspection
RP	Recommended practice
rRNA	Ribosomal RNA
s.u.	sample unit
SC	Standard committee
SLYM	Slime forming bacteria
SME	Subject matter expert
SOB	Sulfur-oxidizing bacteria
SRA	Sulfate-reducing archaea
SRB	Sulfate-reducing bacteria
SRM	Sulfate-reducing microorganisms
SUM	Sulfur-utilizing microorganisms

TDS	Total dissolved solids
UDC	Under deposit corrosion

List of Equations

Chapter 1: Introduction and Objectives

Microbiologically influenced corrosion (MIC) is a form of corrosion that is caused by the presence and activity of asset-threatening microorganisms that adhere to the asset surface (**Figure 1.1**). Water is the conducive medium for MIC to take place [1,2]. Water both transports microorganisms, carrying them along the system, and provides the nutrients utilized for their metabolism.

Consequently, MIC is routinely found in oil and gas production facilities and pipelines, as well as in other sectors where a water environment is not only present but also in contact with the surface of the asset (e.g., utilities, wastewater processing, marine). When water has enough contact time with the surface of the asset, a biofilm is formed. The biofilm can take place in both internal and external surfaces of pipelines, tanks, and vessels where there is water and sedimentation either due to low flow, stagnant conditions, or accumulation of hydrophilic solids (e.g., deposits, soil) [3,4].

Corrosion is defined as the deterioration or loss of structure/properties of a material, usually a metal, due to its interaction with the surrounding environment. In a more mechanistic definition of metal deterioration, corrosion is the electrochemical process where the anode deteriorates (i.e., loses mass) due to the migration of electrons to the cathode. For corrosion to occur, a flow of electrons has to be stablished between the anode and the cathode by the reducible species in the electrolyte while return current path is maintained [5].

While MIC has been known as a corrosion mechanism for over a century [6,7], both interest in the topic and major advancements in MIC assessment and diagnosis have only occurred in the past 20 years [8–10]. Part of the issue is the complexity and challenge in

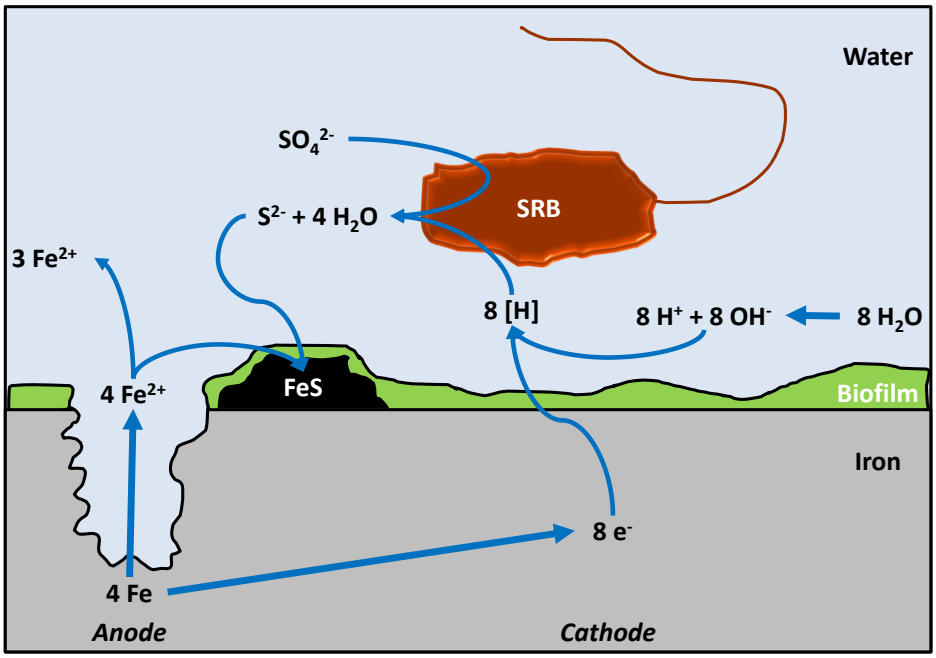

Figure 1.1 Schematic of iron corrosion by sulfate reducing bacteria (SRB) according to cathodic depolarization theory – adapted with permission from the International Digital Organization for Science Information (IDOSI): Kakooei, Saeid, M. Che Ismail, and Bambang Ariwahjoedi. "Mechanisms of microbiologically influenced corrosion: a review." World Applied Science Journal, Vol. 17, No. 4 (2012): 524.-531 [11].

characterizing MIC indicators conclusively. As a result, diagnosing MIC is difficult due to the synergistic interaction between a large number of biotic (microorganisms) and abiotic (chemical and physical environment) factors. From a practical point of view, this also necessitates expertise in a large number of technical areas and disciplines (e.g., microbiology, chemistry, materials science and engineering), which is often challenging to find from one source/individual.

Although MIC has been recognized as a problem in the oil and gas industry for some time, its occurrence relative to other corrosion threats has not been well documented or quantified. Many studies in the literature regularly cite that MIC is responsible for anywhere between 10% to 40% of all corrosion issues in the sector [9,12–18]. This range of estimated numbers; however, is often quoted without citing the original source or providing the

methodology used to justify these numbers. In fact, the original sources of these prevalence numbers are difficult to find. For example, one of the most commonly cited references in the MIC-related literature is Graves and Sullivan [19]. In reviewing the original paper (which was published in 1966 not 1996 as commonly cited), it was determined that there, in fact, was no reference to MIC prevalence. It is unclear when the first instance of this erroneous citation occurred, but it has since been copied in subsequent MIC-related papers.

The economic impact due to MIC has been disseminated by a few studies. However, the determination of MIC-related economic impact is often obtained by multiplying the total cost of corrosion times the *estimated* prevalence of MIC, which provides numbers that range from 10% to 40% depending on the context in which the calculations were carried out (e.g., country, sector) [9,12–18,20]. As such, in order to better inform both industry and the research community, there is a need to better quantify and document the prevalence of MIC relative to other corrosion threats.

In theory, the prevalence of MIC can be determined using a variety of methodologies: 1) the occurrence of MIC-related corrosion in a system based on maintenance or inspection data/reports, 2) the total cost of maintenance/repair due to MIC-related corrosion based on accounting records, or 3) the number of failure incidents due to MIC. Each of these methods will likely produce a different value or percentage relative to other corrosion threats. Of the three methods, quantifying failure incidents is likely the easiest method to estimate MIC due to the availability of public pipeline failure statistics and reports in many jurisdictions. Many of these reports include third-party failure assessments, which provide details on the likely root cause of failure including MIC.

A broader question, however, is whether the failure analysis methodologies used in both current and historical assessments are accurate, particularly with regard to MIC, which has seen significant growth over the past few decades in terms of new knowledge and technological developments [8–10,21]. The key technological development has been the slow adoption of DNA-based molecular microbiological methods (MMM) for identifying and characterizing microorganisms in systems and continued improvement in diagnostic and integrative methodologies for assessing MIC threats and failures [22–26]. In addition to microbiology, a multilayered integration between chemical, metallurgical/corrosion, and operating -related evidence is required for a conclusive MIC diagnosis.

Hence, the work carried out in this thesis is an attempt to better understand the underlying factors of MIC failures in order to drive improved asset design, more accurate monitoring programs, and more reliable mitigation programs where MIC is taken into account. Therefore, the *goal* of this thesis is to improve the understanding of MIC by providing additional aids to augment MIC management practices and to incite the consideration of MIC in respect to installation design and asset integrity management. Consequently, the improvement in knowledge of MIC damage and failures undertaken by this thesis can lead to safer energy production, and enhanced protection of both the environment and human health through the reduction of leaks and spills.

To this end, the specific *objectives* of this thesis are outlined as follows:

1. Provide updated, reliable and detailed statistics on the prevalence of MIC in oil and gas upstream pipeline systems.

2. Highlight key areas necessary to improve diagnosis of MIC failures in oil and gas upstream pipeline systems, and provide guidance on the development of future recommended practices and standards.
3. Develop an expert system (a practical tool) to assist with the screening of MIC failure investigations in any engineered system, particularly by users who lack multidisciplinary knowledge of MIC.

These objectives are systematically addressed in the subsequent chapters. Chapter 2 (literature review) highlights the state of the art related to MIC and the sources utilized to assess it through the lenses of failure analysis. In addition, an overview of expert systems and machine learning methods used in engineering applications are summarized. Chapter 3 summarizes the occurrence of MIC in Alberta's oil and gas sector, and highlights the types of pipeline systems most affected by MIC. Chapter 4 details a comprehensive gap analysis of actual MIC failure assessment reports, and provides recommendations for future improvements to MIC failure assessment procedures. Chapter 5 outlines the development of a novel expert system based on machine learning techniques to assist integrity engineers in assessing MIC failures. Finally, Chapter 6 summarizes the key findings and novelty of the thesis, and provides recommendations for future research in this area.

Chapter 2: Literature Review

2.1. Microbiologically Influenced Corrosion

Microbiologically influenced corrosion (MIC) is a degradation mechanism assisted by the metabolic activity of microorganisms where the asset can be either directly degraded, due to electron uptake, or indirectly, due to the effect of biotic byproducts [1,27] . Dinh et al. 2004 [28] describe the reactions related to iron corrosion by sulfate-reducing bacteria (SRB), and Enning et al. 2012 [29] and Enning and Garrelfs 2014 [30] classify these reactions based on how directly microorganisms influence iron degradation. The indirect influence of dissimilatory products from microbiological metabolism is classified as “chemical microbially influenced corrosion” (CMIC); while the direct uptake of electrons from iron is referred as “electrical microbially influenced corrosion” (EMIC).

Different groups of microorganisms play different roles in MIC depending on the surrounding conditions of the asset. Microorganisms that may pose a threat to the integrity of the asset under a specific combination of operating-, chemistry-, and metallurgy/corrosion-related conditions may pose no threat under a different set of conditions. Therefore, knowing the diversity (the different types) of the microorganisms present is essential to link microbiology to the abiotic aspects of MIC (i.e., chemistry, metallurgy/corrosion, and operating parameters). Hereby, the different types of microorganisms are classified based on their metabolic pathways, also referred as microbial functional groups (MFG).

Table 2.1 lists the MFG most commonly associated with MIC [1,25]. These MFG are extensively discussed by Sharma and Voordouw 2017 [31].

Table 2.1 Microbial functional groups most commonly associated with MIC and their respective parameters – adapted with permission from DNV: DNVGL-RP-G101, Recommended Practice Risk-based inspection of offshore topsides static mechanical equipment, Copyright (2021) [1].

Microbial functional group	Abbreviation	Temperature (°C)	pH	Metabolic input	Metabolic output
Sulfate-reducing bacteria	SRB	10 – 74	4 – 9.5	Organic and aromatic compounds, hydrocarbons, alcohols, lactate, acetate, H_2, SO_4^{2-}, S^0, $S_2O_3^{2-}$	H_2S, sulfide (HS^-), iron sulfide (FeS)
Sulfate-reducing *archaea*	SRA	60 – 95	4 – 9.5		
Methanogenic *archaea*	MA	37 – 85	5 – 6	Organic compounds, CO_2 (or soluble CO_3^{2-}, HCO_3^-, H_2CO_3) or H_2	Methane (CH_4), carbon monoxide (CO)
Nitrate-reducing bacteria	NRB	15 – 25	7 – 8	Organic compounds, O_2, NO_3^-	NO_2^-, N_2O, NO, N_2
Iron-reducing bacteria	IRB	21 – 40	4 – 9	Fe^{3+} (insoluble ferric iron), O_2, NO_3^-	Fe^{2+}
Acid-producing bacteria	APB	15 – 90	< 7	Organic compounds, hydrocarbons, O_2	Organic acids (e.g., formic, acetic), CO_2
Sulfur-oxidizing bacteria	SOB	20 – 50	0.5 – 8	Sulfide, sulfite, S^0 (elemental sulfur), $S_2O_3^{2-}$ (thiosulfate), organic compounds, O_2, CO_2	H_2SO_4 (sulfuric acid), S^0
Iron / Manganese -oxidizing bacteria	IOB / MnOB	10 – 40	1 – 10	Fe^{2+} (soluble ferrous iron), Mn^{2+}	Fe^{3+}, Mn^{4+}

Microorganisms are seldomly alone in the system. They form a consortium of multiple MFGs, where they synergistically coexist. Therefore, the combination of multiple MFGs tend to pose a greater MIC threat than a specific MFG would on its own. **Figure 2.1** illustrates a biofilm comprised by the MFGs most usually associated with MIC [29–32].

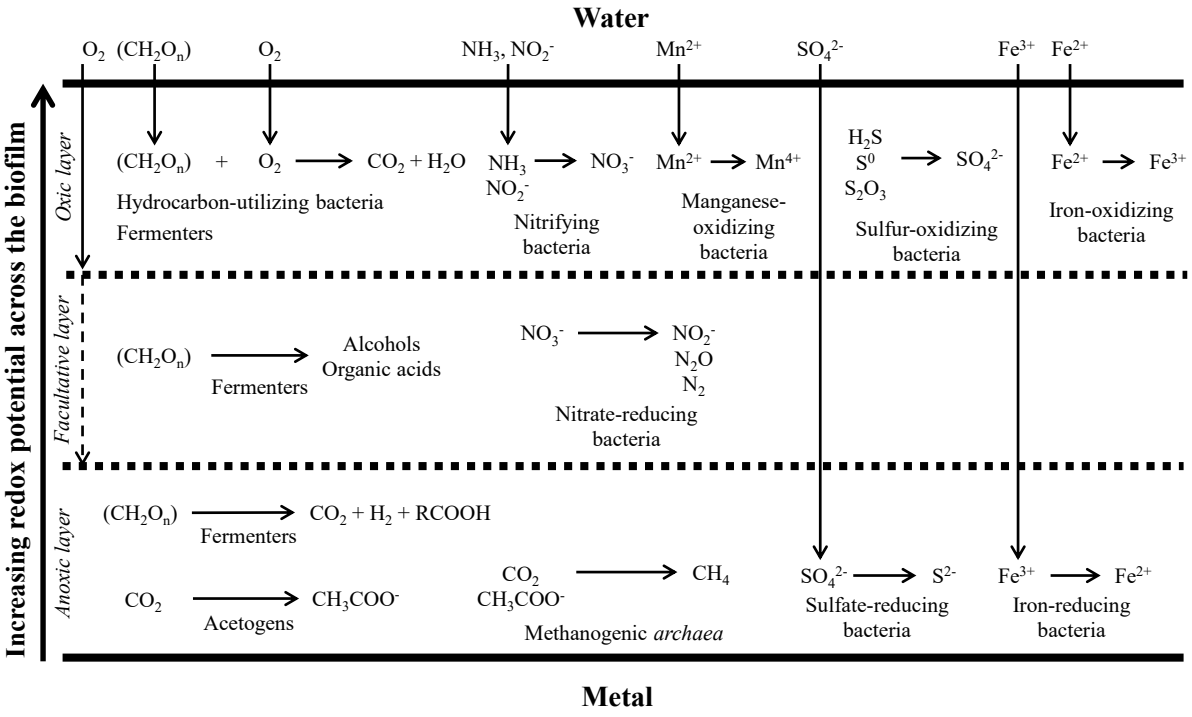

Figure 2.1 Distribution of microbial functional groups most commonly associated with MIC across the biofilm (region limited by both the water and the metal interface thick black horizontal lines) in relation to the redox potential of their metabolic pathways – adapted with permission from NACE International: B.J. Little, P. Wagner, Myths Related to Microbiologically Influenced Corrosion, Materials Performance. 36 (1997) 40–44 [32].

The position of specific MFGs across the biofilm will depend on the outer environment; whether it is oxic or anoxic, and it relates to the optimum redox potential range of the environment in which those microorganisms can carry out their metabolic processes (**Figure 2.1**). In an anoxic environment, as illustrated in **Figure 2.1**, the deeper a MFG is within the biofilm (closer to the asset surface), the lower is the environmental redox associated with their metabolic pathways. SRB and MA, for example, are at the bottom of the biofilm, while more oxygen friendly microorganisms are located at the top. This illustrates the synergetic relationship between aerobic (top of the biofilm) and anaerobic (bottom of the biofilm) microorganisms. This synergy between aerobic and anaerobic microorganisms means that even in an oxygen-containing system, strict anaerobes may be a threat. In an anoxic

system for instance, where anoxic seawater is present as a source of sulfate (i.e., SO_4^{2-}), SRB would be on the top at the outer layer of the biofilm. Hence, it is important to distinguish between anoxic and oxic environments when evaluating the positions of MFGs across the biofilm, as their position will depend on the redox potential of the environment. Additionally, as described by Skovhus et al. 2010 [33] and Larsen et al. 2010 [34], **Figure 2.2** summarizes the synergy between sulfate-reducing microorganisms (SRM) and MA that results in cathodic depolarization MIC. Based on this synergistic effect, the following chemical reactions can be described as follows (**Equations 2.1** and **2.2**):

Sulfate reduction $4Fe^0 + 3H_2S + SO_4^{2-} + 2H^+ \rightarrow 4FeS + 4H_2O$ (2.1)

Methane production $4Fe^0 + 4H_2S + CO_2 \rightarrow 4FeS + 2H_2O + CH_4$ (2.2)

When a comparison is made between the American Society of Materials (ASM) Handbook data available for MIC failure investigations between two decades ago and now [3,27], advancements in the MIC area become evident. Not only innovations were made regarding microbiological testing and mitigation methods, but the understanding over MFGs other than only SRB also increased.

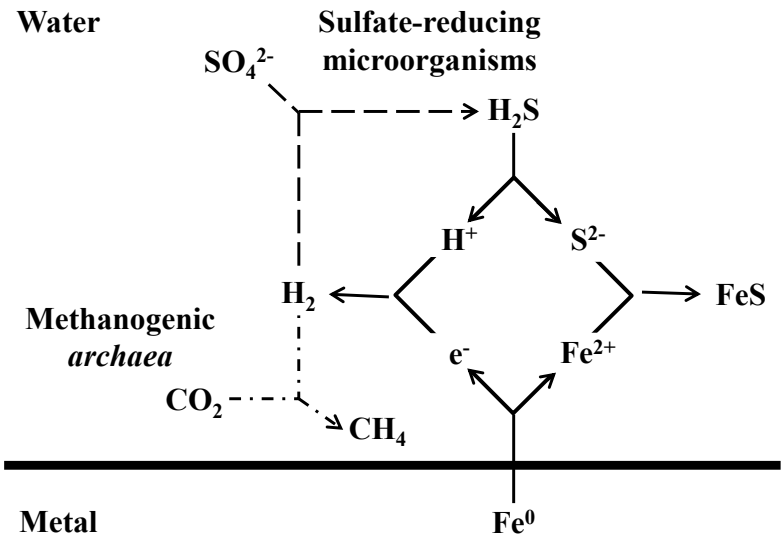

Figure 2.2 Synergistically relationship between sulfate-reducing microorganisms and methanogenic *archaea* – Adapted by permission from Springer Nature Customer Service Centre GmbH: Springer Netherlands, Applied Microbiology and Molecular Biology in Oilfield Systems, Problems Caused by Microbes and Treatment Strategies: Rapid Diagnostics of Microbiologically Influenced Corrosion (MIC) in Oilfield Systems with a DNA-Based Test Kit, T.L. Skovhus, K.B. Sørensen, and J. Larsen [33], Copyright (2010).

Jack 2021 [3] lists mechanisms in which MIC can occur: (1) direct involvement in the electrochemical corrosion cell (EMIC), (2) generation of corrosive metabolites (CMIC), (3) alteration of chemical conditions at the metal surface, (4) disruption of passivating layers, and (5) degradation of coatings, cathodic protection, and treatment chemicals.

Only when a biofilm is formed on the metal surface (when microorganisms transition from planktonic state to sessile state), MIC driven degradation can take place. Therefore, as MIC is a biofilm dependent mechanism, MIC degradation morphology, density and distribution will depend on the biofilm characteristics. Bacteria and *archaea* cells may vary in size from 0.2 micrometer (μm) to more than 700 μm (0.7 millimeter) [35]. Consequently, MIC tends to be a highly localized mechanism, usually resulting in localized corrosion

(pitting) and the MIC potential will depend on the biofilm's growth, reproducibility, and viability [36,37].

To fully assess the MIC threat, microbiological, chemical, metallurgical/corrosion, and operating -related parameters must be evaluated [1–3,26]. Skovhus and Eckert 2021 [38] describe the microbiological tools required to address the microbiological aspect of MIC. The microbiological aspect of MIC is fully addressed when diversity, abundance, and activity of the microorganisms present are evaluated [1,38].

The Association for Materials Protection and Performance (AMPP, formerly NACE International) has published multiple documents to shed light on the challenge of MIC (**Table 2.2**). These documents address microbiological sample and handling, various testing methodologies, mitigation methodologies (e.g., biocides) among other fronts [1,39].

Other organizations have also published guidelines and standards related to MIC including the American Petroleum Institute (API) [40], the American Society of Materials (ASM) [3,41–43], the American Society for Testing and Materials (ASTM) [44], the Det Norske Veritas (DNV) [1,45], and the Energy Institute (EI) [46,47]. Particular attention has to be given to DNVGL-RP-G101 [1], as its appendix B is fully dedicated to a risk-based inspection (RBI) approach to assess MIC. It encompasses microbiological considerations, corrosion-related testing, mitigation and monitoring, historical operating aspects, and metallurgical/corrosion considerations. All in all, Appendix B of DNVGL-RP-G101 [1] provides a practical overview to RBI approaches related to MIC and it was developed as part of the present research.

Table 2.2 MIC dedicated standards, guidelines, and recommended practices by AMPP – adapted from Failure Analysis of Microbiologically Influenced Corrosion, T.L. Skovhus, R.B. Eckert, Standards for MIC Management in Engineered Systems, 459–465 [39], Copyright (2015), reproduced with permission of Taylor and Francis Group LLC (Books) US through PLSclear.

Document	Status
TM0194, Standard Test Method – Field Monitoring of Bacterial Growth in Oil and Gas Systems	Latest version from 2014
TM0106, Standard Test Method – Detection, Testing, and Evaluation of Microbiologically Influenced Corrosion (MIC) on External Surfaces of Buried Pipelines	Latest version from 2016
TM0212, Standard Test Method – Detection, Testing, and Evaluation of Microbiologically Influenced Corrosion on Internal Surfaces of Pipelines	Latest version from 2018
TM21465, Molecular Microbiological Methods – Sample Handling and Laboratory Processing	Under development, expected publishing 2022*
TM21495, Laboratory Evaluation of the Effect of Biocides on Biofilms	Under development, expected publishing 2023*

*Personal communication with the AMPP SC-22 Chair (Dr. Torben Lund Skovhus).

2.2 Review of MIC failure investigation methods in the literature

There have been numerous studies published in the literature highlighting MIC failure cases and their approaches. Historically, there are two high-profile failures that are associated with MIC in the oil and gas industry: 1) Carlsbad, New Mexico and 2) Prudhoe Bay, Alaska [26].

The Carlsbad incident occurred in 2000 with the explosion of a 75 cm (30 in) diameter natural gas transmission line. An ignition resulted in a rupture that killed 12 people nearby and resulted in over $1 million in damages. Investigations confirmed the presence of blackish oily

solids blocking 70% of the cross section of the pipe [48,49]. The features associated with MIC included: interconnecting pits with undercutting features; chloride concentration increasing from top to bottom inside the pits; the presence of SRB, acid producing bacteria (APB), and general aerobic and anaerobic bacteria at corrosion pits 630 m away from the rupture; and pH from fluid and solid debris of between 6.2 to 6.8.

The Prudhoe Bay incident occurred in 2006 on an above ground oil production pipeline, releasing over 200,000 gallons of fluid [50,51]. A 6.4 mm hole at the bottom of the pipe resulted in an unnoticed leak that lasted for several days; which led to the largest oil spill on Alaska's north slope to date [52,53]. Microorganisms (e.g., SRB) were found to be present in the system and were associated to the internal pitting that eventually led to the through-wall perforation. As the system was working at low capacity, the stagnant flow conditions resulted in accumulation of both water and solids at the bottom of the pipe.

Both the Carlsbad and Prudhoe Bay cases, although being high-profile MIC incidents, were diagnosed without the integration of all biological, chemical, metallurgical/corrosion, and operating layers of evidence together. While technology (e.g., MMM) and the understanding of MIC has significantly progressed since these incidents (in the past 15 to 20 years), the uptake and use of novel methods and techniques has still been limited in terms of analyzing suspected MIC failures.

In terms of microbiological evidence, culture-based analysis methods (as opposed to MMM) are still primarily used by industry due to their availability and convenience. Some failure studies have highlighted the use of DNA-based tests; however, their significance and potential has not yet been fully appreciated or utilized [54–57]. In particular, quantification

and identification of microorganisms are not necessarily correlated with available chemical, metallurgical/corrosion, and/or operating data.

Another common indicator that has been historically used to identify MIC failures is pitting morphology. A number of studies have suggested that pitting morphology alone can be used to identify the activities of specific microorganisms or microbial functional groups [54]. For example, terraced pits were commonly associated with SRB, while serrations and tunneling were associated with APB [58,59]. The evidence for these types of relationships, however, is weak and does not account for the fact that these specific pitting morphologies could also be caused by abiotic conditions that often accompany MIC-related mechanisms. While MIC generally results in localized corrosion damage (pitting), this idea of MIC specific morphological fingerprints has since been discounted [15,23,60].

The presence of specific chemical signatures (i.e., elements or microbial nutrients) is also common in historical studies. For example, high amounts of both carbon and oxygen (between 20% to 30% and above) identified by energy-dispersive X-ray spectroscopy (EDS) tests were used as indicators for MIC based on the assumption that the presence of biomass (biofilm) would be an additional source of such elements [61]. However, in oil-related systems, both oxygen and carbon can be present from sources other than biofilms that can also result in EDS peaks – as the elements identified by EDS have no discrimination regarding their parent structure. For instance, organic acids (i.e., carbon sources) are abundantly present in oil and gas systems while oxygen may be related to CO_2 conditions and not necessarily indicative of biofilms.

Finally, the integration of data during MIC failure analyses has also evolved over the past number of years. For example, many studies have integrated nutrient availability in MIC

failure analyses [56,58,62–70], while only fewer carried out DNA testing [54–57]. The lack of failure investigations that use both chemical and microbiological evidence over the years illustrate that procedures and integration steps to diagnose MIC are still inconsistent.

In summary, MIC failure case studies in the literature over the past two decades (1998 to 2019) have shown a lack of procedural consistency with respect to the diagnosis of MIC. As the understanding of MIC has evolved, testing and integration methodologies have improved over time. However, even newer case studies often do not fully adopt the current best practices and instead rely on older approaches to determine the root cause of corrosion which, ultimately, may not be accurate or conclusive.

2.3. Expert Systems and Artificial Neural Network

Due to the complexity associated with MIC, there is currently neither a computer model nor a mechanistic/phenomenological model that accurately assesses it. As a result, in order to bridge the current gap in MIC assessments, the present study chose the "expert system approach" as the method to assist both experts and non-experts in screening internal MIC failures related to oil and gas upstream pipeline operations, as well as to any engineering system susceptible to MIC. Such an expert system would be a valuable resource particularly for non-specialists since considerable time and effort is often required to master MIC diagnosis and assessment.

Expert systems are rule-based object-oriented systems. They capture the knowledge, experience and know-how of experts by mimicking the human decision process [71,72]. Expert systems do so by assimilating the interconnections an expert inherently makes when diagnosing multivariate topics [73,74].

Expert systems is a mature area of artificial intelligence and has been applied to a number of different sectors including finance [75–77], agriculture [78–82], medicine [83–87], and engineering [88–91]. At the rise of expert system implementation (late 1980s and early 1990s), expert systems dedicated to healthcare applications dominated the topic [71]. Now, expert systems have expanded to a number of challenging and complex problems including diagnosing medical illnesses [72,92] (which is a good proxy to diagnosing MIC failures).

A variety of computational methods and approaches have been used to implement expert systems including fuzzy logic functions [93–96], rule-based methods [74,97,98], Bayesian methods [99–101], genetic algorithms [102–104], and most recently, artificial neural networks [105–107]. An artificial neural network (ANN) is a machine learning approach of artificial intelligence that is related to supervised learning [108], and it is the approached chosen to build the expert system developed in this thesis' work due to its practicality and easy of implementation. With the recent advancements in computing science, machine learning techniques are seen as a viable avenue for implementation of expert systems. Machine learning is a field within artificial intelligence where knowledge and preferred decision making pathways can be learned from the data itself, rather than being explicitly programmed into an algorithm [109]. To that end, ANNs mimic biological neural networks as they are able to capture the multilayered relationships between interconnected variables [110]. ANNs use neurological-like paths to account for the interdependency of multiple considerations (multiple parameters). Therefore, similar to brain neurons, ANNs are built on "autonomous computational units". Relative weights are assigned to each variable in order to connect the inputs to the hidden layer of neurons and then to output classes. The stronger the interrelationship between neurons, the stronger the relative weights of the decision pathways

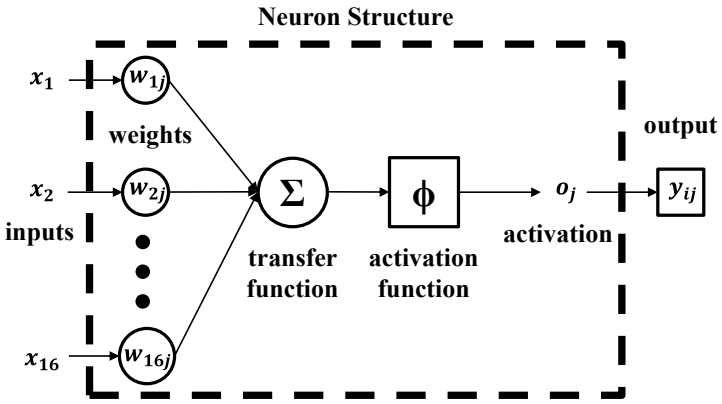

Figure 2.3 Artificial neuron structure – reprinted from Measurement: Journal of the International Measurement Confederation, 67, Z.J. Viharos, and K.B. Kis, Survey on Neuro-Fuzzy systems and their applications in technical diagnostics and measurement, 126–136 [110], Copyright (2015), with permission from Elsevier.

and subsequently, the greater the influence of a specific input variable on the resulting output class (**Figure 2.3**) [110,111].

As shown in **Figure 2.3**, the transfer function is the algorithm responsible for balancing out the relative weights that will result in the output class from a specific combination of inputs [112–115]. The activation function introduces non-linearity to the neurons' interrelationships [112]. It influences the output by combining the relative weights and biases that should be activated while ignoring the ones that should not. The neurons are structured into layers (**Figure 2.4**) and each layer fully connects to the following one though the weights and biases. The weight and bias values are iterated at each training cycle, and the values associated with them will determine the degree of influence that each neuron will have on each other. In **Figure 2.4**, the weights (W_{inp}, W_{out}) and biases (b_{inp}, b_{out}) are represented by the arrows that connect the neurons. The input layer is composed by the number of input

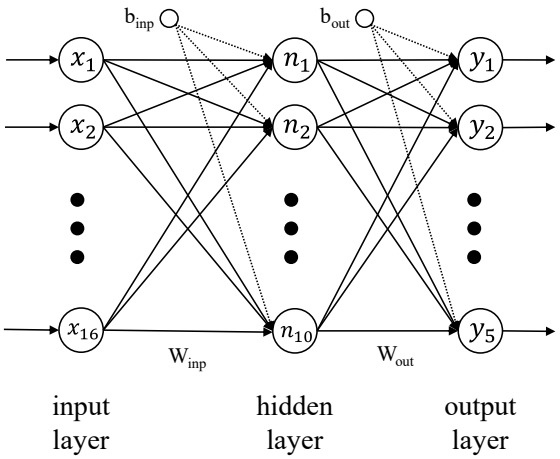

Figure 2.4 Structure of a typical shallow ANN (layers and neurons) – reprinted from International Journal of Fatigue, 99, J.F. Durodola, N. Li, S. Ramachandra, A.N. Thite, A pattern recognition artificial neural network method for random fatigue loading life prediction, 55–67 [116], Copyright (2017), with permission from Elsevier.

variables to the model. The hidden layer is composed by the number of neurons used to build the ANN. The output layer is composed by the number of output classes.

ANNs work with supervised learning which means they require targets (correct outputs) to be linked with the inputs. That is called the 'input-output pair relationship'. At each training cycle a backpropagation algorithm calculates the derivative of the network's error. Backpropagation is the training algorithm which is based on a minimization method. It is responsible for tracking the output error to the error source in order to increase modelling accuracy [117].

In order to decrease the final error, the associations between relative weights and biases are adjusted until the stopping criteria is met. The stopping criteria is met whether the minimum gradient is reached, the maximum number of epochs (training cycles) is achieved, or validation error increases consecutively for a number of iterations [110,118,119].

Chapter 3: Prevalence of MIC-Related Failures in Alberta's Upstream Oil and Gas Operations

3.1. Overview of Alberta's Oil and Gas Sector and Regulatory Structure

The Province of Alberta is the center of the oil and gas industry in Canada with the third largest proven oil reserves in the world (only behind Venezuela and Saudi Arabia). The sector accounts for 97% of Canada's petroleum inventory [120], and is responsible for approximately 82% of Canada's oil production [121]. The vast majority of Alberta's reserves (over 90%) are related to unconventional production, which includes in-situ heavy oil and mined oilsands. Since the first discovery of oil in the province over 70 years ago, the oil and gas sector has grown substantially in Alberta to create Canada's largest petrochemical supply chain that includes upstream production (conventional and unconventional), pipeline transport, and downstream processing (upgrading, refining and associated petrochemical processing).

Regulation of these pipelines mainly fall under the jurisdiction of two government bodies: a) the Alberta Energy Regulator (AER) which regulates all pipelines that do not cross provincial or international borders, and b) the Canadian Energy Regulator (CER) that regulates all pipelines (mainly large transmission lines) that cross provincial or international borders. Within Alberta, the AER regulates over 433,000 km of pipelines that are used for the transportation of both produced crude and refined products, and includes operating, discontinued, abandoned and permitted pipelines [122]. These pipelines consist of a broad range of pipe sizes (upstream, midstream and transmission pipelines) and products types (e.g., crude oil, water, natural gas, sour gas, natural gas liquids, refined products). The AER enforces compliance with various Canadian legislative and technical standards and

requirements (e.g., CSA Z662:19 [123], Pipeline Act [124], Pipeline Rules [125]) throughout the operating life of pipelines and facilities in order to ensure public safety and environmental protection [126]. The regulatory framework starts with the application process (before construction begins), and extends to inspection of the construction, operation and maintenance (integrity management), monitoring, surveillance, leak detection, emergency response, discontinuation and abandonment.

In the event of an incident, the responsible party (e.g., operating company) must report it immediately to the regulatory bodies, and is responsible for all levels of incident response (e.g., isolation, containment, recovery of lost product, remediation and reclamation). In the case of a pipeline damage incident, the operating companies are required to investigate and implement measures to prevent reoccurrence [123]. The AER conducts the incident review by assessing the information the companies provide. Companies often use third-party labs and consultants to aid in their assessment (e.g., materials failure analysis labs). The regulatory bodies provide oversight to this process in order to understand the causes of the incident and to ensure that compliance is met and deficiencies are addressed. As failure assessments are conducted, various pieces of evidence are gathered, including failure reports carried out by third-party consultants to identify the degradation mechanism that led to the failure. Information of pipeline incidents are made publicly available by both federal and provincial regulators to provide transparency to both the public and industry, and to better track and classify these incidents in order to ultimately identify trends, improve safety and ensure compliance.

In Alberta, a dedicated database managed by AER is made publicly available for incident classification and inventory. Pipeline related incidents in the province are classified

under a number of different damage types [127] as shown in **Table 3.1**. These include important damage modes that commonly occur during normal operation of pipelines such as leaks, ruptures, and mechanical damage; and also include damage modes that occur during pipeline construction, commissioning and maintenance, such as integrity tests and pressure tests (specific definitions of each damage type are provided as a footnote in **Table 3.1**). Leaks are further classified into a number of descriptors including "leaks" (which typically encompass failures in main pipe bodies due, for example, to corrosion), "GSPT Releases" (which include any releases due failure of gaskets, seals, packing glands, or threaded fittings) and "installation leaks" (which encompass releases specifically at auxiliary sites along the pipeline such as compressor, pumping or metering stations).

Table 3.1 also lists the number of incidents in the province of Alberta based on damage type between January 1, 2017, and December 31, 2019. Of the 1,479 total incidents during the three-year period, "leaks" account for the majority (62%) of pipeline related incidents in the province, while "GSPT releases" (i.e., leaks in gaskets or fittings) represent 16% of total incidents. Releases resulting from pipeline "integrity tests" and "pressure tests" only represent 8% and 4% of all incidents, respectively. It should be noted that failures from these tests are somewhat beneficial in that they successfully locate weaknesses in the system and do not take place under normal operating conditions [126]. While pipeline "ruptures" (bursts) have the potential for most harm due to an abrupt release of fluid content, it can be seen that these are relatively infrequent (only 3% of all incidents over the three-year period).

In addition to the main damage types outlined in **Table 3.1**, the AER database also categorizes specific failure modes within these broad damage types. For pipeline corrosion failures, for example, two categories have been historically used to track incidents since 1975:

Table 3.1 Number of Pipeline Incidents[a] by Pipe Damage Type in Alberta, Canada from January 1, 2017 to December 31, 2019, as per the AER Database Classification [127].

Pipe Damage Type Category[b]	2017	2018	2019	Total Number of Incidents per Category	Total Percentage per Category
Leak	309	324	291	924	62%
GSPT Release	63	79	80	222	16%
Integrity Test Failure	44	46	30	120	8%
Hit	41	28	21	90	6%
Pressure Test Failure	22	18	20	60	4%
Rupture	21	12	14	47	3%
Installation Leak	2	5	9	16	1%
Total per Year	502	512	465	1479	100%

a Note that these statistics are dynamic in nature, and may not represent the AER database at any specific point in time due to possible changes during ongoing reviews.

b In the table, "Leak" refers to incidents where the substance released does not immediately stop the operation. "GSPT Release" refers to leaks specifically due to failure (or lack of sealing) of gaskets, seals, packing glands, or threaded fittings (GSPT). "Integrity Test Failure" are leak incidents originating from failures occurring during an integrity test. "Pressure Test Failure" refers to a failure during qualification of new pipe construction. A "Hit" is an incident that occurs due to contact damage to a pipe or its coating due to a ground disturbance event that do not result in substance release (e.g., backhoe impact during construction). "Rupture" means a burst where the pipeline immediate ceases to operate. "Installation Leak" relates to releases which take place at auxiliary sites along the pipeline (e.g., compressor, pumping or metering stations).

"internal corrosion" and "external corrosion". While these two general categories are useful for classifying and tracking corrosion failures, they do not identify and differentiate specific mechanisms involved in the incident. Subcategories have historically been added to the database to better identify these various mechanisms, and are based on the failure assessments by the operator or third-party consultants. This extended classification allows for improved tracking and classification of common corrosion issues.

3.2. Prevalence of MIC Related Failures in Alberta

This section aims to quantify the prevalence of MIC related failure incidents in Alberta. The intent is to provide a better understanding of failure statistics associated with MIC in comparison with other common failure modes. The data was further analyzed based on operating factors such as pipe diameter/length and fluid type to identify where MIC is most commonly found.

This analysis was conducted by reviewing the AER's internal database and files associated with all corrosion incidents classified in the "leak" damage category over a three-year period from January 1, 2017 to December 31, 2019. For this period, there was a total of 573 corrosion related incidents with 447 classified as internal corrosion (78% of all corrosion related incidents) and 126 classified as external corrosion failures (22%). Each of these 573 incident files were manually reviewed to flag those cases where MIC was identified as either the main corrosion mechanism or a contributing cause. This was determined based on third-party failure reports and/or by information provided by the pipeline operator.

Overall, there was a total of 67 MIC related failures (or 11.7%) out of the 573 corrosion related leak incidents reported over the three-year period. These MIC related incidents were then sub-divided into internal corrosion failures or external corrosion failures based on categorizations in the database and files. As shown in **Table 3.2** and **Table 3.3**, MIC was involved in 13.6% of all internal corrosion incidents (61 out of 447 cases) and 4.8% of all external corrosion incidents (6 out of 126 cases), respectively. For the internal corrosion cases, MIC was found to be the main cause or a contributing factor under a number of corrosion sub-categories in the AER database including microbiologically influenced corrosion (as expected), multi-mechanism corrosion, under deposit corrosion, CO_2 corrosion, and others.

Table 3.2 Breakdown of all internal corrosion related "leak" incidents in Alberta based on reported damage mechanism (including MIC) over a three-year period from January 1, 2017 thru December 31, 2019.

Subcategories for Internal Corrosion	Total Incidents Per Subcategory	Number of MIC Related Failures	MIC Related Failures as a Percentage of Total Internal Corrosion Incidents
Equipment Failure - Internal corrosion	140	19	4.3%
Multi Mechanism	124	13	2.9%
Under Deposit Corrosion	60	7	1.6%
Microbiologically Influenced Corrosion	27	19	4.3%
CO_2 Corrosion	24	2	0.4%
Corrosion Under Internal Coating	18	1	0.2%
Interference Corrosion	13	-	-
Corrosion at Valve or Fitting	7	-	-
H_2S Corrosion	6	-	-
Corrosion at Internally Coated Riser	5	-	-
Preferential Weld Corrosion	5	-	-
Corrosion Behind Plastic Liner	4	-	-
Other	4	-	-
Corrosion Under Cement Lining	3	-	-
Oxygen Induced Corrosion	3	-	-
Corrosion at Inline Coupler	2	-	-
Erosion Corrosion	2	-	-
Total Internal Corrosion Incidents	447	61	13.6%

Table 3.3 Breakdown of all external corrosion "leak" incidents in Alberta based on reported damage mechanism (including MIC) over a three-year period from January 1, 2017 thru December 31, 2019.

Subcategories for External Corrosion	Total Incidents Per Subcategory	Number of MIC Related Failures	MIC Related Failures as a Percentage of Total External Corrosion Incidents
Equipment Failure - External corrosion	43	4	3.2%
Coating Disbonded or Shielding	34	2	1.6%
Missing or Damaged Coating	30	-	-
Corrosion Under Insulation	11	-	-
Atmospheric	5	-	-
Soil-to-Air Interface	2	-	-
Corrosion at Valve or Fitting	1	-	-
Total External Corrosion Incidents	126	6	4.8%

For the external corrosion cases, MIC occurred in two sub-categories: equipment failure (external) and coating disbondment. This broad range of categories where MIC was found highlights the breadth and complexity of potential MIC impacts, and the associated challenges faced by the industry and regulators in assessing and classifying MIC related failures.

It should be noted that these numbers reflect failures caused by MIC and not the prevalence of MIC found from inspection and integrity management programs (i.e., non-failure events). To the authors' knowledge, these MIC failure statistics (13.6% of all internal corrosion incidents and 4.8% of all external corrosion incidents) represent the first time that the prevalence of MIC has been accurately quantified in the literature based on a single, reliable data set.

Table 3.4 Frequency of MIC Incidents by Total Length of Steel Pipelines for Various Carrier Fluid Types Over a Three-Year Period from January 1, 2017 thru December 31, 2019.

Fluid Type	Number of MIC Incidents Over 3 Year Period	Total Steel Pipeline Length (km)[a]	MIC Incidents per km per year
Water	11	2,438	150×10^{-5}
Multiphase	31	22,735	45×10^{-5}
Natural Gas	23	152,913	5×10^{-5}
Sour Gas	1	13,952	2×10^{-5}
Other	1	31,937	1×10^{-5}
Crude Oil	0	13,809	0
Total	67	237,784	N/A

a Note that these lengths only represent steel pipelines (excludes non-metallics) that are either in operation or discontinued (excludes abandoned and permitted lines).

To further understand where MIC failures most commonly occur, the 67 MIC related cases were further categorized based on the pipeline contents and size of pipe. **Table 3.4** highlights the number of MIC incidents and their frequency (per km per year) for various pipeline fluid types. It can be seen that MIC is most prevalent in water and multiphase pipelines at 150×10^{-5} and 45×10^{-5} MIC incidents per km per year, respectively. This translates to one MIC failure (on average) every 667 kilometers in water pipelines and every 2,222 kilometers in multiphase pipelines, each year.

This same analysis was also performed based on pipeline outside diameter (O.D.), as shown in **Table 3.5**. This table shows that all recorded MIC incidents occurred in relatively small diameter pipelines (i.e., 220.3 mm O.D./8 in. nominal or less), which are more representative of upstream production flowlines and collection systems. Furthermore, a

Table 3.5 Frequency of MIC Incidents by Total Length of Steel Pipelines for Various Outer Diameters of Pipe Over a Three-Year Period from January 1, 2017 thru December 31, 2019.

Pipe Outer Diameter	Number of MIC Incidents Over 3 Year Period	Total Steel Pipeline Length (km)[a]	MIC Incidents per km per year
82.6 mm – 101.6 mm (3 in. and 3½ in. nominal)	29	49,205	20×10^{-5}
≤ 80.9 mm (≤ 2½ in. nominal)	11	20,698	18×10^{-5}
114.0 mm – 116.8 mm (4 in. nominal)	14	63,405	7×10^{-5}
139.7 mm – 177.8 mm (5 in. and 6 in. nominal)	9	47,107	6×10^{-5}
219.0 mm – 220.3 mm (8 in. nominal)	4	20,782	6×10^{-5}
≥ 255.3 mm (≥ 10 in. nominal)	0	36,587	0
Total	67	237,784	N/A

a Note that these lengths only represent steel pipelines (excludes non-metallics) that are either in operation or discontinued (excludes abandoned and permitted lines).

majority of MIC failures occurred in pipelines with outside diameters less than 101.6 mm (3½ in. nominal pipe sizes or less). The highest MIC failure frequency was 20×10^{-5} MIC incidents per km per year which was found in pipelines with an O.D. between 82.6 mm and 101.6 mm (3 in. and 3½ in. nominal pipe diameters). This translates to one MIC failure (on average) every 5,000 kilometers per year. The next highest MIC failure frequency was 18×10^{-5} MIC incidents per km per year which was found in pipelines with an O.D. less than 80.9 mm (2½ in. nominal pipe sizes or less). This translates to one MIC failure (on average) every

Table 3.6 Frequency of MIC Incidents by Total Length of Steel Pipelines for Various Outer Diameters and Fluid Types of Pipe Over a Three-Year Period from January 1, 2017 thru December 31, 2019.

Fluid Type	Pipe Outer Diameter	Number of MIC Incidents Over 3 Year Period	Total Steel Pipeline Length (km)[a]	MIC Incidents per km per year
Water	≤ 80.9 mm (≤ 2½ in. nominal)	7	497	470×10^{-5}
Water	114.0 mm – 116.8 mm (4 in. nominal)	3	405	247×10^{-5}
Multiphase	82.6 mm – 101.6 mm (3 in. and 3½ in. nom.)	18	9,297	65×10^{-5}
Water	82.6 mm – 101.6 mm (3 in. and 3½ in. nom.)	1	594	56×10^{-5}
Multiphase	114.0 mm – 116.8 mm (4 in. nominal)	7	5,155	45×10^{-5}
Multiphase	219.0 mm – 220.3 mm (8 in. nominal)	2	1,526	44×10^{-5}
Multiphase	≤ 80.9 mm (≤ 2½ in. nominal)	2	2,037	33×10^{-5}
Multiphase	139.7 mm – 177.8 mm (5 in. and 6 in. nominal)	2	3,692	18×10^{-5}
Other	219.0 mm – 220.3 mm (8 in. nominal)	1	3,043	11×10^{-5}
Natural Gas	82.6 mm – 101.6 mm (3 in. and 3½ in. nom.)	10	34,323	10×10^{-5}
Sour Gas	139.7 mm – 177.8 mm (5 in. and 6 in. nominal)	1	4,594	7×10^{-5}
Natural Gas	139.7 mm – 177.8 mm (5 in. and 6 in. nominal)	6	34,309	6×10^{-5}
Natural Gas	≤ 80.9 mm (≤ 2½ in. nominal)	2	12,301	5×10^{-5}
Natural Gas	219.0 mm – 220.3 mm (8 in. nominal)	1	11,521	3×10^{-5}
Natural Gas	114.0 mm – 116.8 mm (4 in. nominal)	4	50,005	3×10^{-5}
Remaining Combinations of Fluid Type and Pipe Outer Diameter		0	64,486	0
Total		67	237,784	N/A

a Note that these lengths only represent steel pipelines (excludes non-metallics) that are either in operation or discontinued (excludes abandoned and permitted lines).

5,556 kilometers each year. The main reason for the high MIC failure frequencies in small diameter pipelines is likely due to the fact that many of these systems have significant water content in the fluid (i.e., produced water, or unprocessed crude emulsions), which is a necessary precursor for MIC to occur. Additionally, smaller diameter lines are often more difficult to inspect and maintain (e.g., pig) relative to larger diameter pipelines that may also contribute to the frequency of MIC incidents.

Finally, the fluid type and outer diameter datasets were combined to identify specific field conditions where MIC was found to be most prevalent. As shown in **Table 3.6**, water pipelines with outer diameters smaller than 80.9 mm (2-1/2 in. nominal pipe size) and 114 – 116.8 mm (4 in. nominal pipe size) had the highest MIC failure frequencies at 470 x 10^{-5} and 247 x 10^{-5} incidents per km per year, respectively. This translates to one MIC failure (on average) every 213 and 405 kilometers, respectively each year. The remainder of fluid-diameter combinations in **Table 3.6** have much lower failure frequencies, and consist of a mixture of multiphase and water pipelines of varying diameters. Natural gas pipelines had the lowest MIC failure frequencies between 3 x 10^{-5} and 10 x 10^{-5} incidents per km per year suggesting these lines were typically carrying dehydrated natural gas.

3.3 Conclusions

This chapter highlights a review and analysis of MIC related pipeline incidents in the province of Alberta, Canada over a three-year period (2017-2019). The intent was to present an analysis of the occurrence of MIC failures relative to other corrosion mechanisms.

Over this three-year period, MIC was found to be involved in 13.6% of all internal corrosion incidents (61 out of 447 cases) and 4.8% of all external corrosion incidents (6 out of

126 cases), either as the main failure mechanism or as a contributing factor. Furthermore, all of these failures occurred in small diameter upstream pipelines (with less than or equal to 220.3 mm outside diameter) mainly carrying produced water or multiphase fluids (oil-water emulsions). The highest MIC failure frequencies occurred in water pipelines with outer diameters smaller than 80.9 mm (2-1/2 in. nominal pipe size) and 114 – 116.8 mm (4 in. nominal pipe size) at 470 x 10^{-5} and 247 x 10^{-5} incidents per km per year, respectively. This translates to one MIC failure (on average) every 213 and 405 kilometers, respectively each year. To the authors' knowledge, this is one of the few well documented instances documenting MIC prevalence in the open literature with supporting evidence and data.

Chapter 4: Review and Gap Analysis of MIC Failure Investigation Methods in Alberta's Upstream Oil and Gas Operations

In this section, MIC failure investigation and analysis methods were reviewed from assessments of recent pipeline failure incidents in Alberta over a three-year period from January 1, 2017 to December 31, 2019 (see **Chapter 3** for more details). Fifty failure assessments were sampled for the period of interest and each was reviewed to identify the information that was typically collected during these assessments and how this information was used to confirm MIC. These assessments consisted of reports from third-party consultants or from summaries prepared by AER inspectors based on available information/data from the incident and operations. All incident information regarding specific operators, asset name and location, and the third-party consultant has been blinded to ensure confidentiality.

As shown in **Table 4.1**, a broad range of assessments was used in this review, covering cases where MIC was either identified as the primary failure mechanism or as a contributing (secondary) factor in conjunction with some other possible failure mechanism (e.g., CO_2 or H_2S corrosion). Out of the 50 incidents that were reviewed, 19 were categorized as "MIC", 10 as "multi-mechanism", 6 as "under deposit corrosion", 1 as "under internal coating" while 14 were categorized simply as internal corrosion (subcategory not discriminated). Although there is a dedicated category for MIC, it can be seen that MIC is often reported in addition with several other failure causes.

The information compiled from these assessments was then compared to the latest best practises used to diagnose MIC failures as determined through expert elicitation and from methodologies published in the open literature [24,26,128]. The intent of this exercise was to identify gaps in current MIC failure assessment methodologies, and suggest improvements on

Table 4.1 Breakdown of the 50 mic failure assessments considered in this study based on corrosion subcategory and primary/secondary contribution.

Corrosion Subcategory Classification in AER Database	Number of Reviewed Assessments where MIC was the Primary Mechanism	Number of Reviewed Assessments where MIC was a Secondary Mechanism	Total Number of Reviewed Assessments
Microbiologically Influenced Corrosion	*17*	*2*	*19*
Multi-Mechanism	4	6	10
Under Deposit Corrosion	2	4	6
Under Internal Coating	1	–	1
<Subcategory not discriminated>	8	6	14
Total	32	18	50

how industry and regulators can better identify potential MIC incidents. To accomplish this task, a checklist [21,23,124] of information and methods was created based on the current best practises, and was used to evaluate each of the 50 MIC assessments from the AER database to identify potential gaps in both the data and/or analysis methods used. The checklist was grouped into five major information and analysis groups as shown in **Figure 4.1**. These categories outline the main layers of evidence required to conduct a successful assessment for MIC. These include four key information groups (microbiological, chemical, metallurgical/corrosion, and operating data) and a data integration step, which is required to properly identify MIC as a possible failure mechanism. In addition to these five main categories, this gap analysis also examined a number of other important factors that may affect a successful MIC diagnosis, including proper sampling and the availability/use of standards.

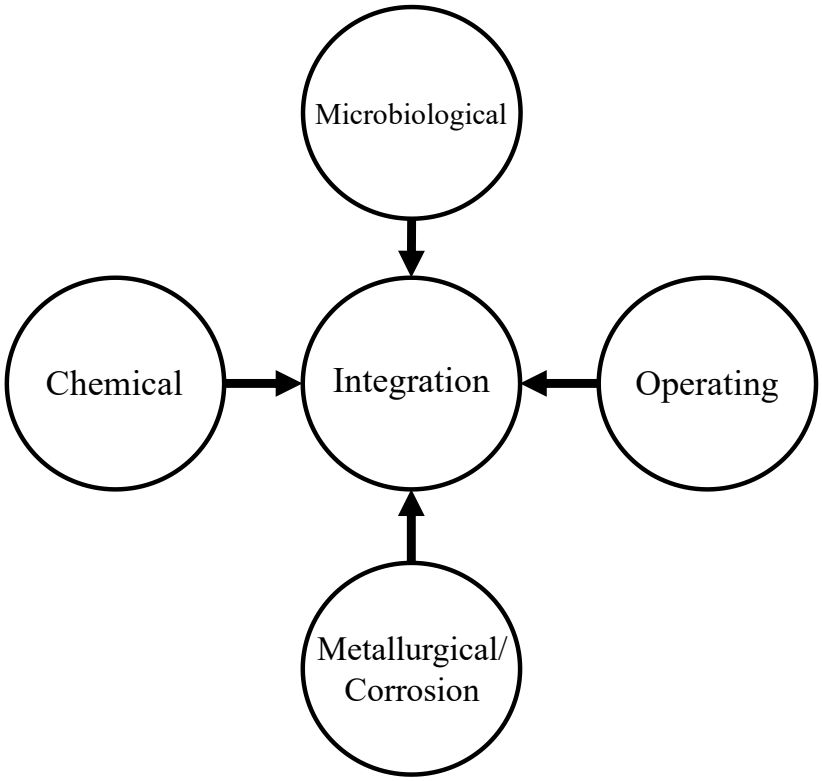

Figure 4.1 Major information and analysis groups required for conclusive and reliable MIC diagnosis.

Details for each of these categories and results from the gap analysis are provided in the following sections. The results are presented in comprehensive figures that identify whether a particular MIC failure assessment (numbered 1 thru 50) has included a specific dataset/analysis method or not. This allows quantification of select layers of evidence, and an overall indicator of whether certain analytical practises are being followed. In addition, the same 50 MIC failure cases are used throughout the remainder of the chapter to ensure consistency in the gap analysis.

4.1. Overall Summary

One goal of a failure assessment is to understand why the failure took place at a specific location and the underlying cause. For assessing suspected MIC related corrosion failures, there is a need to determine whether the failure mechanism was due to abiotic factors (e.g., CO_2, H_2S, O_2, Cl^- in the system), biotic factors (due to microbiological processes), or a combination of both. It is the contrast and integration between the multiple layers of evidence, as shown in **Figure 4.1** (microbiological, chemical, metallurgical/corrosion, and operating data, and its integration), that can lead to the most conclusive and reliable diagnosis given the limits of current technology and knowledge.

In general, all five of these layers of evidence were to some extent fulfilled in a majority of the 50 MIC assessments reviewed, as listed in **Table 4.2**. Over 90% of the 50 MIC assessments reviewed took chemical data, metallurgical/corrosion data, operating data, and integration steps into consideration. However, the greatest gap is observed for microbiological data, where only *70%* of the MIC assessments reviewed conducted some sort of microbiological analysis. While this shows that most of the MIC assessments incorporated the five general categories of information in their reports (other than microbiological), a larger discrepancy can be seen when exploring specific details within each category as outlined in the following sections.

Table 4.2 Inclusion of key information and analysis groups in the reviewed mic failure assessments.

Information and Analysis Group	Percentages of Failure Assessments that Included Specific Information and Analysis Groups
Microbiological	*70%*
Chemical	92%
Metallurgical/Corrosion	98%
Operating	92%
Integration	90%

4.2. Reported Microbiological Data

Microbiological information is a key component to identify MIC. MIC can only occur if specific types of microbial functional groups (MFG) are present at the surface of the pipe as part of a biofilm (sessile microorganisms). Furthermore, these microorganisms must be active for MIC to occur. It should be noted that many species of microorganisms commonly exist in oil and gas systems; however, not all are responsible for MIC. For this reason, it is important to assess three key microbiological factors in the investigation: microbial diversity, activity and abundance. Diversity characterizes the community of microorganisms present in a system (both MIC and non-MIC related functional groups). Activity indicates whether the microorganisms present are actively involved in metabolic functions (versus those that are either dormant or deceased). Finally, abundance quantifies the numbers of specific microorganisms present in the system.

A detailed listing of the microbiological information used in the 50 MIC failure assessments is shown in **Figure 4.2**, including sample type and whether microbiological analysis was performed using modern MMM or older culture-based techniques (e.g., Most

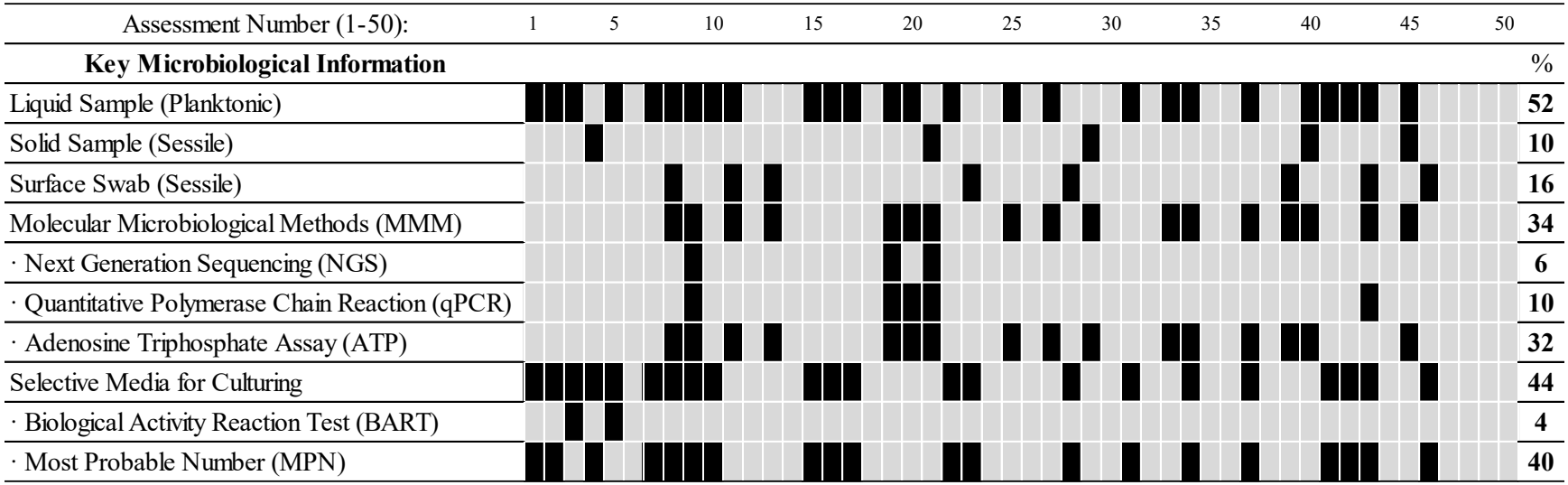

Figure 4.2 Inclusion of specific microbiological information and analysis methods for each of the failure assessments reviewed (1 thru 50).

Probable Number [MPN] from serial dilution or Biological Activity Reaction Tests, [BART]). The figure represents a matrix highlighting the pieces of information or analyses that were performed (rows) for each MIC failure assessment 1 thru 50 (columns). Those intersections that are marked in "black" indicate that a given piece of information or method was used in that particular failure assessment/report. The failure assessment numbers are consistent throughout each figure in the remainder of the chapter, which allows the reader to cross-reference different data sets based upon the same set of data.

4.2.1. Microbiological Sample Type

As shown in **Figure 4.2**, a majority of the 50 MIC failure assessments performed microbiological testing using liquid samples (52%), followed by solids (10%) and surface swabs (16%). In terms of best practices, swabbing at or near the failure location is considered the most representative microbiological sample since MIC is highly dependent on activity happening at the pipeline surface. Microbiological sampling of solids is also considered a reasonable indicator if the sample is related to the corrosion location. Both swab and solid samples represent potential sessile microorganisms (those found to congregate at surfaces in the form of biofilms), while fluid samples can only identify planktonic (free floating) microorganisms in the system. While fluid samples are relatively easy to obtain, it has been shown that planktonic microorganisms do not necessarily represent sessile (surface) populations and should only be used as supplementary information [24,33,122–124].

It should be noted that a number of failure reports commented that no microbiological samples were collected due to the absence of liquid material on the cut-out pipe samples. In such cases, surface solids collection via swabbing is still a viable option for microbiological

assessment. However, in some cases, swab or solid sampling may not be possible due to poor preservation of the failure location, or possible disruption of the surface during the investigation (e.g., inadvertent cleaning to examine the corrosion defect). In these cases, fluid sampling may be the only option.

4.2.2 Microbiological Analysis Methods

In terms of microbiological testing methodologies, 34% of assessments used some aspect of newer MMM while 44% of the assessments used culture-based techniques including MPN or BART, as shown in **Figure 4.2**.

Of the MMM tests conducted, the Adenosine Triphosphate assay (ATP) was most commonly used (32%) followed by Quantitative Polymerase Chain Reaction (qPCR) at 10% and Next Generation Sequencing (NGS) at 6%. ATP measures microbiological activity in the system which is critical for MIC to occur. NGS measures microbiological diversity, which can identify a range of MIC related MFG present in any given sample, and is a key factor for identifying MIC as the links between microbiology and chemistry (both from potential corrosion products to energy sources and electron acceptors in the environment measured in other samples). qPCR measures the abundance of a particular microorganism or functional gene present in a sample and it may be a good indicator of the MIC related microorganisms that are most likely responsible for the observed corrosion. In terms of portability, ATP assays can be performed in the field [129], while qPCR and NGS testing are still moving to be more portable and are mostly conducted in a laboratory setting. However, results from ATP tests only represent microbiological activity at one specific point in time (i.e., one value does not

indicate historical activity). In all three cases (ATP, qPCR, and NGS), tests should be conducted on actual or preserved samples as soon as possible to ensure representative results.

DNA sequencing of 16S ribosomal RNA (rRNA) genes via NGS allows for the identification of all bacteria and *archaea* present in the system, while qPCR of functional genes uses primers targeted to specific MFG based on their metabolic pathways [23,25]. When it comes to assessing microbial diversity, activity and abundance to diagnose MIC, MMM outputs reliable results that can be linked to other layers of evidence, such as corrosion products and environment chemical composition [21,26,128–136].

Of the culture-based methods conducted, the determination of MPN via serial dilution was most common (40%) with only a few of the assessments using BART (4%). MPN and BART both identify the presence and quantity of specific microorganism groups or traits (e.g., slime forming bacteria) based on their response to conditions in the culture medium. Many third-party consultants and test labs are familiar with these methods, and prefer them due to availability, low cost and ease of use (e.g., they do not require sophisticated equipment for analysis). Culture-based methods can also provide some clues regarding the operating environment inside the pipeline if properly linked to other layers of evidence (such as chemical, corrosion and/or operating data). However, the main challenge with culture-based methods is the fact they can only identify a limited number of MIC related microorganisms based on selective growth media available. As a result, they may not be able to characterize the full diversity of the actual microbiological community present in the sample [23]. By contrast, MMM-based NGS has a distinct advantage in that it can provide a full analysis of the microbial community present in any given sample. This does not preclude the use of culture-based methods; however, there is a possibility that some MIC related microorganism present

in the system are not being properly identified (i.e., false negatives due to a lack of selective media for a particular microbial function group). Another challenge with culture-based methods is that they do not distinguish between active and dormant microorganisms in the actual environment since all living microorganisms (whether active or dormant) can grow during lab-based culturing. Conversely, commercially available ATP assays currently only identify those microorganisms that are active (and not dormant) at the time of testing.

The difference between MMM and culture-based methods in their ability to measure microbiological diversity can be clearly seen in **Figure 4.3** for each of the MIC failure incidents studied. Note that the figure only represents the types of tests conducted, not necessarily the microorganisms that were found. Those assessments that used MMM (NGS and qPCR) were able to distinguish a wide range of possible MFG, including sulfate reducing bacteria, sulfate reducing *archaea*, thiosulfate reducing bacteria, methanogenic *archaea*, acid producing bacteria, nitrate reducing bacteria, sulfate oxidizing bacteria, iron reducing bacteria, iron oxidizing bacteria, manganese reducing bacteria, and manganese oxidizing bacteria. Conversely, those failure assessments that used culture-based techniques were only able to test for a limited number of MIC related microbial functional groups (e.g., APB, SRB). The list of culture-based tests; however, also includes assays for a number of broad groups of microorganisms, such as aerobic (AERO), anaerobic (ANA), iron related bacteria (IReB), low nutrient bacteria (LNB), slime forming bacteria (SLYM), and heterotrophic anaerobic bacteria (HAB). While these media may provide some additional information on the pipeline environment, they have limited use in assessing MIC directly as they are not specific to MIC related microorganisms. Historically, these general groups were often characterized to compensate for the limited ability to identify the microbiological diversity of MIC species.

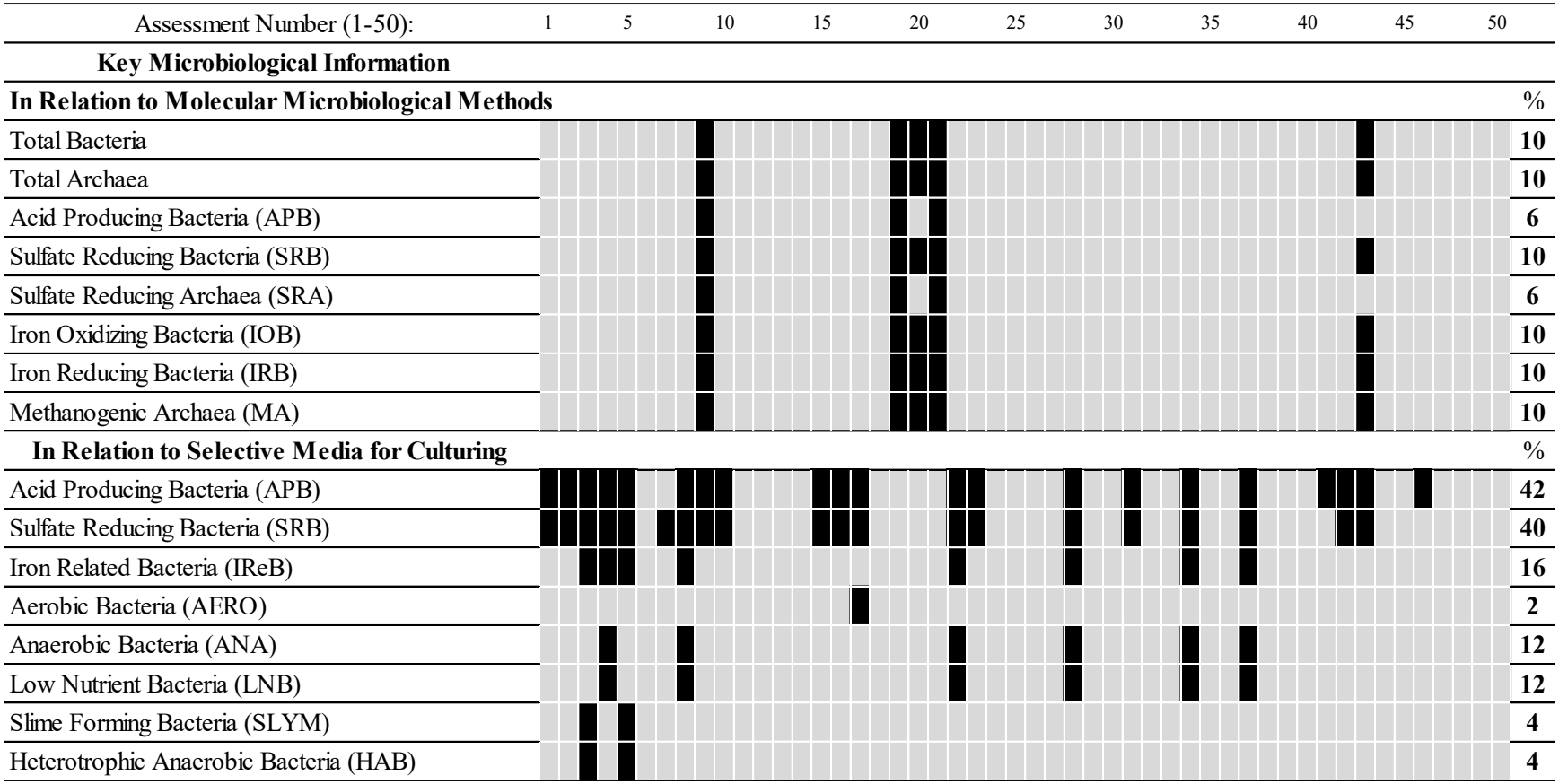

Figure 4.3 Contrast between the microbial functional groups (MFG) identified by molecular microbiological methods and culture-based methods for each of the failure assessments reviewed (1 thru 50).

The intent was to look for other traits that could suggest the presence of microorganisms in the system. With the increasing availability (and declining cost) of more comprehensive Microbiological Molecular Methods, these assays are not as relevant today.

In terms of microorganisms linked to the failure assessments reviewed, 60% of all failure incidents examined were attributed to either SRB and/or APB, while the remaining 40% of assessments diagnosed MIC without identification of any specific MFG. Instead of using available microbiological tests, such as serial dilution, qPCR or NGS, some of these latter assessments inferred MIC related MFG or mechanisms based on either chemical analysis of the corrosion products (26%) or visual analysis of the pitting morphology (12%). While analysis of corrosion products is an important step in confirming specific MIC mechanisms, it alone cannot give a conclusive diagnosis of MIC without other layers of evidence including microbiological diversity data. Conversely, correlating corrosion morphology with specific MFGs has been shown to be inconclusive since common MIC morphologies can also be associated with abiotic corrosion mechanisms [15,22,23,60]. It should be pointed out that a number of these MIC assessments based solely on corrosion products or morphologies, also conducted ATP measurements to confirm the presence of microbiological activity in the system. However, ATP results are unable to confirm whether any of the “active” microorganisms detected are in fact, MIC related.

4.3 Reported Chemical Analysis Data

Chemical analysis data can validate or invalidate MIC as a viable failure mechanism. The hypothesis is based on the contrast between corrosion products (e.g., solids) and the corrodents present in the water and in the gas. Therefore, the chemical composition of solids,

liquids, and gases should be known in order to answer to what extent the environment supported either microbiological processes or abiotic mechanisms (e.g., CO_2, H_2S).

Figure 4.4 lists the chemical compounds tested in the different MIC failure assessments for solids, liquids and gases. As **Table 4.2** displays, 92% of the failure assessments gathered some sort of chemical data; supporting the importance of chemical considerations for a conclusive failure diagnosis and also demonstrating a better industry familiarity with abiotic drivers.

The importance of chemical evidence to the MIC investigation framework is twofold: (1) it indicates the abiotic and biotic potential for corrosion by comparing dissolved chemical species in the water and in the gas with those found in the corrosion products; and (2) it provides evidence for linking microbiological diversity with corrosion products and dissolved nutrients (i.e., energy sources and electron acceptors) in the water.

4.3.1 Reported Solids Data

Identification of corrosion products is used as evidence to show that a corrosion process took place. In order to track whether the source of corrosion products is abiotic or biotic, their composition is contrasted to the chemistry of the water and the gas in the system, along with microbiological community characterization. As **Figure 4.4** shows, 82% of incidents provided characterization of solids, either by qualitative chemical spot testing (66%), elemental analysis (46%, Energy Dispersive X-ray Spectroscopy [EDS]) and/or mineral analysis (42%, X-Ray Diffraction [XRD]). Spot testing was most routinely performed due to its simplicity and low cost. Qualitative spot testing is commonly used as a high-level

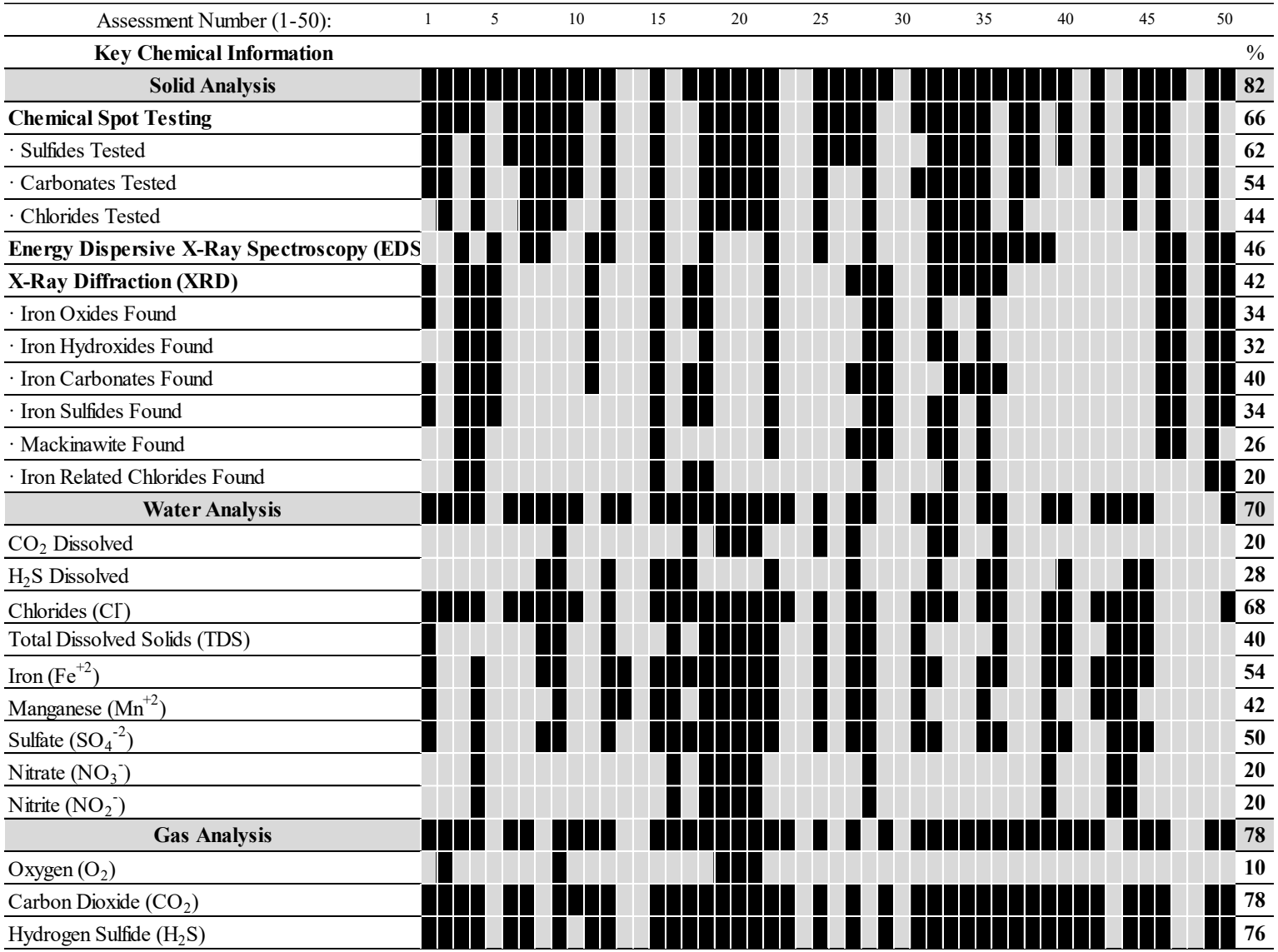

Figure 4.4 Inclusion of specific chemical information and analysis methods for each of the failure assessments reviewed (1 thru 50).

screening step to identify expected corrosion products and was used to check for sulfides (62%), carbonates (54%), and chlorides (44%).

EDS and XRD analyses of solids provide more specific evidence than spot testing as EDS identifies the chemical species at an elemental level (e.g., sulfur, carbon, oxygen, iron, calcium, etc.), while XRD identifies crystalline (e.g., oxides, carbonates, sulfides, etc.) compounds [137–139]. Iron carbonates (40%) and iron sulfides (34%) were the compounds most found by XRD. Mackinawite, an iron sulfide compound, was found in 26% of the failure assessments, accounting for 13 of the reviewed incidents. In 11 of these incidents, SRB were diagnosed as a contributing cause, showcasing how strongly SRB driven MIC is currently attributed to the presence of mackinawite. The correlation between mackinawite as a corrosion product and SRB is believed to be more significant when the system is known to have no obvious sources of hydrogen sulfide (the main abiotic cause of iron sulfide formation).

4.3.2 Reported Water Data

Water soluble chemical species are both the source of nutrients for microbiological activity and potential abiotic corrosion drivers. The evaluation of the water content and composition provides a means to track the source of corrosive constituents and corrosion products and, therefore, to add discrimination as to whether the corrosion is driven abiotically or biotically. Chemical analysis of water samples, present in 70% of the incidents, was used less as evidence of corrosion as compared to solids analyses, 82% (**Figure 4.4**). Although 68% of failure assessments tested for chlorides, only 20% tested for dissolved CO_2 and 28% for dissolved H_2S in the water.

None of the failure assessments tested for O_2 dissolved in the water, most likely because production pipelines are anaerobic environments where CO_2 and H_2S, along with chlorides, are the most significant drivers for abiotic corrosion and oxygen is rarely present. Yet, the presence of oxygen should be taken into consideration, as it can be more corrosive than both CO_2 and H_2S [140] and its concentrations may lead to shifts in MIC potential and microbiological community populations [141,142].

Chloride concentration can also impact MIC in terms of both limitations on growth and the diversity of microorganisms present [137–139]. Therefore, the presence of dissolved chlorides, which contributes to the salinity and the total dissolved solids (TDS) of the water, may help indicate to what extent MIC is a viable failure cause.

In regard to both CO_2 and H_2S corrosion, the levels of these species in a flowing system can give some initial indication of whether there is an abiotic contribution to the corrosion. The presence of dissolved CO_2 and H_2S in water is a function of their concentration (partial pressure) in the gas and system pressure (Henry's law), along with water chemistry. Hence, based on corrosion rate modeling, the CO_2 and H_2S levels provide abiotic corrosion rates that can be used as a starting point for assessing a possible abiotic origin of the corrosion. In contrast, very low gas flow rates or stagnant systems may experience local accumulation of high concentrations of CO_2 and H_2S that are biotically produced. The considerations made by the reviewed failure assessments regarding the relationship between CO_2 gas and H_2S gas to the solids associated with them is discussed later in this chapter.

The concentration of both CO_2 and H_2S in the water indicate to some extent the potential of these corrodents to drive the corrosion process (abiotic) as compared to MIC (biotic). Carbon dioxide is required for the activity of some microorganisms, such as

methanogenic *archaea* and acetogenic bacteria [143,144]. In flowing systems where CO_2 is abundant, iron carbonates will tend to form abiotically. In stagnant systems, consumption of carbon dioxide by microorganisms can result in an increase in both bicarbonate and carbonate alkalinity, along with pH, which can cause precipitation of carbonate minerals (e.g., iron carbonates). Enning and Garrelfs 2014 [30] mention a case where electrical MIC (EMIC) by SRB also can result in iron carbonate precipitation.

On the other hand, the presence of sulfidic corrosion products can be more meaningful evidence to differentiate biotic from abiotic corrosion. Mackinawite formation is associated with the same environmental conditions in which SRB and SRA can be present [145–147]. Therefore, the presence of mackinawite may be considered a potential indicator of the contribution of SRB and/or SRA to the corrosion process when they are found to be present in the system; while other iron sulfide forms (e.g., troilite, pyrrhotite, pyrite, marcasite, greigite, etc.) indicate either abiotic H_2S corrosion or potential decomposition of mackinawite [60] or other iron sulfides. Hence, when H_2S is not present in the gas (and consequently not dissolved in the water) but iron sulfides are present, that can be a significant indication that SRB and/or SRA may be contributing to the degradation process, since there is no apparent source for sulfide formation except for microbial activity. However, when H_2S is present, this comparison becomes more complex, as there are now two potential sources for iron sulfide formation. One way to discriminate between biotic and abiotic sulfidic corrosion products is by comparison of stable S isotope ratios [148–150]; however, this was not observed to be common practice.

Regarding dissolved chemical species that influence MIC, electron acceptors/donors (e.g., Fe, Mn, S, SO_4^{2-}, NO_3^-, NO_2^-, etc.) are of particular importance [36,140] as they may

represent a limiting factor for microbial growth in oil and gas systems. Therefore, their presence indicates to what extent the operating environment could support the microorganisms identified (diversity) and their potential activity. However, while electron donors/acceptors were used as indication for abiotic potential, the reviewed failure assessments overlooked the ability to use this evidence to support MIC as a credible failure cause.

In terms of carbon that can be used as energy source by microorganisms, as the reviewed pipeline environments handle hydrocarbons, some form of carbon will nearly always be present for microorganisms to metabolize [134,145,146]. Additionally, oilfield chemicals related to production, drilling, completion, hydraulic fracturing can also work as sources of carbon and nutrients.

While 52% of the failure assessments concluded the failure to be SRB driven (either due to microbiological, chemical, and/or metallurgical/corrosion related evidence), and 50% tested for SO_4^{2-} (**Figure 4.4**), only 24% of the cases both tested for SO_4^{2-} and concluded the failure to be SRB driven. Therefore, as sulfate was not considered in many cases as an essential electron acceptor for SRB activity, this identifies a current shortcoming in the approach to water composition evidence to support a MIC diagnosis.

Hence, for the chemical species listed in **Figure 4.4**, it is possible that relevant chemical data were assessed in some cases; however, some failure assessments missed the opportunity to use the information to support the MIC diagnosis.

4.3.3 Reported Gas Data

Gas concentration is used with operating pressure to determine the partial pressure of each gas present. The partial pressure of some gases allows one to assess to some extent whether abiotic drivers are reasonable contributors to the corrosion process or not [151].

In respect to gas analysis, 78% of failure assessments determined gas compositions (**Figure 4.4**). CO_2 and H_2S were tested in 78% and 76% of the time, respectively, as they are the main drivers for abiotic corrosion in anaerobic oil and gas systems [152]. As these compounds were tested in the gas, that may explain why they were not as extensively tested in water samples.

4.4 Reported Metallurgical/Corrosion Data

Evidence of metal loss as supporting proof of corrosion was gathered in 98% of failure assessments reviewed (**Table 4.2**). Visual features related to pipe wall loss due to chemical and/or microbiological reactions are the first indicators of corrosion degradation. It is the contrast of microbiological (diversity, activity, abundance), chemical and operating factors between the corroded and non-corroded areas that best helps determine the failure mechanism.

Figure 4.5 displays the metallurgical/corrosion data gathered by the failure assessments reviewed. Only 42% of failure assessments had samples analyzed from the failure/corrosion location. In respect to MIC, the comparison between the evidence at the failure/corroded area and the non-corroded area is essential. MIC is biofilm dependent, therefore, it is highly localized [23,34,147–152]. Consequently, diversity, activity and abundance results may vary considerably between the corroded area and the non-corroded area when MIC is the cause of failure.

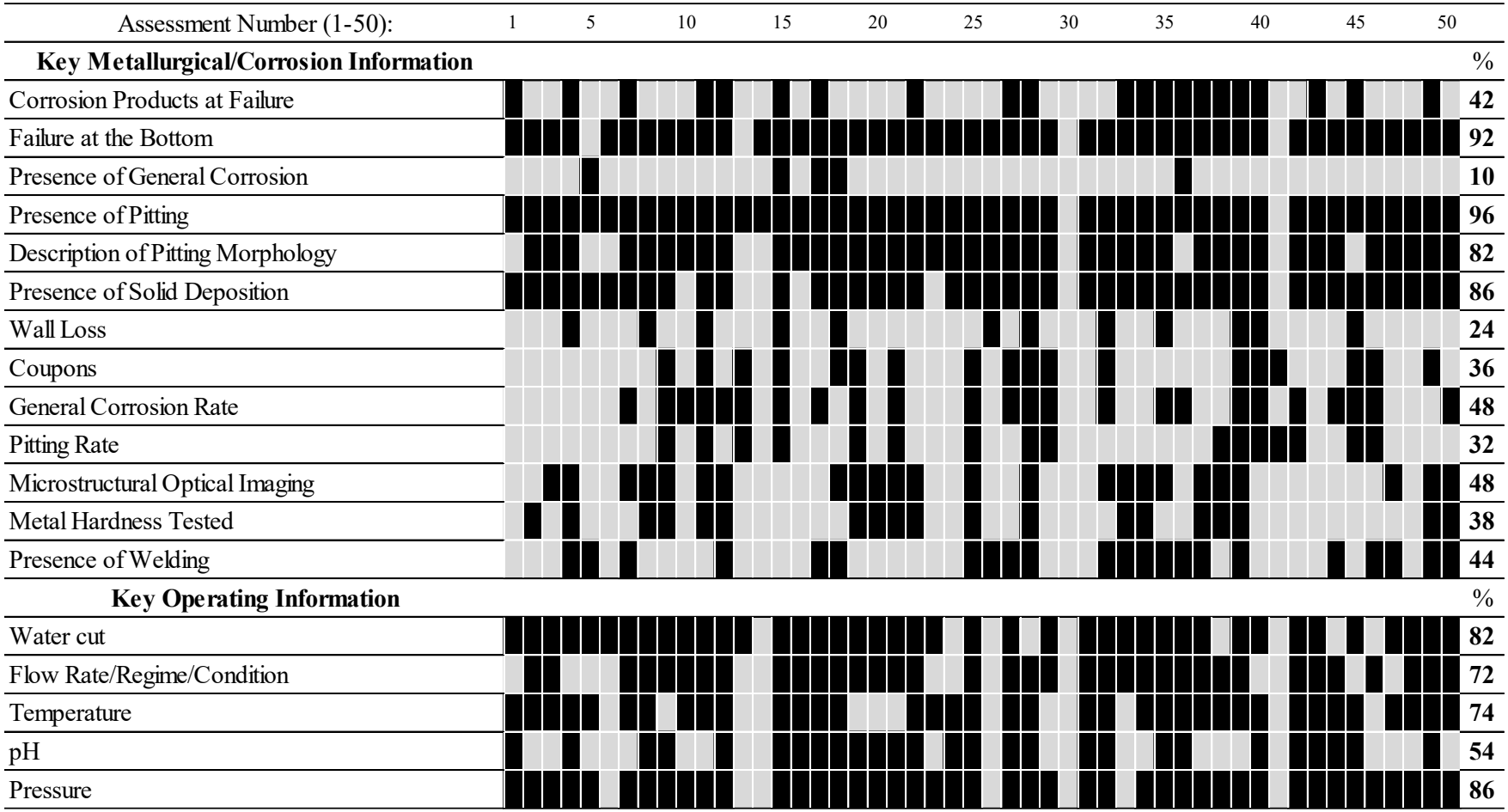

Figure 4.5 Inclusion of specific metallurgical/corrosion and operating information and analysis methods for each of the failure assessments reviewed (1 thru 50).

Additionally, although ruptures account for only 3% of the incidents in Alberta between 2017 and 2019 (**Table 3.1**) and no rupture was caused by MIC between this time period, the effect of ruptures can affect the validity of MIC failure samples. Sometimes damage by post rupture events (e.g., leak, fire, ignitions, groundwater intrusion in underground pipes) affect the substance at the through-wall perforation where the leak originates, which causes the evidence no longer to be representative. Hence, when evidence at the leak site is compromised by post rupture events, sampling from a nearby corroded area (where corrosion products are still present in the pits) is a valid strategy to obtain undisturbed representative evidence.

In terms of corrosion, pitting was the dominant feature, present in 96% of incidents, while general corrosion was present in only 10% (and always in conjunction with pitting). The vast majority (92%) of the failure assessments identified that the failure occurred at the bottom half of the pipes, which may be interpreted as demonstrating the contribution of water accumulation on the degradation process.

Pitting morphology was described in 82% of the failure assessments, showcasing how strongly diagnoses take this layer of evidence into consideration. MIC was reported to be associated with tunneling, undercutting, pits within pits ("bulls' eye" appearance) and faceted pitting morphologies, even though pitting alone is not diagnostic for MIC as it cannot be related to a unique type of MIC morphology [20,57,147].

Solid deposition (e.g., deposits, scales, corrosion products, biomass) on the pipe surface was identified by 86% of failure assessments. However, no clear distinction between deposits, scales and corrosion products was made and such terms were used interchangeably.

General corrosion rates were estimated in 48% of failure assessments, either as part of the third-party failure report (where the wall loss was measured and divided by the length of time the pipe was operating) or as provided by coupon monitoring results. Averaging corrosion rates over the entire life of an asset may be non-conservative, as higher corrosion rates may have initiated later in the asset life when conditions changed.

Coupon monitoring, corrosion pitting rates and general wall loss, either from previous inspection or from examination of the pipe sample, were pieces of information included in 36%, 32% and 24% of the failure assessments, respectively. MIC is known to occur at unpredictably high rates, being normally associated with “premature” failures. However, when a leak occurs on a pipeline that is 30 years old, there is no way to determine when the corrosion began and therefore a linkage between corrosion rate and MIC is unfeasible.

Metallographic examination of the failure cross-section surface and metal hardness testing were assessed in 48% and 38% of the failure assessments, respectively. Based on these two factors, none of the cut outs were deemed to be out of specification. However, neither spectrographic analysis for chemical composition nor mechanical strength testing (e.g., tensile strength, yield strength, percent of elongation) were carried out to augment material compatibility verification for comparison with pipe manufacturing specifications.

In terms of welding, electric resistance welding (ERW) seams and/or girth welds were present in 44% of the failure assessments reviewed. Aside from one specific case where MIC was directly related to the welding position due to the presence of morphological features (e.g., tunneling and undercutting) over the weld line, MIC was not associated with welding features in the reviewed failure assessments. Although 4 cases tested for the hardness of the

weld heat affected zone (HAZ), no failure assessment included a cross-section of the weld to evaluate the potential influence of weld microstructure on the failure.

4.5 Reported Operating Data

Operating parameters serve to validate (or invalidate) either MIC and abiotic failure mechanisms. The corrosion products and microorganisms (e.g., metabolic functional groups) identified are correlated with operating conditions in order to determine which corrosion mechanisms (biotic, abiotic or both combined) could be supported.

Operating parameters (e.g., temperature, pH, flow velocity, oil/water wetting) not only are some of the most influential parameters towards pipeline internal corrosion [36] in general, but also play a major role in MIC as they influence the activity and abundance of the MFG (diversity) present in the system. Consequently, operating data may rule out MIC if historical temperature, pH and water accumulation do not support MIC as a credible failure cause.

Figure 4.5 displays the operating data gathered by the failure assessments tabulated. Water cut and flow conditions were gathered by 82% and 72% of failure assessments, respectively. Although MIC is directly related to the presence of water (biofilm formation and corrosion requires water wetting on the metal surface), water data was not significantly correlated to the potential for MIC.

Temperature and pH were reported in 74% and 54% of the failure assessments, respectively. pH was either calculated or measured as a part of the water analyses. The fact that pH is a parameter not as readily available as temperature explains its lower percentage. Even though specific ranges of temperature and pH have an effect on microbiological

proliferation [41,128], no failure assessment took these two parameters into account as supporting evidence to diagnose MIC.

Similarly, pressure was not explicitly linked to either biotic or abiotic conditions, although 86% of failure assessments gathered such information. Pressure is relevant when combined with gas composition. The partial pressure of H_2S and CO_2 provides some degree of aid to determine if these abiotic corrosion drivers are expected to contribute to the failure.

4.6 Integration of Data

Although not an information group per se, data integration is a key element for effective MIC failure analysis, as no information group is diagnostic on its own; a consequence of the multidisciplinary nature of MIC. Therefore, only by adequately integrating multiple layers of evidence (microbiological, chemical, metallurgical/corrosion, and operating factors), is it possible to conclusively diagnose MIC as the failure cause with the technologies currently available.

Figure 4.6 shows the integration steps taken into consideration by the reviewed MIC failure assessments. The top of **Figure 4.6** tabulates the microbiological data considered for the diagnosis of the failure assessments reviewed. In the middle of **Figure 4.6**, the chemical considerations used to either validate or invalidate MIC (diversity and abiotic drivers contrasted to corrosion products, water and gas) are tabulated. And finally, on the bottom of **Figure 4.6**), the considerations regarding metallurgical/corrosion and operating are included. data.

Although microbiological activity was tested for 32% of failure assessments (**Figure 4.2**), only 10% of assessments considered that activity in their MIC diagnoses. Similarly, 10%

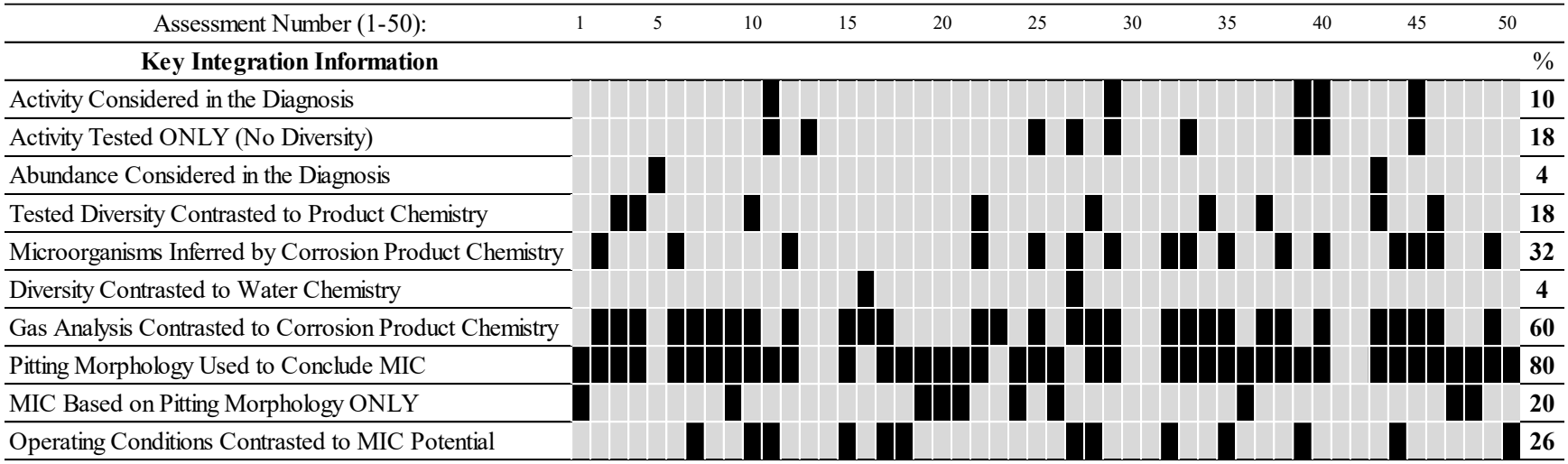

Figure 4.6 Inclusion of key integration steps for each of the failure assessments reviewed (1 thru 50).

of failure assessments tested for microbial abundance (**Figure 4.2**), but only 4% used abundance as an integration piece. It has been stated that no layer of evidence (microbiologically related or not) is diagnostic on its own. However, ATP activity was used as the sole layer of microbiological evidence for 18% of the failure assessments. Therefore, as microbiological evidence is not as frequently used for integration (**Figure 4.6**) as it is gathered (**Figure 4.2**), it is reasonable to say that the use and integration of microbiological evidence to draw a conclusive diagnosis is yet not fully understood. Therefore, the significance of microbiological evidence in the MIC diagnosis is under appreciated. This lack of appreciation results in the statistical mismatch observed between **Figure 4.6** and **Figure 4.2**.

Microbiological diversity was gathered either by culture-based techniques or MMM (**Figure 4.2** and **Figure 4.3**). However, only 18% of failure assessments compared microbial diversity to corrosion product chemistry. More than twice as many failure assessments, 38%, inferred a contribution by APB and/or SRB either from carbonate and sulfide corrosion products, respectively, or due to corrosion morphology; without any evidence of microbiological diversity to support the conclusions.

In terms of solids chemistry and microbial diversity integration, the reviewed failure assessments strongly related mackinawite to SRB, particularly when the gas composition analysis found no H_2S to be present. As a result, the identified sulfides were assumed to be of biotic origin. A similar rationale was used for APB when CO_2 was absent: the presence of iron carbonate (siderite) was the key evidence for assuming the participation of acid producing bacteria in the failure. However, the relationship between APB and siderite finds no support in the literature as it currently stands, as siderite formation is a function of abiotic CO_2 corrosion

[153], rather than APB driven MIC. APB participation in MIC is usually associated with production of organic acids, not CO_2 or siderite.

The correlation between the composition of the gas and the composition of the solids was the strongest piece for integration used in the reviewed failure assessments and it was used to either conclude or invalidate the role of MIC. When corrosion products were present in the absence of their abiotic drivers, MIC was concluded as the failure cause. Additionally, the extent of contribution by specific damage mechanisms in the degradation process was directly related to the amounts of their respective mineral corrosion products (XRD) in the solids.

The significance of water chemistry and operating conditions to the MIC diagnosis were in general overlooked in the reviewed failure assessments. In regard to water chemistry and microbial diversity evaluation, only 4% of failure incidents linked nutrient availability to microbiological potential; despite the fact that 70% of failure assessments had water composition data in their records. Operating conditions (temperature, pH and the potential for water accumulation) were taken into consideration in 26% of failure assessments for the MIC diagnosis. The majority of the cases related to water settlement and how this factor is conducive to MIC. The low percentage of nutrient availability and operating conditions being considered in the failure assessments indicates that the importance of integrating supporting conditions to the potential for MIC is yet being overlooked in the MIC diagnosis.

Metal loss features were frequently associated with MIC diagnosis. In fact, out of the 45 cases (90% of the total 50 assessments reviewed) that made some sort of integration between the different information groups included in the diagnosis, 30 used pitting morphology as supporting evidence to conclude MIC as the mechanism, along with other

complementary layers of evidence. In fact, 10 (20% of the 50 total) of the cases reviewed used pitting morphology as the *sole* diagnostic evidence to conclude MIC, even though MIC has no unique morphological fingerprint.

As per **Figure 4.6**, pit morphology (80%) and the comparison between gas composition and corrosion product chemistry (60%) were the two layers of evidence most often considered in the reviewed failure assessments to diagnose MIC. Consequently, it can be concluded that although the reviewed failure assessments did a fair job in terms of integrating the data gathered, there are still gaps related to integration that must be addressed to increase the reliability of MIC diagnoses.

4.7 Sampling and Preservation

Sampling and preservation have a marked importance in the validity of the analytical data used to diagnose MIC. Microbiological and chemical changes to samples take place over time and as soon as the samples are exposed to air. Since the chemical and microbiological conditions must be integrated to identify MIC, significant misconclusions can occur if potential shifts in microbiological community and/or degradation of corrosion products after sampling are not taken into consideration [128,134].

Figure 4.7 displays factors that influence validity of microbiological and chemical samples in terms of time of sampling and analysis. Assessing the time between the failure, sample collection and sample analysis can provide aid to determine the degree of degradation that a sample may have undergone. Only 12% of failure assessments explicitly mention cut out dates and even fewer, 8%, mention when the cut-out sections were received for analysis. Consequently, only the 4% of failure assessments (which recorded the dates of the incident,

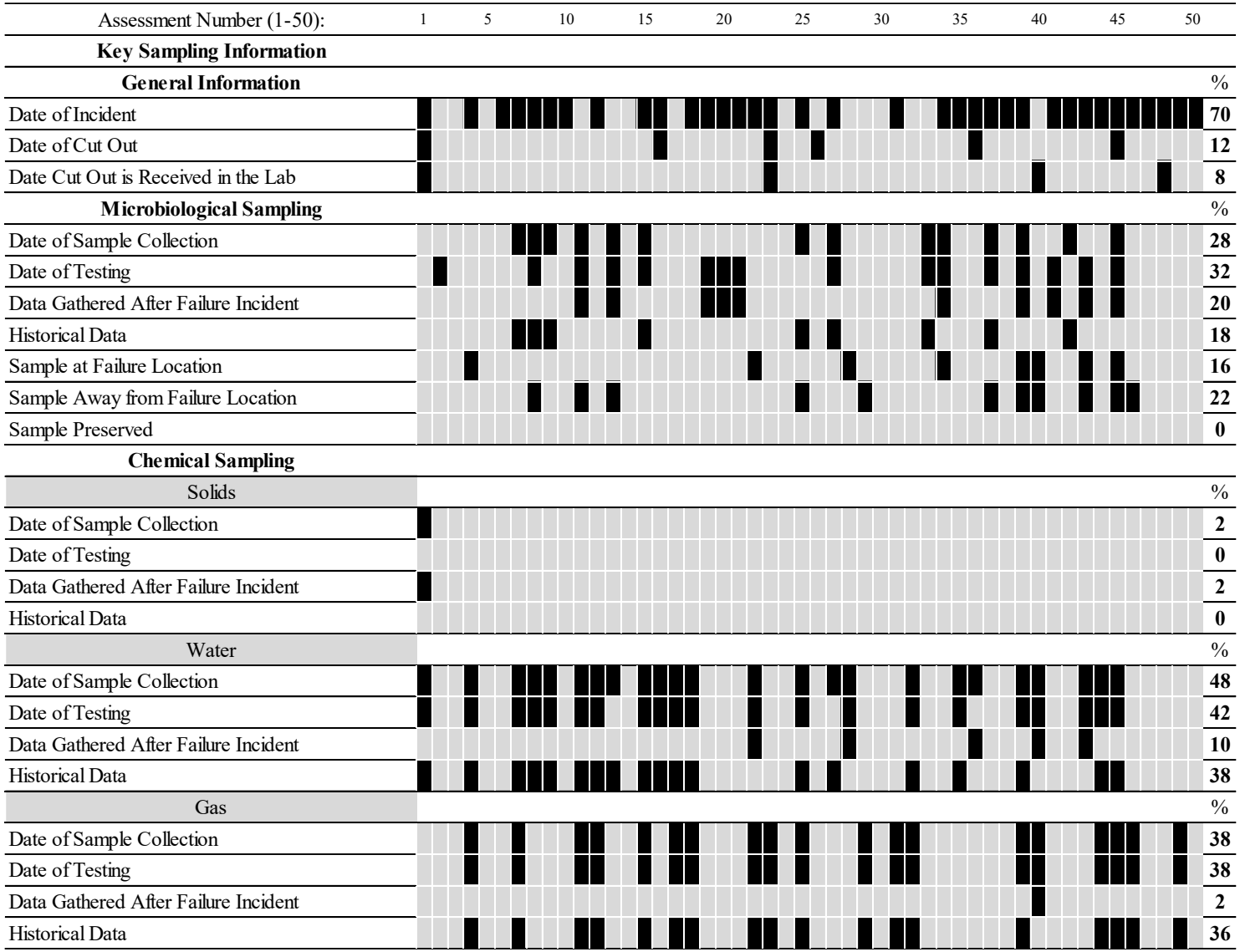

Figure 4.7 Inclusion of specific sampling considerations reported for each of the failure assessments reviewed (1 thru 50).

the cut out, and the lab analysis) would be able to evaluate to what degree the effect of time may have shifted sample characteristics.

Based on the failure assessments that recorded the date when pipe sample cut outs were received for analysis, it was observed that cut outs take from up to 3 days to be received by the third-party failure consultants after being cut, and may take between 10 to 18 days to be received by the third-party failure consultants after the failure date. Despite these delays in sampling and analysis, which could have been enough for significant shifts in both chemical and biological related evidence, no considerations to sample validity were mentioned in the reviewed failure assessments.

In respect to microbiological sampling, only 28% of failure assessments reported the date of sample collection and only 32% indicated the date of testing. Additionally, 18% of failure assessments considered historical microbiological data (as tests were run prior to the failure as part of monitoring programs) while 20% of the cases gathered microbiological data after the failure dates.

Additionally, out of the 16% of failure assessments that had samples taken near the failure location and 22% that had samples taken distal from it, only 8% had samples taken from both locations. Therefore, only 8% of the failure assessments would be able to make a comparison between microbiological diversity, activity, and abundance at the location of the corrosion failure and distal from it (where corrosion was not present); voiding the ability to more accurately determine to what extent MIC was a driver of the corrosion.

In terms of sample preservation, none (*0%*) of the incidents indicated they preserved the samples and no preservation related comments were made in the cases reviewed. Consequently,

the lack of information on preservation decreases the confidence in the final diagnosis, as considerations about sample validity are precluded.

In respect to chemical samples, only one incident mentions the date for solid sample collection, which occurred 33 days after the incident. In terms of water samples, out of the 48% of failure assessments that recorded sampling dates, 10% included dates for samples collected after the incident, which varied between 0 to 36 days. The other 38% of failure assessments took into consideration the results of water samples taken over a variety of time periods prior to the incident. Those taken closest to the time of the incident varied from 3 to 7 months after, while others varied from 1 to 3 years and the most extreme were taken 5 to 9 years prior to the leak.

Regarding gas sampling, out of the 38% of failure assessments that mention sampling dates, only 2% were taken after the incident (32 days after). The other 36% of failure assessments were taken at a variety of time periods prior to the incident. Those closest to the incidents varied from 2 to 10 months, while others varied from 1 to 3 years and the most extreme were taken 5 to 8 years prior to the leak.

Therefore, in most cases both water (38%) and gas (36%) chemical considerations are based on historical evidence, as the information taken into account was collected prior to the incident. In cases where it was unfeasible to collect a reliable sample at the time of failure due to post rupture events, it is reasonable to utilize chemical samples gathered prior to the incident, as they will tend to more accurately represent the conditions at the time of the failure.

Craig 2002 [137], Eckert 2003 [60], Larsen et al. 2008 [130], Kilbane 2014 [154], De Paula et al. 2018 [134], and Gieg et al. 2020 [136] discuss variations that both microbiological and chemical samples may undergo due to changes caused by sampling and preservation methods. Additionally, Price 2012 [155], Eroini et al. 2015 [156], and Eroini et al. 2017 [157]

provided suggestions in terms of sampling and preservation methods that could be used in order to avoid changes in sample composition during collection and transport.

4.8 Standards Referenced in the Failure Assessments

There are few standards that provide guidance on MIC sampling, testing and interpretation that have been published and updated over the years. NACE TM0194 [158] discuss MPN best practices and provides a high-level introduction to MMM. Conversely, TM0106 [159] and NACE TM0212 [160] are best practices dedicated to the use of MMMs to address both external and internal MIC, respectively.

However, only 22% of the reviewed failure assessments explicitly refer to the use of standards in their failure assessments. This number is even lower when it comes to microbiological standards. Only 4% of the failure assessments reviewed mentioned a standard dedicated to microbiological testing: NACE TM0194 [158]. No mention was either made to NACE TM0106 [159] or NACE TM0212 [160]. These low percentages may be one more indicator of the lack of familiarity of the sector with microbiological considerations, which are even more pronounced in relation to applying and interpreting MMM data. **Table 4.3** lists all the standards mentioned in the tabulated failure assessments and how often they were referenced.

Table 4.3 List of standards mentioned in the reviewed mic failure assessments.

Standard ID	Standard Title	Number of Mentions
	General	
ASTM E3[161]	Standard Guide for Preparation of Metallographic Specimens	7
NACE SP0775[162]	Preparation, Installation, Analysis, and Interpretation of Corrosion Coupons in Oilfield Operations	3
ASTM A370[163]	Standard Test Methods and Definitions for Mechanical Testing of Steel Products	2
ASTM D93[164]	Standard Test Methods for Flash Point by Pensky-Martens Closed Cup Tester	1
ASTM D422[165]	Standard Test Method for Particle-Size Analysis of Soils	1
ASTM E1404[166]	Standard Specification for Laboratory Glass Conical Flasks	1
	Microbiological	
NACE TM0194[158]	Field Monitoring of Bacterial Growth in Oil and Gas Systems	2

4.6 Conclusions

This chapter highlights a gap analysis of MIC failure investigation techniques based on a review of 50 failure reports submitted to the Alberta Energy Regulator (AER) over a three-year period (2017-2019). This gap analysis was performed to assess MIC failure investigation and analysis methods compared to current state-of-the art and best practises as determined by expert elicitation and recent literature. A total of 50 failure assessments/third party failure reports from MIC related pipeline failures in Alberta that occurred over a three-year period (2017-2019) were reviewed in detail to identify the information that was typically collected during these

assessments and how this information was used to confirm MIC as a cause. Specific analysis methods, collected data, and integration steps of key information groups (microbiological, chemical, metallurgical/corrosion, and operating data) were evaluated.

Overall, over 90% of the 50 MIC assessments reviewed included chemical data, operating data, metallurgical/corrosion data and integration steps, however, only *70%* of the MIC assessments reviewed conducted some sort of microbiological testing. In addition, only half of all assessments reviewed included tests to identify specific MFG, either using culturing methods or more advanced Microbiological Molecular Methods (MMM). This lack of identification of both diversity and abundance of specific microbial groups significantly reduces the confidence in a MIC diagnosis.

Furthermore, it was found that current failure assessments are not utilizing more modern microbiological (MMM) testing approaches, such as qPCR and Next Generation Sequencing. These advanced methods provide more robust datasets as compared to culture-based methods that can only identify a fraction of the possible MIC related microorganisms in a system. While MMM approaches are currently more expensive than MPN (but decreasing over time) their value can be justified by a more accurate diagnosis of MIC (and specific MIC mechanisms), which allows for improved selection of tailored mitigation approaches to prevent future incidents.

The lack of microbiological testing suggests that industry and the failure analysis community are most familiar with methods used for assessing abiotic corrosion mechanisms (e.g., CO_2 and H_2S corrosion in oil and gas systems). This is not surprising since most failure analyses are performed by materials/metallurgical engineers/technicians who are not specifically trained in microbiology, which is a significant challenge in the multidisciplinary field of MIC.

In terms of metallurgical analysis, a significant number of failure assessments diagnosed MIC solely based on corrosion products and/or pit morphology without identification of specific microbial functional groups (a requirement to confirm MIC). Those diagnoses based on corrosion products used chemical analysis to infer the presence of specific microorganisms, which cannot be conclusive without microbiological testing. While MIC most commonly manifests itself as localized corrosion (pitting), the use of morphological features alone (such as tunnelling and undercutting) has been refuted in current best practices and standards since these morphological features can also be created by abiotic (non-MIC) corrosion mechanisms. Again, microbiological testing is an indispensable step to help confirm MIC mechanisms.

In terms of integration of data, the biggest gap was found in the correlation of microbiological data with chemical, metallurgical/corrosion, and operating data to conclusively confirm specific MIC mechanisms, and to identify MIC as a primary or secondary contributor to the failure. In general, the integration of microbiological data (activity, diversity and abundance) along with the chemical composition of corrosion products, gas analysis and elimination of abiotic corrosion mechanisms, are the key pieces of information required to conclusively confirm MIC specific mechanisms.

Overall, this gap analysis highlights the need for further education and training with respect to diagnosis of MIC particularly with respect to microbiological methods, and integration of biotic and abiotic data to confidently confirm MIC. Standardized guidelines, protocols and analysis tools (e.g., online checklists) should also be developed to allow both specialists and non-specialists to better assess and diagnose MIC for both failure analysis and maintenance/integrity management activities. Finally, further work is also required to develop low-cost, rapid and easy-to-use microbiological diagnostic methods that can be handled in the field by both specialists and

non-specialists. These recommendations will go a long way to improve how the industry diagnoses and prevents MIC failures in the future.

Chapter 5: Development of an Expert System for Assessing Failures in Oil and Gas Pipelines due to Microbiologically Influenced Corrosion (MIC)

5.1. Introduction

Microbiologically influenced corrosion (MIC) is a degradation mechanism in oil and gas operations resulting from the activity of microorganisms. When MIC related microorganisms are present and active, they enhance local deterioration of pipelines and facilities by the formation of biofilms that may result in accelerated corrosion [1,2]. MIC is challenging to manage and prevent [167], mostly because it can result in unexpected, localized failures [59,63–65,70,168–171] with corrosion rates as high as 0.93-2.43 mm/year [167,172,173]. An example of this failure mode is highlighted in **Figure 5.1** which shows tubercles in the presence of localized (pitting) corrosion in a carbon steel tubing subjected to intermittent flow (i.e., a few hours a day) from an enhanced oil recovery (EOR) water injection well. The tubing depicted in **Figure 5.1** was inside a casing and in contact with produced water. A recent study by the authors analyzing corrosion failures of oil and gas pipelines over a three-year period (2017-2019) in the province of Alberta, Canada, found that MIC accounts for 13.6% of all internal corrosion failures, and 4.8% of all external corrosion failures [2]. In contrast, Kock et al. [18] mentioned that MIC is estimated to account for 20 to 30% of all corrosion in pipelines. Additional statistics also speak to the prevalence of MIC, but its occurrence has not been well quantified [2,9,12–18,20].

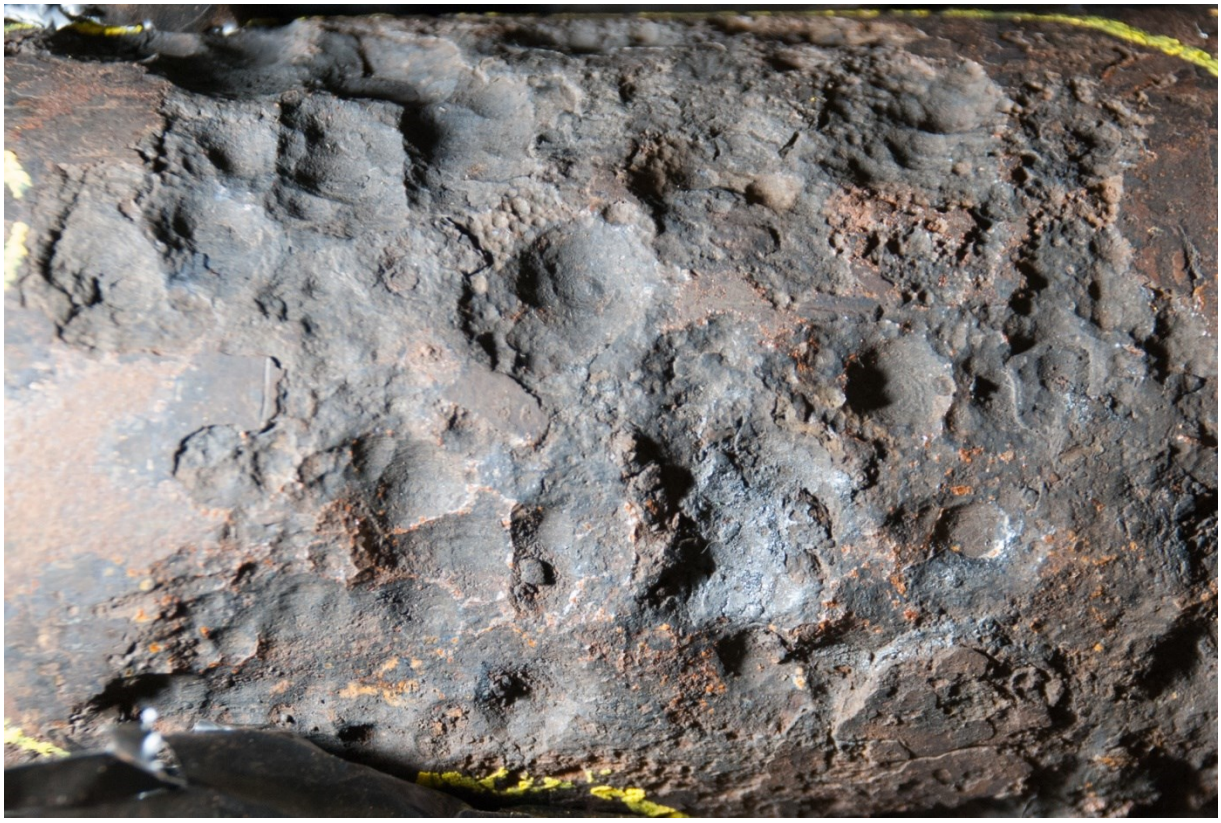

Figure 5.1 Presence of tubercles in conjunction with pitting degradation driven by MIC in a carbon steel tubing subjected to intermittent produced water flow.

In general, MIC is a complex corrosion mechanism, and a conclusive diagnosis requires data from at least four information groups: microbiology, chemistry, metallurgy/corrosion, and operating related parameters [26,174]. To fully cover the microbiological aspect of MIC, three microbiological parameters need to be assessed: diversity (speciation), abundance, and activity [1,38]. When evaluating the microbiological aspects of MIC, multiple types of microorganisms can be present in the system and can influence the corrosion process. The microorganisms involved in MIC are often classified into specific microbial functional groups (MFGs) based on the function that different nutrients will play in their metabolism. **Table 5.1** lists the MFGs (types of microorganisms) most commonly associated with MIC. Understanding the diversity of the microbial population allows for the

Table 5.1 Microbial functional groups most commonly associated with MIC and their nutritional requirements and byproducts – adapted with permission from DNV: DNVGL-RP-G101, Recommended Practice Risk-based inspection of offshore topsides static mechanical equipment, Copyright (2021) [1].

Microbial functional group (MFG)	Metabolic input	Metabolic output
SRB Sulfate-reducing bacteria SRA Sulfate-reducing *archaea*	Organic and aromatic compounds, hydrocarbons, alcohols, lactate, acetate, H_2, SO_4^{2-}, S^0, $S_2O_3^{2-}$	H_2S, sulfide (HS^-), iron sulfide (FeS)
MA Methanogenic *archaea*	Organic compounds, CO_2 (or soluble CO_3^{2-}, HCO_3^-, H_2CO_3) or H_2	Methane (CH_4), carbon monoxide (CO)
NRB Nitrate-reducing bacteria	Organic compounds, O_2, NO_3^-,	NO_2^-, N_2O, NO, N_2
IRB Iron-reducing bacteria	Fe^{3+} (insoluble ferric iron), O_2, NO_3^-,	Fe^{2+}
APB Acid-producing bacteria	Organic compounds, hydrocarbons, O_2	Organic acids (e.g., formic, acetic), CO_2
SOB Sulfur-oxidizing bacteria	Sulfide, sulfite, S^0 (elemental sulfur), $S_2O_3^{2-}$ (thiosulfate), organic compounds, O_2, CO_2	H_2SO_4 (sulfuric acid), S^0
IOB/MnOB Iron/Manganese-oxidizing bacteria	Fe^{2+} (soluble ferrous iron), Mn^{2+}	Fe^{3+}, Mn^{4+}

integration of microbiological information and abiotic data (i.e., chemical-, metallurgical/ corrosion-, and operating-related information). Furthermore, microorganisms need to be both abundant and active in the system for MIC to occur. As such, the potential for MIC can be determined by the presence of active and abundant MFGs and a supporting environment conducive to biofilm formation (i.e., fluid chemistry, operating conditions). For example, a group of sulfate-reducing bacteria (SRB) in combination with acid-producing bacteria (APB) and methanogenic *archaea* (MA) will tend to pose more of a MIC threat than APB alone, as the synergy between SRB, APB, and MA may compensate for nutritional limitations of the environment [32,33,57,144]. Consequently, the integration of MFG characterization with abiotic data is paramount for a reliable MIC failure assessment, and it is directly related to the potential for MIC leading to a failure.

The confidence in the microbiological data will depend on the testing method carried out to evaluate diversity, abundance, and activity. Molecular microbiological methods (MMM) which are based on the evaluation of the DNA and/or the enzymes associated with the microorganisms present in the system tend to provide greater confidence when contrasted with culture-based media for testing. Culture-based media related methods such as most probable number (MPN) and biological activity reaction test (BART) depend on media selection and incubation times and temperatures, which have been found to evaluate only up to 15% of the viable microorganisms [130,175].

The chemical characterization in a MIC failure assessment encompasses the testing of constituents present in the system which includes any liquids (e.g., the water phase and the chemical species dissolved in it; the oil phase and the carbon species present in it), gases (e.g., presence and compositions of CO_2, H_2S, hydrocarbons) and/or available solids (e.g., wax, sand,

deposits, corrosion products) [2]. As certain chemical constituents associated with MIC are also associated with abiotic corrosion mechanisms [60,145–147], identifying the source of chemical constituents in the system is essential to add confidence to the discrimination between MIC and abiotic corrosion drivers [26].

Characterization of the metallurgy of the failed pipe or vessel allows the investigator to assess the susceptibility of the specific material of construction to the different MIC related degradation mechanisms. This will depend on material composition, manufacturing process, and assembling/construction processes (e.g., welding) [56,58,169,171]. Furthermore, corrosion surface features (i.e., morphology, failure position), corrosion products, and their spatial relationship are also required to properly assess MIC. Information from both corrosion and chemical testing can also help differentiate whether the failure mechanism is due to biotic (MIC related), abiotic (non-microbiological), or possibly both [2,26].

Operating factors describe conditions in the system in terms of temperature, pressure, ratio of solids and fluids present (e.g., water cut, solid deposits, presence of wax), flow conditions (e.g., velocity, rate) and other conditions inherent to the process. Each of the parameters listed influence each other and can also change over time (temporal) [60,176]. In addition to specific operating parameters, operational history of the pipeline system including construction, commissioning (hydrotesting), repair and corrosion mitigation (e.g., mechanical pigging and/or chemical treatment) also provides important information.

In summary, these four information groups (microbiology, chemistry, metallurgy/corrosion, and operating-related factors) are all essential to link the cause of the failure to the degradation mechanism that drove it. However, even with these datasets, failure investigators often face a number of challenges in diagnosing MIC including 1) how to properly

integrate the available datasets, 2) questions regarding data accuracy (e.g., confidence in the sampling and/or analysis method used), and 3) lack of available information from operators (e.g., missing data) [2]. The complexity driven by the multiple lines evidence required to conclusively assess MIC also results in variability of the data gathered and the testing methods carried out in MIC failure assessments.

In a recent gap analysis of failure assessment methods used to assess MIC in upstream pipeline failures, Abilio et al. 2021 [2] found that there was considerable variability in data collected and lack of consistency used to assess MIC. In this study, over 90% of the failure assessments included aspects of chemical, metallurgical/corrosion, and operating data, but only 70% assessed microbiology (which is critical to confirm MIC). When these statistics are more closely evaluated, the significant variation of methods used between assessments and the different levels of data availability for the diagnoses becomes clear (different failure assessments have different pieces of missing data to base their diagnoses). Some failure assessments may include characterization of corrosion products based on X-ray diffraction (XRD), others based on energy-dispersive X-ray spectroscopy (EDS), some on chemical spot testing (CST), while others combine some of these methods. Some failure assessments may combine corrosion evaluation with activity evaluation of microorganisms via adenosine triphosphate assays (ATP), while others use culture-based testing (e.g., most probable number [MPN]) and/or quantitative polymerase chain reaction (qPCR) to assess microbiological diversity and/or abundance. More surprising, 30% of the failure assessments did not perform any microbiological evaluation at all with many basing their diagnosis solely on corrosion morphology which has been proven to be inadequate [3]. As a result, data availability and data confidence are key considerations in MIC failure assessments.

Various approaches to integrate available datasets and to diagnosis potential MIC related failures have been proposed in the literature, although there is no universal consensus yet as to the best overall methodology [15,22–26]. This is further complicated by the fact that the scientific knowledge about MIC and the methods used to characterize both biotic and abiotic samples are continuing to evolve [9,10,177,178]. While a number of mechanistic/ phenomenological models have been developed to predict MIC, they are often too simplistic to be used to accurately assess real life (field) conditions [179,180]. As a result, practical MIC failure assessments are most often performed by experts or specialists with significant knowledge and working experience in this topic.

For other complex failure mechanisms, expert systems have been developed to assist (both experts and non-experts) in assessing failure mode and root cause [181–183]. Expert systems are rule-based, object-oriented tools that capture the knowledge, experience and know-how accumulated by experts [72]. Expert systems translate the interconnections an expert inherently makes when diagnosing intricate, multivariate topics [73,74] and assist non-specialists in decision making when experts are scarce. Consequently, the expert system approach poses itself as an advantageous evaluation methodology that can combine concepts from various disciplines and sources to diagnose specific failure modes.

There are different approaches to develop expert systems [93–104]. With recent advancements of computing science, machine learning techniques are seen as a viable avenue for the implementation of expert systems. Machine learning is a field within artificial intelligence where knowledge and preferred decision-making pathways can be learned from the data itself, rather than being explicitly programmed into an algorithm [109]. Artificial neural networks (ANNs) stand out as a machine learning technique that is able to learn and capture the inherent

considerations and correlations used by experts in their decision making. As ANN is able to build a non-parametric, non-linear model, it can not only outperform conventional polynomial techniques [184–186], but can also capture the intricate considerations an expert may consider when determining an outcome. These correlations between the input variables and outcomes are stored in "autonomous computational units" called neurons. The stronger the interrelationship between inputs and outputs, the greater the weight assigned to each neuron. For these reasons, ANNs have been utilized for a variety of corrosion assessment applications, and are well known for mimicking the human decision process [102,185,187–190]. Castellanos et al. [191,192] utilized ANN methods to build an expert system to assess the failure analysis of multiple mechanisms associated with onshore pipeline incidents, however, this system did not include MIC. Their tool was concluded to be useful, and they highlighted the influence of quantity and quality of data for the ANN training. Additionally, they stress that the ANN output has to be taken with caution when the system does not deal with oil and gas. Based on a different approach, Bastian et al. [193] also developed a pattern recognition ANN but to classifying general corrosion severity using visual images of corroded sites. Bastian et al. [193] pointed out that their approached outperformed the two convolutional neural network architectures used for image classification to which they compared their model.

The objective of the current study is to highlight the development of a novel expert system for assessing internal pipeline failures due to MIC. This model was developed using machine learning algorithm (ANN based), and was based on the evaluation of 65 failure cases assessed by 15 international experts with experience in MIC failure assessment. Two versions of the model were created including one version that includes confidence level of the predicted

outcome, and one that does not. The intent is to create a simple tool to be used by both experts and non-experts for the preliminary screening of potential pipeline failures due to MIC.

5.2. Materials and Methods

Development of the MIC failure expert system was conducted in 5 steps as outlined in **Figure 5.2**. First, a list of key input parameters necessary to identify a MIC failure, and possible failure assessment outcomes were determined based on best practises used to diagnose MIC failures as determined through expert elicitation and from methodologies published in the open literature. Using these inputs, a series of case studies were developed to provide a wide range of possible failure assessment outcomes. A group of subject matter experts (SMEs) were recruited to review these case studies and provide their assessment based on a set of possible outcomes. This combined dataset (input parameters and SME derived outcomes) was then used to create an expert system using an artificial neural network (ANN) approach. Details of each step are provided in the sections below.

5.2.1. Determination of Key Input and Output Parameters

Key input parameters for the expert system model were determined based on the latest best practises determined through three sources: 1) expert elicitation, 2) from suggested failure analysis methodologies published in the open literature [24–26,51,56,61,62,64,67,69,70,171], and 3) from the authors' gap analysis of MIC failure investigation reports of pipeline incidents in the province of Alberta, Canada from 2017 to 2019 [2]. As shown in **Table 5.2**, 16 input parameters were selected from the four main information groups required to assess internal pipeline failures due to MIC (i.e., microbiological data, chemical data, metallurgical/corrosion

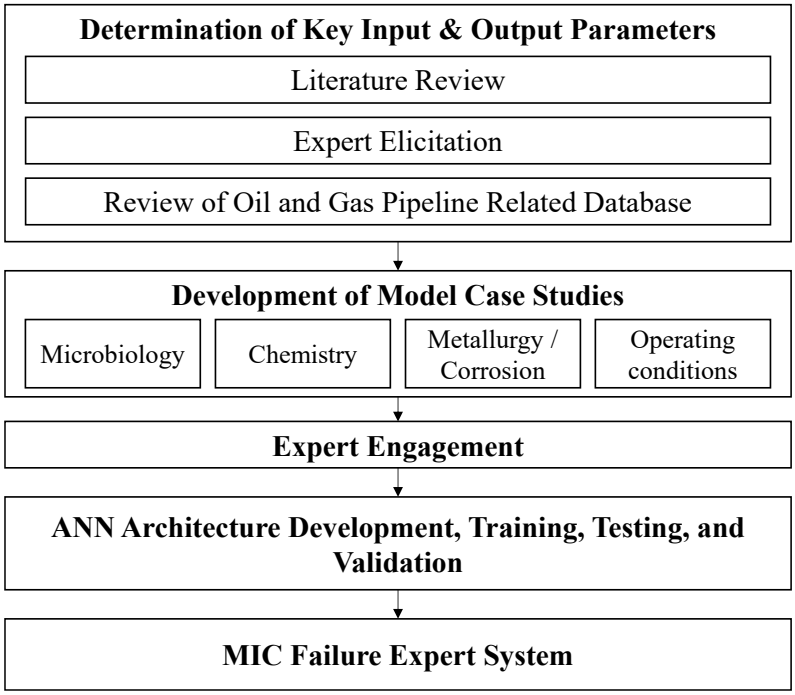

Figure 5.2 Research methodology.

data, and pipeline operating conditions). These are the necessary parameters that would be collected by the user of the expert system during a pipeline failure investigation.

Operating related parameters speak to the potential for biofilm formation (i.e., water wetting), as it relates to settlement potential [176]; and to what extent the environment provides conducive environment for the different MFGs present, as the operating temperature relates to the optimum metabolic temperature for the microorganisms identified, indicating to which extent microorganisms can be threatening [128,140,194].

Chemistry related parameters speak to how conducive the environment is to the threat posed by the MFGs present, where the logic used for temperature also applies for pH ranges [140,195–198]. The logic of water wetting applies to total dissolved solids (TDS), as TDS are also related

Table 5.2 Artificial neural network input parameters and their information groups.

Input Variable Number	ANN Input Variable
	Operating related parameters
1	Water wetting
2	Temperature
	Chemistry related parameters
3	pH
4	Total dissolved solids (TDS)
5	H_2S
6	CO_2
	Metallurgy/corrosion related parameters
7	Corrosion product testing method (EDS[a], XRD[b], CST[c])
8	Presence of sulfur related species
9	Contrast of sulfur related species (corroded vs. non-corroded area)
10	Degradation morphology: general corrosion, pitting uniformly distributed, isolated pits
	Microbiology related parameters
11	Microbiological sample type: swab (cm^{-2}) vs. liquid (mL^{-1})
12	Microbiological testing method: MMM vs. MPN
13	Activity level (ATP above/below 10E6 M.E.[d]/s.u.[e])
14	Contrast of activity (corroded vs. non-corroded area)
15	MIC related microorganisms
16	Contrast of diversity and abundance (corroded vs. non-corroded area)

[a] Energy-dispersive X-ray spectroscopy

[b] X-Ray diffraction

[c] Chemical spot testing

[d] Microbial equivalent

[e] Sample unit (cm^{-2} or mL^{-1})

to settlement potential and how settled solids can work as both additional surface for biofilm formation and a protection barrier for the biofilm within the pipeline [133]. Complementarily, chemistry related parameters provide the first lines of evidence that allow to contrast between MIC and abiotic corrosion drivers (e.g., H_2S, CO_2) [26].

Metallurgy/corrosion related parameters work as additional lines of evidence to discriminate between MIC and abiotic corrosion drivers (e.g., elemental sulfur [EDS] and iron sulfides [XRD, CST]), introduce the importance of contrasting the corroded area versus the non-corroded area in order to provide greater confidence in contrasting between MIC and abiotic corrosion drivers [137,145–147,153]. Confidence has a greater level of complexity in relation to metallurgy/corrosion related parameters, where data is not only absent or present at different combinations, but also different testing methods are considered (i.e., CST, EDS, and XRD). Finally, it considers the corrosion morphology related to the failure spot as an indicator of MIC likelihood, where an isolated pit is a stronger indicator of MIC while general corrosion is a stronger indicator that it is not MIC, despite MIC not outputting a unique morphological fingerprint [3,23].

Microbiology related parameters also include additional complexity in terms of confidence, as different sample types (i.e., swab, and liquid), and testing methods (i.e., MMM, and MPN) are contrasted. Similarly to metallurgy/corrosion related parameters, data is contrasted between the corroded area and the non-corroded area to enhance confidence in the discrimination between MIC and abiotic corrosion mechanisms [24–26] but in this informational group it speaks to diversity, abundance, and activity [8].

In terms of output parameters, two different output classifications were considered and their performance contrasted. The first expert system was designed with 5 output classifications

(5OC) as shown in **Table 5.3**. The output of the 5OC model is intended to identify whether a given failure scenario is due to MIC or not, or whether the dataset provided is inconclusive (i.e., needs more data). The latter outcome (inconclusive) is possible due to a lack of available data which is common in actual pipeline failure investigations [2]. In addition to the main outcomes, the 5OC model also includes variations of the predicted outcome in terms of confidence of the assessment.

The second expert system model was designed with 3 output classifications (3OC) as shown in **Table 5.4.** This 3OC model is a simplified version of the 5OC model expert system but does not account for confidence level of the assessment. It is derived from the same dataset obtained from expert engagement but combines the "MIC High Confidence" and "MIC Low Confidence" scores from the 5OC model into a simple "MIC" only category (without a confidence indicator). In addition, the "No MIC High Confidence" and "No MIC Low Confidence" scores are also combined into a "No MIC" only category. The inconclusive category (i.e., needs more data) is kept the same. The intent of examining two separate expert system models (5OC and 3OC) is to evaluate the accuracy and utility of a more simplified model (3OC) versus a more complex model that incorporates confidence level (5OC).

5.2.2. Development of Model Case Studies

Sixty-five (65) model case studies were developed for training, validation and testing of the artificial neural network (56 cases for training and validation, and 9 for testing). These case studies mimicked information commonly found in investigations of internal corrosion failures in carbon steel upstream operation pipelines, and were built based on a review of both the literature

Table 5.3 5-Output classification (5OC) model categories.

#	Output Class	Abbreviation	MIC Potential	Data Confidence
1	MIC High Confidence	MH	Likely	High
2	MIC Low Confidence	ML	Likely	Low
3	Need More Data	ND	Inconclusive	Negligible
4	No MIC Low Confidence	NL	Unlikely	Low
5	No MIC High Confidence	NH	Unlikely	High

Table 5.4 3-Output classification (3OC) model categories.

#	Output Class	MIC Potential
1	MIC	Likely
2	Need More Data	Inconclusive
3	No MIC	Unlikely

and actual failure investigation reports as reviewed by Abilio et al. 2021 [2]. Each case study included full or partial datasets of the 16 key parameters outlined in the previous section.

The 56 cases for training and validation were divided into 3 subsets. The first subset comprises 14 case studies (1-14), where all 4 information groups are fully populated. The second subset of 14 cases (15-28) is partially populated to evaluate the importance of the contrast between the corroded and the non-corroded area for microbiological and metallurgical/corrosion related considerations needed in MIC failure investigations [26]. The third subset comprises 28 cases (29-56) with missing data at various levels across the 4 main information groups (microbiology, chemistry, metallurgy/corrosion, and operating related parameters). The remaining 9 cases for testing were depicted within the 3 subsets as follows: 2 fully populated

cases (57-58), 3 partially populated (59-61), and 4 with various levels of missing data (62-65). The major conditions encapsulated in the developed case studies are: a) presence and/or absence of data at various levels, but specially related to microbiological information, which is currently the primary gap for internal MIC failure analyses in oil and gas upstream pipelines [2]; b) the need of contrast between the corroded and the non-corroded area for both corrosion and microbiological evaluation; and c) the influence of corrosion morphology in the final MIC diagnosis. These three major conditions were the drivers to depict the case studies into 14 cases fully populated, 14 cases partially populated and the 28 cases with missing data.

The effect of testing methods on confidence for both the corrosion and microbiological data gathered was also evaluated. For the confidence in corrosion assessments, the developed case studies account for the comparison between qualitative chemical spot testing and quantitative x-ray-based testing (EDS alone or in combination with XRD). For microbiology, confidence was assessed for the contrast between MMM and MPN methods. Additionally, the effect of measurement units for microbiological testing of planktonic (cells/mL) versus swabs (cells/cm^2) was also assessed. The presence/absence of microbiological datasets on the outcome confidence was also assessed by testing various combinations of available microbiological data include ATP assays, qPCR, next generation DNA sequencing (NGS) and/or MPN. These tests are included in the case studies in different arrangements: no microbiological data at all, ATP alone, ATP in combination with MPN, ATP in combination with MMM (qPCR and NGS), MPN alone, or MMM (qPCR and NGS) alone.

In order to evaluate the weight of corrosion morphology in diagnosing MIC, 3 possible morphological scenarios were also included: isolated pits, pitting uniformly distributed, and general corrosion with no pitting. The variations in presence/absence of data, contrast between

the corroded and the non-corroded areas, microbiological tests, corrosion tests, microbiological sampling units and morphological combinations were used to build the final case studies which are detailed in **Appendix A**.

5.2.3. Expert Engagement

Fifteen (15) subject matter experts (SMEs) in MIC were recruited to participate in the current study, and were tasked with reviewing the case studies and providing their expert opinion (i.e., recommended failure assessment outcome as per **Table 5.3**). As a highly specialized set of experts was needed, the participants were directly invited to participate. The SMEs recruited each had a minimum of 12 years of practical experience in evaluating MIC, and consisted of participants from both industry (operators and service providers) and academia. In total, 355 man-years of MIC based experience was captured in the present expert system (average of 23 years per expert).

Each SME only reviewed up to 22 case studies each due to the time-consuming nature of the process. Each case study, however, was reviewed by multiple SMEs in order to capture variation in opinions. For the 56 training and validation cases, each was evaluated by 4 to 6 different experts, while the 9 cases for testing was evaluated by 2 to 4 different SMEs. As a result, a total of 329 individual failure assessments were completed in this exercise.

Of the 65 cases developed, a unique combination of 22 cases was provided to each expert to evaluate. Twenty cases for the training and validation set (5 cases fully populated, 5 cases partially populated, 10 cases with missing data), and 2 cases for the testing set (1 fully populated or partially populated, and 1 with missing data). To evenly distribute the 65 cases among the 15

SMEs, bipartite matching coding algorithms were developed to randomly assign cases to individuals.

Each SME was asked to provide three answers for each of the case studies reviewed: 1) the failure output category based on their assessment (**Table 5.3**), 2) comments as to how they came up with their diagnosis/decision, and 3) five "yes-no" questions on whether the expert agrees if the provided conditions are conducive to MIC or not. As the present model is dedicated to MIC assessments, SMEs were asked to overlook the impact of abiotic corrosion in their evaluations so a MIC focused diagnosis could be obtained. The combination of input parameters that forms the case studies and the output categories provided by the SMEs (targets) were ultimately used to train the ANN as outlined in the next sections. The commentary from the experts were used to provide context of the final results and any variation in opinion.

5.2.5. ANN Architecture Development, Training, Testing, and Validation

The final expert system was implemented using the pattern recognition toolbox in MATLAB® (*nprtool*) based on a supervised shallow ANN model. Supervised ANNs require targets linked to the inputs (input-output pairs) to learn their relationships. Datafiles with all analyzed cases were compiled with both inputs (key parameters in **Table 5.2**) and targets (failure analysis outcomes from the SMEs in **Table 5.3** and the merged output classes in **Table 5.4**) and fed into the ANN platform.

The input values from the case studies were translated into one of three values: (1) when the variable is within the range, (0) when it is outside of the range, and (-1) when the specific variable is absent (missing data). This approach allows one to decrease the number of input variables to train the ANN without compromising the scenarios developed for the experts to

evaluate. Additionally, as ANNs do not perform well with incomplete datasets [118], this approach circumvents the challenge of real-life case scenarios that often have missing data. Therefore, the considerations included in the cases evaluated by the experts are condensed in the 16 input variables used to train, validate and test the ANN used to develop the present expert system. The translated version of the case studies is included in **Appendix B**.

The ANNs use targets as the true values from which the interrelationships between inputs will be built upon to develop the classification network. The training function used to develop the present ANN is the scaled conjugate gradient method (*trainscg*). Conjugate gradient methods locate local minimums at multiple fronts of search along conjugate directions. As a result, conjugate gradient methods achieve faster convergence in contrast to gradient-descent methods, and therefore are preferred for classification problems [119,185] .

Two transfer functions are used in the current ANN model. The transfer function used for both the input and hidden layers is the *sigmoid* function provided in **Equation (5.1)**, while the output layer utilizes the *softmax* function provided in **Equation (5.2)**, which is the indicated transfer function for classification problems [112–115]. The ANN related features for the present expert system are listed in **Table 5.5**.

$$f(x) = sigmoid(x) = \frac{1}{1 + e^{-x}} \tag{5.1}$$

$$f(y) = softmax(y_j) = \frac{e^{y_j}}{\sum_{k=1}^{K} e^{y_k}} \; for \; j = 1, \dots, K \tag{5.2}$$

Since the 65 case studies were evaluated multiple times by different SMEs for replication, the same inputs were associated to different targets and equated to a database with

Table 5.5 Features of the developed ANN.

ANN Feature	Description
Number of data points (input-output pairs)	329
Number of input variables	16
Number of hidden layers	1
Number of hidden neurons	10
Number of output classes	5
Performance	Cross entropy
Training Algorithm	Scale conjugate gradient
Input/Hidden layer transfer function	Sigmoid
Output layer transfer function	Softmax

329 data points. The database was manually divided into 3 datasets by the utilization of specified indices (*divideind*): training set, validation set, and test set, which contained 74% (242 cases), 18% (58 cases), and 9% (29 cases) of the data points, respectively. The test set was a fully independent set of case studies separate from the training and validation test sets. The performance of pattern recognition ANNs is delivered by the cross-entropy error (*crossentropy*) of the validation samples. Training halts when generalization stops improving. For the present ANN, training continued until validation error increased consecutively for more than 6 iterations. The final output classification is a result of the iteration of weights and biases of each neuron accumulated over each training cycle (epoch) [110,119,199].

5.2.6. Classification Performance Metrics and Sensitivity Analysis

The metrics used to evaluate the classification performance of the present ANN-expert system were overall accuracy (**Equation (**5.3), precision (**Equation (**5.4), and sensitivity (**Equation (**5.5). A true result occurs when the predicted outcome by the ANN matches the

target determined by the expert. A false result takes place when the ANN predicts an output different from the target provided by the expert. The 'positive' and 'negative' terms relate to the specific class evaluated. For example, when evaluating output class 1 (MIC High Confidence), class 1 is positive and the other output classes are negatives. The same rationale applies when evaluating other classes. "TP" stands for true positive, "TN" for true negative, "FP" for false positive, and "FN" for false negative.

$$Accuracy = \frac{\sum TP + \sum TN}{\sum TP + \sum TN + \sum FP + \sum FN} \tag{5.3}$$

$$Precision = \frac{\sum TP}{\sum TP + \sum FP} \tag{5.4}$$

$$Sensitivity = \frac{\sum TP}{\sum TP + \sum FN} \tag{5.5}$$

The accuracy of the model relates to how close the outputs predicted by the model are to the overall consensus among the experts. The precision of a class identifies how many of the predicted items are true, instead of resulting in false positives (error type I). Finally, sensitivity of a class identifies how many of the true items are correctly predicted, instead of resulting in false negatives (error type II).

In order to evaluate the relative influence of each input variable in the experts' considerations, Garson's equation is used and is given by **Equation (5.6)** [200–202],

$$I_j = \frac{\sum_{m=1}^{m=N_h}\left(\left(\left|W_{jm}^{ih}\right| / \sum_{k=1}^{N_i}\left|W_{km}^{ih}\right|\right) * \left|W_{mn}^{ho}\right|\right)}{\sum_{k=1}^{k=N_i}\left\{\sum_{m=1}^{m=N_h}\left(\left|W_{km}^{ih}\right| / \sum_{k=1}^{N_i}\left|W_{km}^{ih}\right|\right) * \left|W_{mn}^{ho}\right|\right\}} \quad (5.6)$$

where I_j is the relative importance of the j^{th} input variable on the output variable, N_i and N_h are the numbers of input and hidden neurons, respectively; W represents the connection weights, the superscripts 'i', 'h' and 'o' refer to input, hidden and output layers, respectively; and subscripts 'k', 'm' and 'n' refer to input, hidden and output neurons, respectively.

5.3. Results and Discussion

5.3.1. Accuracy, Precision, and Sensitivity Analysis of the MIC Failure Expert Systems

The results from the 5OC model (with confidence level) and 3OC model (without confidence level) are shown in **Figure 5.3** and **Figure 5.4**, respectively. These plots display "confusion matrices" (a term commonly used in machine learning theory), which represent the classification performance of pattern recognition problems [203–205]. Using the true positive, true negative, false positive, and false negative counts from the confusion matrix, the performance metrics of the model can be calculated using Equations 5.3 thru 5.5.

Based on this method, the overall accuracy for 5OC model was calculated to be 62.0% (**Figure 5.3**). This accuracy is relatively low which is due mainly to differences of expert opinion of the case studies evaluated. The output class with the highest precision in the 5OC model is the inconclusive category (need more data) at 68.9% followed by 'no MIC high confidence' category at 63.0%. Regarding sensitivity, 'no MIC high confidence' category had the best performance at 76.7%, followed by the 'MIC high confidence' category at 72.5% and inconclusive (need more data) category at 70.7%. The 'MIC low confidence' classification had

		Expert Response					
		MH	**ML**	**ND**	**NL**	**NH**	**Precision**
Model Prediction	**MH**	**29**	**14**	**5**	**3**	**0**	56.9%
	ML	**9**	**20**	**10**	**1**	**0**	50.0%
	ND	**1**	**17**	**82**	**12**	**7**	68.9%
	NL	**1**	**2**	**9**	**27**	**7**	58.7%
	NH	**0**	**4**	**10**	**13**	**46**	63.0%
	Sensitivity	72.5%	35.1%	70.7%	48.2%	76.7%	**62.0%**

Figure 5.3 Confusion matrix for the 5-output classification (MH = MIC High Confidence, ML = MIC Low Confidence, ND = Need Data/Inconclusive, NL = No MIC Low Confidence, NH = No MIC High Confidence).

		Expert Response			
		MIC (MH + ML)	**ND**	**No MIC (NL + NH)**	**Precision**
Model Prediction	**MIC (MH + ML)**	**79**	**22**	**6**	73.8%
	ND	**11**	**74**	**17**	72.5%
	No MIC (NL + NH)	**7**	**20**	**93**	77.5%
	Sensitivity	81.4%	63.8%	80.2%	**74.8%**

Figure 5.4 Confusion matrix for 3-output classification (MIC, ND = Need Data/Inconclusive, No MIC).

the lowest performance (precision of 50.0% and sensitivity of 35.1%), indicating the difficulty that the ANN model had in evaluating the different perspectives of the experts for this outcome.

Conversely, the overall accuracy of the 3OC model (**Figure 5.4**) was calculated to be 74.8% which is significantly higher than the overall accuracy of the 5OC model. For the 3OC

model, the ‘no MIC’ category had the highest precision at 77.5%, while the ‘MIC’ category had the highest sensitivity at 81.4%. Additionally, the 3OC has a better distribution of cases across its diagonal than the 5OC model.

The noted difference in performance between the 3OC and 5OC model highlights the subjective nature of assessing confidence level attributes. The threshold of ‘high’ and ‘low’ confidence is seen to be inherently different amongst the various experts participating in the study. As a result, the simplified 3OC expert system model is shown to perform better in predicting failure analysis outcomes, and ultimately, may have more utility in actual practice.

In order to assess the relative influence of each of the 16 input parameters on the final output, sensitivity analyses were carried out for both the 5OC and the 3OC models. The calculations of the sensitivity analyses are included in **Appendix D**. **Table 5.6** lists the relative weights and ranks the importance (highest to lowest) of each input variable for both the 5OC and the 3OC models, and also their relative rankings, in accordance with **Equation (5.6)** [200,201,206–208].

Overall, the importance of the various input parameters ranged from 11.8% to 3.2% for the 5OC model, and 10.5% to 2.8% for the 3OC model which is quite similar. In addition, the degradation morphology (input variable 10) was seen to be the most influential parameter for both models. However, the ranking order of the remaining input parameters were quite different between the two models. For the 5OC model, the degradation morphology (input variable 10) was the most influential parameter at 11.8% followed by microbiological testing method (input variable 12), at 9.2%; and presence of MIC related organisms (input variable 15) at 7.8%. For the 3OC model, the degradation morphology (input variable 10) was the most influential parameter at 10.5% followed by the presence of sulfur (input variable 8) and microbiological sample type

Table 5.6 Sensitivity analysis of the 16 input variables for the 5- and 3-output classifications.

Input Variable	ANN Input Variable	5 Output Classification		3 Output Classification	
		Relative Weight	Rank	Relative Weight	Rank
	Operating related parameters				
1	Water wetting	4.2%	15	3.8%	15
2	Temperature	5.9%	8	5.2%	11
	Chemistry related parameters				
3	pH	6.0%	6	5.8%	9
4	Total dissolved solids (TDS)	5.9%	9	4.4%	13
5	H_2S	5.9%	7	4.2%	14
6	CO_2	6.8%	5	6.9%	7
	Metallurgy/corrosion related parameters				
7	Corrosion product testing method (EDS[a], XRD[b], CST[c])	5.4%	11	4.7%	12
8	Presence of sulfur related species	7.8%	4	8.2%	2
9	Contrast of sulfur related species (corroded vs. non-corroded area)	3.2%	16	7.6%	6
10	Degradation morphology: general corrosion, pitting uniformly distributed, isolated pits	11.8%	1	10.5%	1
	Microbiology related parameters				
11	Microbiological sample type: swab (cm^{-2}) vs. liquid (mL^{-1})	5.1%	13	8.2%	3
12	Microbiological testing method: MMM vs. MPN	9.2%	2	7.9%	5
13	Activity level (ATP above/below 10E6 M.E.[d]/s.u.[e])	5.7%	10	5.7%	10
14	Contrast of activity (corroded vs. non-corroded area)	4.2%	14	6.2%	8
15	MIC related microorganisms	7.8%	3	8.0%	4
16	Contrast of diversity and abundance (corroded vs. non-corroded area)	5.1%	12	2.8%	16

[a] Energy-dispersive X-ray spectroscopy
[b] X-Ray diffraction
[c] Chemical spot testing
[d] Microbial equivalent
[e] Sample unit (cm^{-2} or mL^{-1})

(input variable 11), both at 8.2%. The least influential input parameter for the 5OC model appeared to be the contrast between the corroded and the non-corroded areas for sulfur related species (input variable 9). For the 3OC model, the least influential input parameter was the contrast of diversity and abundance between the corroded and the non-corroded areas (input variable 16). While there are differences between the rankings, it should be noted that the importance of all input parameters is of a similar order of magnitude indicating that the relative influence of each is relatively equal from an ANN perspective (i.e., no one variable dominates the outcome). Any small variation in importance is likely due to some differences in how each SME integrates data from the case studies and comes to a conclusion in the failure assessment. This is in-line with published best practices for MIC assessment in the literature which suggests that multiple lines of evidence are required to conclusively diagnose MIC as opposed to drawing a conclusion based on only 1 or 2 pieces of information [1,174].

5.3.2. Consensus Amongst the Experts

There were points of both agreement and disagreement between the experts in terms of the pieces of data included in the case studies, their significance, and how they integrated the available datasets for a final MIC diagnosis. In terms of consensus, cases 1 (MH), 14 (NH), 15 (NH), 29 (ND), 33 (ND), 41 (ND), 45 (ND), and 46 (ND) were conclusively agreed upon by all experts reviewing those specific cases (note: abbreviations in brackets refer to the outcome predicted by the model – see **Table 5.3** for definitions). These 8 cases include 3 high confidence assessments (one MIC and two No MIC) and 5 inconclusive (need data) assessments, but no low confidence assessments.

In addition to the selection of a specific outcome (diagnosis), each expert was also asked to provide comments explaining how they made their decision. These comments are an important set of information to better understand the rationale behind the outcomes chosen. Based on the experts' comments, one of the most important factors in the decision-making process was the contrast of corrosion and microbiological data between the corroded and non-corroded areas. Lack of one of these datasets was often the driver to shift a diagnosis from high confidence to low confidence or to inconclusive (need more data).

The contrast between planktonic (fluid) and sessile (surface) samples also drove shifts in classification. Swab-based (biofilm) samples shifted confidence to high while planktonic samples did the opposite. However, the influence of microbiological testing method (i.e., MMM versus MPN) was not as important as the sample type. For the majority of the experts, MMM increased the confidence of the assessment while MPN reduced it. However, certain experts preferred MPN data to fully make sense of the DNA-related data available in the cases (determined via MMM). The desire to use traditional MPN data, even though it is known to be less definitive, indicates that there are biases which exist which may impact a resulting failure assessment. These biases may be due to the familiarity with certain test methods, or lack of knowledge/interest in more modern approaches.

Multiple experts also agreed on the influence of sulfur-utilizing microorganisms (SUM) in MIC. More specifically for sulfate-reducing bacteria (SRB), where the absence of sulfate reducers was enough to shift a MIC classification to a 'no MIC', even when methanogens, fermenters and/or acetogens were present. However, the presence of multiple microbial functional groups (MFGs) in combination with sulfate reducers was taken as a stronger indication of MIC as opposed to SUM alone.

The relationship between corrosion products and abiotic corrosion drivers (e.g., H_2S and CO_2) was also present in the experts' comments. There were cases where the confidence on the final classification was increased even when limited pieces of data were present because sulfur and/or iron sulfide corrosion products were found in conjunction with SUM, while H_2S was otherwise absent in the pipeline fluids.

The role of corrosion morphology was a bit controversial based on the experts' comments. It was clear to the experts that isolated pitting was a strong indication of MIC, and that general corrosion was a strong indication that the corrosion mechanism was not MIC related. However, the presence of uniformly distributed pitting caused some disagreement. For specific cases that were based on the same set of conditions, certain experts considered pits uniformly distributed as an indication of MIC, while others considered pits uniformly distributed as an indication of some other corrosion mechanism other than MIC.

5.3.3. Variation in Experts' Opinions

In order to better understand and quantify the variation in responses between experts, a quantitative analysis was performed. To accomplish this, each output class for the 5OC and 3OC model was assigned a numerical index (1 thru 5 for the 5OC model, and 1 thru 3 for the 3 OC model) as shown in **Table 5.3** and **Table 5.4**, respectively. Using these numeric indices, the mean value and standard deviation of all the experts' responses for each case was calculated. The standard deviation of the responses represents the variation of expert opinion for any given failure assessment case study; the greater the standard deviation in responses, the greater the difference in expert opinion.

Based on this methodology, the top 10 cases with the highest standard deviations were highlighted for the 5OC model and for the 3OC model in **Table 5.7** and **Table 5.8**, respectively. In these tables, the responses from each of the experts that reviewed each case is provided (up to 6 experts per case). Also, the cells highlighted in light blue indicate that the output predicted by ANN matched the target used to train it, while cells highlighted in light red indicate that the prediction of the ANN did not match the target provided by the expert. The variation of responses for entire 65 case studies for both the 5OC and the 3OC models are provided in **Appendix C**.

By comparing **Table 5.7** and **Table 5.8**, it can be seen that a number of cases with the highest standard deviations overlap in both the 5OC and 3OC models. Seven of the same cases are listed for both models (i.e., 3, 5, 13, 17, 23, 25, and 26), three are unique to the 5OC (i.e., 9, 22, and 47) and other three are unique to the 3OC (i.e., 8, 18, and 24).

It can be observed that for the 5OC model, 5 out of the 10 top cases with the greatest standard deviation (i.e., greatest difference in expert opinion) are related to the 'no MIC high confidence' class (NH) and 2 to the 'MIC high confidence' (MH). This lack of consensus likely resulted from the different MFGs presented in these case studies, which indicates that even among experts, there is no clear consensus on the exact MFG or combination of MFGs that cause MIC. There were cases where either acid producing microorganisms (APM), or methanogenic *archaea* (MA) were present alone. This fact was a driver for disagreement among experts. Some experts considered that the presence of APM and MA alone pose a threat, while other experts considered that the presence of sulfur utilizing microorganisms (SUM) would be a requirement for APM and MA to pose a threat.

In relation to the unique high standard deviation cases for the 3OC model, all 3 were similarly limited in available data used to make a determination, which resulted in the variation observed. Since the microbiological data was limited, the corrosion morphology neither point toward nor away from a MIC diagnosis. Furthermore, the corrosion product results were also limited with low confidence in testing. These uncertainties resulted in wide range of responses from the experts including each possible outcome (i.e., 'MIC', 'inconclusive/need more data', and 'no MIC' were all selected outcomes).

Based on the experts' comments that were provided in their submissions, we are able to discern some of the reasons for the variations that occur. This list for all the top 10 variants related to both the 5OC and the 3OC is shown **Table 5.9**.

Based on the variations pointed out for the top 10 cases with the highest standard deviations, it can be observed that there was no clear threshold between high and low confidence, as different combinations of available data may influence the MIC diagnosis. Similarly, the overlap between MIC and abiotic degradation mechanisms (which was not intended to be included in the experts' assessments) also contributed to higher standard deviations. Case 9 is illustrative that on top of microbiological data, MIC cannot be conclusively diagnosed without considering drivers of abiotic corrosion. Also, due to the complex relationship between multiple MFGs, there is still disagreement on the role that MFGs play either individually or in mixed communities. Hence, there remains a need to develop a standardized methodology for MIC failure analysis, including the necessary data to collect, the role of abiotic corrosion with MIC, the roles of various MFGs and the integration framework to assist in decision making.

Table 5.7 Top 10 cases with greatest standard deviation on experts' consensus for the 5-output classification.

5 Output Classes[a]											
Top 10	Case Number	Case Data Type[b]	Model Prediction	Expert Response A	Expert Response B	Expert Response C	Expert Response D	Expert Response E	Expert Response F	Average Expert Response	Response Standard Deviation
1	17	P	5	2	5	3	2	4	5	3.5	1.4
2	13	F	5	5	2	5	5	5	–	4.4	1.3
3	26	P	3	5	5	3	3	2	–	3.6	1.3
4	25	P	5	2	5	5	4	3	–	3.8	1.3
5	3	F	2	1	1	2	3	4	1	2.0	1.3
6	5	F	1	3	1	1	2	4	1	2.0	1.3
7	23	P	1	1	4	1	2	3	1	2.0	1.3
8	22	P	3	2	3	3	5	2	3	3.0	1.1
9	9	F	5	5	4	3	3	5	5	4.2	1.0
10	47	M	5	4	3	5	5	5	3	4.2	1.0

a "1" represents output class 'MIC high confidence'. "2" represents output class 'MIC low confidence'. "3" represents output class 'need more data'. "4" represents output class 'no MIC low confidence'. "5" represents output class 'no MIC high confidence'.

b "F" (fully) refers to cases where all layers of evidence included are fully populated. "P" (partially) refers to cases where all layers of evidence included are fully populated, but the corrosion and microbiological related results associated to the non-corroded area (allowing for no contrast). "M" (missing) refers to cases with missing data at various levels across the 4 information groups.

Table 5.8 Top 10 Cases with Greatest Standard Deviation on Experts' Consensus for the 3-Output Classification.

3 Output Classes[a]											
Top 10	Case Number	Case Data Type[b]	Model Prediction	Expert Response A	Expert Response B	Expert Response C	Expert Response D	Expert Response E	Expert Response F	Average Expert Response	Response Standard Deviation
1	17	P	3	1	3	2	1	3	3	2.2	0.9
2	8	F	3	1	3	3	3	3	–	2.6	0.8
3	13	F	3	3	1	3	3	3	–	2.6	0.8
4	25	P	3	1	3	3	3	2	–	2.4	0.8
5	18	P	3	3	3	2	2	1	–	2.2	0.8
6	24	P	2	2	1	3	2	3	–	2.2	0.8
7	26	P	2	3	3	2	2	1	–	2.2	0.8
8	3	F	1	1	1	1	2	3	1	1.5	0.7
9	5	F	1	2	1	1	1	3	1	1.5	0.7
10	23	P	1	1	3	1	1	2	1	1.5	0.7

a "1" represents output class 'MIC'; "2" represents output class 'need more data'; "3" represents output class 'no MIC'.

b "F" (fully) refers to cases where all layers of evidence included are fully populated. "P" (partially) refers to cases where all layers of evidence included are fully populated, but the corrosion and microbiological related results associated to the non-corroded area (allowing for no contrast). "M" (missing) refers to cases with missing data at various levels across the 4 information groups.

Table 5.9 Causes of variation regarding the top 10 cases with most variation based on the experts' opinions for both the 5-output classification and the 3-output classification.

Case Number	Causes of variation based on the experts' comments
Case 17	The variation in case 17 may be associated to the fact that its operating, chemical, and metallurgical/corrosion pieces of data were conducive to MIC, while the microbiological evidence indicated low to negligible microbiological influence on the failure. Also, experts associated iron related bacteria (IRB) and nitrate reducing bacteria (NRB) identified by NGS as possible MIC drivers, which shifted the provided answers toward the 'MIC low confidence' side.
Case 13	Regarding case 13, only one of the experts associated the failure with 'MIC low confidence'. The other 4 diagnosed it as 'no MIC high confidence'. In this case, operating, corrosion and chemical data are not conducive to MIC and indicate the potential for abiotic degradation mechanisms (e.g., H_2S, CO_2). Additionally, similarly to case 17, the presence of IRB and NRB identified by NGS was the reason that shifted the answer of one of the experts toward the 'MIC low confidence' side.
Case 26	Case 26 was targeted as 'MIC low confidence, 'need more data', and 'no MIC high', and classified as 'need more data' by both 5OC and 3OC. Although temperature was conducive to MIC, pH and TDS were out of the usual ranges for MIC. Hydrogen sulfide gas was absent while carbon dioxide concentrations were significant, indicating possible participation of abiotic CO_2 corrosion. The lower confidence method for corrosion product evaluation (qualitative CST) indicated no sulfides but with no results for the non-corroded area to be contrasted. Similarly, microbiological evidence was also of low confidence – based on liquid (planktonic) data for ATP and MPN, and without contrast between the corroded and the non-corroded area. Both ATP and MPN indicated low to no microbiological influence. These low confidence factors with low indication on MIC could shift the case to 'no MIC low confidence', however none of the experts deemed case 26 as such. The 'no MIC high confidence' classifications were driven by the low to negligible level of microbiological results, in combination with the significant potential for abiotic CO_2 corrosion. While the 'need more data' classification was driven by the low confidence results from both corrosion products and microbiological evidence, and sample type.

Table 5.9 (continued)

Case Number	Causes of variation based on the experts' comments
Case 25	Case 25 has operating conditions conducive to MIC, but the low pH and the presence of abiotic corrosion drivers (H_2S and CO_2) shifted the case to no MIC. Corrosion product evaluation indicates significant sulfur and iron sulfides present that may be due to H_2S present or sulfur related microorganisms – depending on microbiological data. The high confidence microbiological information (swabs and MMM) indicated low to no microbiological influence on the failure. These conditions together directed two of the expert answers to be 'no MIC high confidence', which was also the predicted answer by the 5OC model.
Case 3	The lack of consensus on case 3 can be linked to its pH, the MFGs identified by NGS, and the high potential for abiotic CO_2 corrosion. Acetogens (ACE) and fermenters (FER), both considered APM, were identified in combination with NRB at the corroded area, while the non-corroded area was comprised by IRB and NRB. Therefore, despite the high numbers for microorganisms (qPCR) and high activity (ATP), the presence of APM alone in combination to CO_2 affected the consensus among experts.
Case 5	Similar to case 3, case 5 also had lower consensus due to the presence of APM. The high standard deviation of case 23 was also due to low pH, that shifted one of the responses to the opposite side of the spectrum (to no MIC). However, the high results for activity, abundance and diversity directed the diagnoses to the potential of MIC, as three of the responses were 'MIC high confidence'. But the lack of contrast data between the corroded and the non-corroded area led one of the experts to classify the case as 'MIC low confidence'.
Case 22	Case 22 had also high standard deviation due to low pH and the potential for abiotic CO_2 corrosion which led one of the experts to classify it as 'no MIC high confidence'. The other 4 responses were related to low confidence ('MIC low confidence' and 'need more data') which resulted in the 'need more data' class predicted by 5OC and 3OC.

Table 5.9 (continued)

Case Number	Causes of variation based on the experts' comments
Case 9	The variation in opinion related to case 9 was a result of uncertainty around the potential for abiotic mechanisms. As case 9 (like all other cases in this study) had no data related to oxygen presence or descriptors of the TDS present to evaluate under deposit corrosion (UDC), this inherent lack of info resulted in the lack of consensus for the case. But as all its responses were on the side for no potential of MIC, the model classified case 9 as 'no MIC high'.
Case 47	Case 47 is similar to case 9. All responses are related to no potential of MIC, which resulted in the 'no MIC high' classification by the model. The variation in opinion was related to the extent of confidence in the data. As both CST and MPN were carried out without contrast between the corroded and the non-corroded areas, the responses varied between 'need more data' and 'no MIC low confidence'.
Case 8	Case 8 had a relatively high standard deviation because while 4 of the classifications pointed out to 'no MIC', there was one pointing to MIC. This is due to the relative low confidence that can be assigned to this case study. Although there was available contrast information between the corroded and the non-corroded areas for microbiological data, it was related to ATP and MPN only. Additionally, although the contrast could potentially indicate MIC due to the significant difference in the numbers, temperature was out of the usual conducive range for MIC. Pitting morphology neither indicated nor excluded MIC and the CST, which provides a relative lower confidence for corrosion products, was positive for sulfide at both the corroded and the non-corroded areas in a H_2S reach environment. Therefore, without surface related microbiological data, in an environment conducive to both MIC and abiotic corrosion with no strong indicators (or combination of indicators) to either point towards or away from MIC, the variation in classification for case 8 is understandable.

Table 5.9 (continued)

Case Number	Causes of variation based on the experts' comments
Case 18	Case 18, similarly to case 8, have limited pieces of data, and the ones available provide limited confidence. High TDS and the relative high temperature point away from MIC. CST provides lower confidence and identifies sulfides (with no contrast between the corroded and the non-corroded areas) in H_2S reach environment. This fact in combination with pitting morphology neither point toward nor away from MIC. Additionally, the presence of liquid microbiological data for both ATP and MPN, with no contrast between the corroded and the non-corroded areas, can be considered limited to make a determination. Additionally, the high numbers for ATP conflict with the low values found for MPN.
Case 24	Case 24 had all environmental conditions conducive to MIC (i.e., temperature, pH, TDS within the usual ranges for MIC). But the presence of abiotic drivers coupled with limited corrosion product data and corrosion morphology that neither points toward nor away from MIC, made it hard to classify. Specially because the microbiological data is also limited and provided limited confidence, as only ATP and MPN results related to liquid samples are available.

5.4. Conclusions

A novel expert system based on an artificial neural network (ANN) approach was successfully developed to assist both specialists and non-specialists in screening internal MIC failures in oil and gas upstream pipelines. Two versions of the model were created including one which considers confidence level of the predicted outcome (5OC model), and one that does not (3OC model). The ANN model was trained using 65 model case studies reviewed by 15 subject matter experts (SMEs) in MIC failure assessment.

The developed expert systems were shown to have an overall accuracy of 62.0% for the 5OC model (with confidence levels) and 74.8% for the 3OC model (without confidence levels). The lower accuracy of the 5OC model stems from inherent differences of opinion between experts and in the subjective nature of assessing confidence level attributes. As a result, the simplified 3OC expert system model is shown to perform better in predicting failure analysis outcomes, and ultimately, may have more utility in actual practice as a potential MIC screening tool for both experts and non-experts. Based on the results from the sensitivity analyses (where all 16 input parameters had similar relative weights), it can also be concluded that all 4 information groups (microbiology, chemistry, metallurgy/corrosion, and operating factors) are important in assessing a MIC failure diagnosis.

In closing, this study has demonstrated that knowledge from subject matter experts regarding the assessment of MIC failures can be captured in a reasonably effective model. Performance improvement of the expert system may be possible by adding more case studies and/or experts to the existing data set, and re-training the ANN models. However, further improvement in the accuracy of the overall expert system may only be possible with the development and adoption of a standardized methodology for MIC failure analysis based on

expert consensus. While the current expert system model provides a reasonably accurate screening tool, further testing would be required with a broad range of case studies to ensure its general use in practice.

Chapter 6: Conclusions and Recommendations

6.1. Summary of Key Findings

- The present thesis poses itself as a credible source for the prevalence of MIC in oil and gas upstream operations, where it identified that MIC accounts for 13.6% and 4.8% of the internal and external failures, respectively (in Alberta, Canada between the three-year period of January 1, 2017 and December 31, 2019).

- The reviewed failures occurred in small diameters upstream pipelines (with less than or equal to 220.3 mm outside diameter) mainly carrying produced water or multiphase fluids (oil-water emulsions).

- The highest MIC failure frequencies occurred in water pipelines with outer diameters smaller than 80.9 mm (2-1/2 in. nominal pipe size) and 114 – 116.8 mm (4 in. nominal pipe size) at 470 x 10^{-5} and 247 x 10^{-5} incidents per km per year, respectively (one MIC failure (on average) every 213 and 405 kilometers, respectively each year).

- Overall, over 90% of the 50 MIC assessments reviewed included chemical data, operating data, metallurgical/corrosion data, and integration steps, however, only *70%* of the MIC assessments reviewed conducted some sort of microbiological testing.

- Only half of all assessments reviewed included tests to identify specific MFG, either using culturing methods or more advanced Microbiological Molecular Methods (MMM).

- Current failure assessments are not utilizing more modern microbiological (MMM) testing approaches, such as qPCR and Next Generation Sequencing.

- The lack of microbiological testing suggests that industry and the failure analysis community are most familiar with methods used for assessing abiotic corrosion mechanisms (e.g., CO_2 and H_2S corrosion in oil and gas systems).

- A significant number of failure assessments diagnosed MIC solely based on corrosion products and/or pit morphology without identification of specific microbial functional groups (a requirement to confirm MIC).

- The biggest gap was found in the correlation of microbiological data with chemical, metallurgical/corrosion, and operating data to conclusively confirm specific MIC mechanisms, and to identify MIC as a primary or secondary contributor to the failure.

- Overall, the gap analysis highlights the need for further education and training with respect to diagnosis of MIC particularly with respect to microbiological methods, and integration of biotic and abiotic data to confidently confirm MIC.

- A relatively effective expert system to assist both specialists and non-specialists in screening internal MIC failures in oil and gas upstream pipelines was developed.

- This thesis represents the first time that such a large number of MIC related model case studies have been analyzed by fifteen highly experienced MIC SMEs, and the results analyzed and documented.

- The variation in opinion by the experts on the same cases and variables clearly indicated that there remains a need to develop and adopt a standardized methodology for MIC failure analysis, including the necessary data to collect and the means by which the data should be integrated and used for decision making.

- The developed ANN model was shown to have an accuracy of 62.0% (with confidence levels) and 74.8% (without confidence levels).

- The sensitivity analyses indicated that all 16 input parameters had similar relative weights, meaning that all 4 information groups (microbiology, chemistry, metallurgy/corrosion, and operating factors) are comparably influential to MIC, and all are required layers of evidence for a conclusive MIC diagnosis.

- The layers of data included in the model case studies evaluated not only can assist on the development of standards for industry but also can be used to drive checklists and guidelines for scientific experimental design.

- Variation of results can be attributed to the differences in expert opinion especially pertaining to confidence levels and relative assessment of various input parameters (i.e., subjectivity) – current limitation of MIC assessment.

- This thesis has highlighted that the understanding and knowledge about MIC assessment is varied among experts and is still evolving. Based on the variation in opinion by these experts on required data and testing approaches, it is clear that there remains a need to develop and adopt a standardized methodology for MIC failure

analysis, including the necessary data to collect and the means by which the data should be integrated and used for decision making. This also underscores the need for continued education and research on the topic of MIC.

- Performance improvement of the expert system may be possible by adding more case studies and/or experts to the existing data set, and re-training the ANN models. However, further improvement in the accuracy of the overall expert system may only be possible with the development and adoption of a standardized methodology for MIC failure analysis based on expert consensus.

- While the current expert system model provides a reasonably accurate screening tool, further testing would be required with a broad range of case studies to ensure its general use in practice.

6.2. Novelty of work

- The MIC failure statistics (13.6% of all internal corrosion incidents and 4.8% of all external corrosion incidents) tabulated by the MIC prevalence study represents, to the authors' knowledge, the first time that the prevalence of MIC has been accurately quantified in the literature based on a single, reliable data set.

- The reliable identification of the current gap of microbiological considerations on MIC failure investigations (only 70% of MIC related failure assessments take microbiology into consideration).

- The developed approach in this thesis, where the expert system method is coupled with ANN to assess MIC, can be utilized to develop MIC assessment frameworks related to other engineered systems susceptible to MIC.

- This research was able to provide updated, detailed statistics related to the current status of MIC assessments in oil and gas upstream operations.

- This work highlighted a number of current pitfalls in MIC assessments.

- The research identified the most influential parameters to MIC that can be used to drive improved standards and both asset and experimental design.

- The ANN provides a practical and efficient tool to assist both experts and non-experts with screening corrosion failures to determine the potential for MIC.

6.3 Recommendations for future work

- Develop a natural language processing-based system, which would be able to automatically quantify the information included in failure reports, rather than being manually translated (which is a very time-consuming exercise). This will not only increase access to historical failure reports, but could be automated to allow input of data from future failure reports with continual updating of the ANN model.

- Base the expert system on fuzzy logic methods as an alternative to ANN. The use of fuzzy logic methods allow for the utilization of SME comments and insights to

recalibrate the relative weights defined by the ANN. Since fuzzy logic is based on inference rules (i.e., if <premise> then <consequence>), it takes linguistic variables into consideration. Therefore, the commentary by the experts can be potentially used to increase the accuracy of the model.

- Future work can be also carried out in terms of evaluating how the performance of a MIC failure expert system would be affected if based on a non-supervised approach – rather than using experts' targets to supervise its learning, as it has been done in the present thesis.

- Adapt input variables to include the latest microbiological analysis methodologies that are in development (e.g., move from lower resolution ATP results, which are irrespective to diversity characterization, to higher resolution RNA-based data that directly links activity to diversity).

- Other parameters can be included in further iterations of the model such as: steel grade, chemical composition of the material of construction of the pipe, its microstructure, corrosion products other than only sulfides and elemental sulfur; flow rate, water cut; potential microbiological nutrients in the fluid (e.g., sulfate, nitrate, organic carbon, phosphate); RNA results, historical data on previous failures due to MIC. In addition, the ANN model could be expanded to include more temporal data sets in the analysis (i.e., history of previous MIC related failures and/or issues).

- The development of MIC standard for failure assessment would include input and review from a wide range of experts and stakeholders to ensure that methodologies are agreed upon in a normative manner.

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Appendix A. 65 Case Studies Provided to the Experts (Chapter 5)

Appendix A: First set of supplementary data to **Chapter 5**: Tables A1 thru A26

Table A1 Operating, chemistry, and metallurgy/corrosion related parameters included in the case studies provided to the experts – cases 1 thru 5.

Case ID	Case 1	Case 2	Case 3	Case 4	Case 5
Operating related parameters					
Water Wetting (flow information)	Flowing line at stratified flow with continuous contact of water with the metal surface	Water stagnant at a dead leg with continuous water wetting on the metal surface	Water stagnant at a dead leg with continuous water wetting on the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface	Water stagnant at a dead leg with continuous water wetting on the metal surface
Temperature (°C)	24 °C	33 °C	32 °C	24 °C	32 °C
Chemistry related parameters					
pH	5.9	6.5	3.5	6.5	6.9
Amount of Total Dissolved Solids in the water (mg/L)	85,567 mg/L	40,340 mg/L	40,340 mg/L	56,964 mg/L	56,964 mg/L
Amount of H_2S dissolved in the gas (mole fraction, %)	0.00%	3.45%	0.00%	0.00%	0.00%
Amount of CO_2 dissolved in the gas (mole fraction, %)	3.50%	2.54%	12.65%	0.00%	0.00%
Metallurgy/corrosion related parameters					
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - Corroded Area	19.00%	No data	0.00%	No data	0.00%
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - NON-Corroded Area	9.00%	No data	0.00%	No data	0.00%
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - Corroded Area	45%	No data	0%	No data	0%
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - NON-Corroded Area	5%	No data	0%	No data	0%
Did Chemical Spot Testing get POSITIVE for Sulfides at the corroded area?	No data	YES	No data	NO	No data
Did Chemical Spot Testing get POSITIVE for Sulfides at the NON-corroded area?	No data	NO	No data	NO	No data
What is the corrosion morphology in the system?	Isolated pit at 6 o'clock position of the pipe with no uniform corrosion	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Isolated pit at 6 o'clock position of the pipe with no uniform corrosion	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Isolated pit at 6 o'clock position of the pipe with no uniform corrosion

Table A2 Microbiology-related parameters included in the case studies provided to the experts – cases 1 thru 5.

Case ID	Case 1	Case 2	Case 3	Case 4	Case 5
Microbiology related parameters					
Microbiological Sample Type (s.u.)	Swab/Surface (cm^{-2})	Liquid (mL^{-1})	Swab/Surface (cm^{-2})	Liquid (mL^{-1})	Swab/Surface (cm^{-2})
ATP[a] results - Corroded Area	1.00E+08	1.00E+02	1.00E+08	1.00E+02	1.00E+08
ATP results - NON-Corroded Area	1.00E+01	1.00E+02	1.00E+01	1.00E+02	1.00E+01
qPCR[b] results - Corroded Area - Total Bacteria	2.00E+10	No data	2.00E+10	No data	2.00E+10
qPCR results - Corroded Area - Total Archaea	3.00E+09	No data	8.00E+04	No data	8.00E+04
qPCR results - NON-Corroded Area - Total Bacteria	< 1.00E+04	No data	< 1.00E+04	No data	< 1.00E+04
qPCR results - NON-Corroded Area - Total Archaea	< 1.00E+04	No data	< 1.00E+04	No data	< 1.00E+04
NGS[c] results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	54.00%	No data	0.00%	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	8.00%	No data	0.00%	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	12.00%	No data	0.00%	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Acetogens (ACE)	17.00%	No data	45.00%	No data	45.00%
NGS results - Corroded Area - Relative Abundance (%) of Fermenters (FER)	9.00%	No data	35.00%	No data	35.00%
NGS results - Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	0.00%	No data	0.00%	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	0.00%	No data	0.00%	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	0.00%	No data	0.00%	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	0.00%	No data	15.00%	No data	15.00%
NGS results - Corroded Area - Relative Abundance (%) of Others/Unidentified	0.00%	No data	5.00%	No data	5.00%
NGS results - Corroded Area - Relative Abundance (%) - Total	100.00%	No data	100.00%	No data	100.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	0.00%	No data	0.00%	No data	0.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	0.00%	No data	0.00%	No data	0.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	0.00%	No data	0.00%	No data	0.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Acetogens (ACE)	0.00%	No data	0.00%	No data	0.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Fermenters (FER)	0.00%	No data	0.00%	No data	0.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	35.00%	No data	35.00%	No data	35.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	0.00%	No data	0.00%	No data	0.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	0.00%	No data	0.00%	No data	0.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	60.00%	No data	60.00%	No data	60.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Others/Unidentified	5.00%	No data	5.00%	No data	5.00%
NGS results - NON-Corroded Area - Relative Abundance (%) - Total	100.00%	No data	100.00%	No data	100.00%
MPN[d] bacteria/mL as per number of bottles - Corroded Area - Sulfate Reducing Bacteria (SRB)	No data	1.00E+01	No data	1.00E+01	No data
MPN bacteria/mL as per number of bottles - Corroded Area - Acid Producing Bacteria (APB)	No data	1.00E+01	No data	1.00E+01	No data
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Sulfate Reducing Bacteria (SRB)	No data	1.00E+01	No data	1.00E+01	No data
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Acid Producing Bacteria (APB)	No data	1.00E+01	No data	1.00E+01	No data

a Adenosine triphosphate assay (enzymatic assay)
b Quantitative polymerase chain reaction (DNA target quantification)
c Next generation sequencing (DNA sequencing)
d Most probable numbers (culture-based test)

Table A3 Operating, chemistry, and metallurgy/corrosion related parameters included in the case studies provided to the experts – cases 6 thru 10.

Case ID	Case 6	Case 7	Case 8	Case 9	Case 10
Operating related parameters					
Water Wetting (flow information)	Water stagnant at a dead leg with continuous water wetting on the metal surface	Water stagnant at a dead leg with continuous water wetting on the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface	Water stagnant at a dead leg with continuous water wetting on the metal surface
Temperature (°C)	22 °C	75 °C	99 °C	24 °C	24 °C
Chemistry related parameters					
pH	6.2	7	5.7	5.9	6
Amount of Total Dissolved Solids in the water (mg/L)	85,567 mg/L	3,456 mg/L	52,957 mg/L	223,904 mg/L	5,987 mg/L
Amount of H_2S dissolved in the gas (mole fraction, %)	3.45%	0.00%	3.45%	0.00%	0.00%
Amount of CO_2 dissolved in the gas (mole fraction, %)	2.56%	0.00%	2.45%	0.00%	1.54%
Metallurgy/corrosion related parameters					
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - Corroded Area	No data	0.00%	No data	0.00%	No data
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - NON-Corroded Area	No data	0.00%	No data	0.00%	No data
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - Corroded Area	No data	0%	No data	0%	No data
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - NON-Corroded Area	No data	0%	No data	0%	No data
Did Chemical Spot Testing get POSITIVE for Sulfides at the corroded area?	YES	No data	YES	No data	NO
Did Chemical Spot Testing get POSITIVE for Sulfides at the NON-corroded area?	YES	No data	YES	No data	NO
What is the corrosion morphology in the system?	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Isolated pit at 6 o'clock position of the pipe with no uniform corrosion	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline

Table A4 Microbiology-related parameters included in the case studies provided to the experts – cases 6 thru 10.

Case ID	Case 6	Case 7	Case 8	Case 9	Case 10
Microbiology related parameters					
Microbiological Sample Type (s.u.)	Liquid (mL^{-1})	Swab/Surface (cm^{-2})	Liquid (mL^{-1})	Swab/Surface (cm^{-2})	Liquid (mL^{-1})
ATP[a] results - Corroded Area	1.00E+08	1.00E+08	1.00E+08	1.00E+02	1.00E+08
ATP results - NON-Corroded Area	1.00E+08	1.00E+01	1.00E+01	1.00E+02	1.00E+01
qPCR[b] results - Corroded Area - Total Bacteria	No data	8.00E+04	No data	< 1.00E+04	No data
qPCR results - Corroded Area - Total Archaea	No data	2.00E+10	No data	< 1.00E+04	No data
qPCR results - NON-Corroded Area - Total Bacteria	No data	< 1.00E+04	No data	< 1.00E+04	No data
qPCR results - NON-Corroded Area - Total Archaea	No data	< 1.00E+04	No data	< 1.00E+04	No data
NGS[c] results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	No data	0.00%	No data	0.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	No data	0.00%	No data	0.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	No data	80.00%	No data	0.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Acetogens (ACE)	No data	0.00%	No data	0.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Fermenters (FER)	No data	0.00%	No data	0.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	No data	0.00%	No data	35.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	No data	0.00%	No data	0.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	No data	0.00%	No data	0.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	No data	15.00%	No data	60.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Others/Unidentified	No data	5.00%	No data	5.00%	No data
NGS results - Corroded Area - Relative Abundance (%) - Total	No data	100.00%	No data	100.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	No data	0.00%	No data	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	No data	0.00%	No data	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	No data	0.00%	No data	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Acetogens (ACE)	No data	0.00%	No data	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Fermenters (FER)	No data	0.00%	No data	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	No data	35.00%	No data	35.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	No data	0.00%	No data	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	No data	0.00%	No data	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	No data	60.00%	No data	60.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Others/Unidentified	No data	5.00%	No data	5.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) - Total	No data	100.00%	No data	100.00%	No data
MPN[d] bacteria/mL as per number of bottles - Corroded Area - Sulfate Reducing Bacteria (SRB)	1.00E+01	No data	1.00E+09	No data	1.00E+09
MPN bacteria/mL as per number of bottles - Corroded Area - Acid Producing Bacteria (APB)	1.00E+01	No data	1.00E+01	No data	1.00E+08
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Sulfate Reducing Bacteria (SRB)	1.00E+01	No data	0.00E+00	No data	0.00E+00
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Acid Producing Bacteria (APB)	1.00E+01	No data	0.00E+00	No data	0.00E+00

a Adenosine triphosphate assay (enzymatic assay)
b Quantitative polymerase chain reaction (DNA target quantification)
c Next generation sequencing (DNA sequencing)
d Most probable numbers (culture-based test)

Table A5 Operating, chemistry, and metallurgy/corrosion related parameters included in the case studies provided to the experts – cases 11 thru 15.

Case ID	Case 11	Case 12	Case 13	Case 14	Case 15
Operating related parameters					
Water Wetting (flow information)	Flowing line at stratified flow with continuous contact of water with the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface	Water stagnant at a dead leg with continuous water wetting on the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface
Temperature (°C)	2 °C	34 °C	99 °C	2 °C	99 °C
Chemistry related parameters					
pH	3.5	6.9	3.5	6.2	5.8
Amount of Total Dissolved Solids in the water (mg/L)	223,904 mg/L	261,456 mg/L	3,456 mg/L	52,957 mg/L	261,456 mg/L
Amount of H_2S dissolved in the gas (mole fraction, %)	3.45%	3.45%	3.45%	0.00%	0.00%
Amount of CO_2 dissolved in the gas (mole fraction, %)	12.54%	0.00%	12.54%	5.87%	6.74%
Metallurgy/corrosion related parameters					
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - Corroded Area	11.00%	No data	11.00%	0.00%	0.00%
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - NON-Corroded Area	11.00%	No data	11.00%	0.00%	No data
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - Corroded Area	14%	No data	24%	0%	0%
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - NON-Corroded Area	14%	No data	24%	0%	No data
Did Chemical Spot Testing get POSITIVE for Sulfides at the corroded area?	No data	YES	No data	No data	No data
Did Chemical Spot Testing get POSITIVE for Sulfides at the NON-corroded area?	No data	YES	No data	No data	No data
What is the corrosion morphology in the system?	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	General corrosion uniformly distributed all over the pipeline	General corrosion uniformly distributed all over the pipeline

Table A6 Microbiology-related parameters included in the case studies provided to the experts – cases 11 thru 15.

Case ID	Case 11	Case 12	Case 13	Case 14	Case 15
Microbiology related parameters					
Microbiological Sample Type (s.u.)	Swab/Surface (cm^{-2})	Liquid (mL^{-1})	Swab/Surface (cm^{-2})	Swab/Surface (cm^{-2})	Swab/Surface (cm^{-2})
ATP[15] results - Corroded Area	1.00E+02	1.00E+08	1.00E+02	1.00E+02	1.00E+02
ATP results - NON-Corroded Area	1.00E+02	1.00E+01	1.00E+02	1.00E+02	No data
qPCR[16] results - Corroded Area - Total Bacteria	< 1.00E+04	No data	< 1.00E+04	< 1.00E+04	< 1.00E+04
qPCR results - Corroded Area - Total Archaea	< 1.00E+04	No data	< 1.00E+04	< 1.00E+04	< 1.00E+04
qPCR results - NON-Corroded Area - Total Bacteria	< 1.00E+04	No data	< 1.00E+04	< 1.00E+04	No data
qPCR results - NON-Corroded Area - Total Archaea	< 1.00E+04	No data	< 1.00E+04	< 1.00E+04	No data
NGS[17] results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	0.00%	No data	0.00%	0.00%	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	0.00%	No data	0.00%	0.00%	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	0.00%	No data	0.00%	0.00%	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Acetogens (ACE)	0.00%	No data	0.00%	0.00%	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Fermenters (FER)	0.00%	No data	0.00%	0.00%	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	35.00%	No data	35.00%	35.00%	35.00%
NGS results - Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	0.00%	No data	0.00%	0.00%	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	0.00%	No data	0.00%	0.00%	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	60.00%	No data	60.00%	60.00%	60.00%
NGS results - Corroded Area - Relative Abundance (%) of Others/Unidentified	5.00%	No data	5.00%	5.00%	5.00%
NGS results - Corroded Area - Relative Abundance (%) - Total	100.00%	No data	100.00%	100.00%	100.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	0.00%	No data	0.00%	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	0.00%	No data	0.00%	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	0.00%	No data	0.00%	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Acetogens (ACE)	0.00%	No data	0.00%	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Fermenters (FER)	0.00%	No data	0.00%	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	35.00%	No data	35.00%	35.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	0.00%	No data	0.00%	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	0.00%	No data	0.00%	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	60.00%	No data	60.00%	60.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Others/Unidentified	5.00%	No data	5.00%	5.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) - Total	100.00%	No data	100.00%	100.00%	No data
MPN[18] bacteria/mL as per number of bottles - Corroded Area - Sulfate Reducing Bacteria (SRB)	No data	1.00E+09	No data	No data	No data
MPN bacteria/mL as per number of bottles - Corroded Area - Acid Producing Bacteria (APB)	No data	1.00E+08	No data	No data	No data
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Sulfate Reducing Bacteria (SRB)	No data	0.00E+00	No data	No data	No data
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Acid Producing Bacteria (APB)	No data	0.00E+00	No data	No data	No data

a Adenosine triphosphate assay (enzymatic assay)
b Quantitative polymerase chain reaction (DNA target quantification)
c Next generation sequencing (DNA sequencing)
d Most probable numbers (culture-based test)

Table A7 Operating, chemistry, and metallurgy/corrosion related parameters included in the case studies provided to the experts – cases 16 thru 20.

Case ID	Case 16	Case 17	Case 18	Case 19	Case 20
Operating related parameters					
Water Wetting (flow information)	Water stagnant at a dead leg with continuous water wetting on the metal surface	Water stagnant at a dead leg with continuous water wetting on the metal surface	Water stagnant at a dead leg with continuous water wetting on the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface
Temperature (°C)	34 °C	32 °C	72 °C	34 °C	45 °C
Chemistry related parameters					
pH	6.7	5.7	5.9	3.5	6.1
Amount of Total Dissolved Solids in the water (mg/L)	261,456 mg/L	5,987 mg/L	261,456 mg/L	78,456 mg/L	78,456 mg/L
Amount of H_2S dissolved in the gas (mole fraction, %)	3.45%	3.45%	4.53%	3.45%	4.53%
Amount of CO_2 dissolved in the gas (mole fraction, %)	0.00%	0.00%	4.53%	12.65%	2.56%
Metallurgy/corrosion related parameters					
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - Corroded Area	No data	19.00%	No data	19.00%	No data
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - NON-Corroded Area	No data	No data	No data	No data	No data
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - Corroded Area	No data	45%	No data	45%	No data
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - NON-Corroded Area	No data	No data	No data	No data	No data
Did Chemical Spot Testing get POSITIVE for Sulfides at the corroded area?	NO	No data	YES	No data	YES
Did Chemical Spot Testing get POSITIVE for Sulfides at the NON-corroded area?	No data	No data	No data	No data	No data
What is the corrosion morphology in the system?	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Isolated pit at 6 o'clock position of the pipe with no uniform corrosion	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline

Table A8 Microbiology-related parameters included in the case studies provided to the experts – cases 16 thru 20.

Case ID	Case 16	Case 17	Case 18	Case 19	Case 20
Microbiology related parameters					
Microbiological Sample Type (s.u.)	Liquid (mL^{-1})	Swab/Surface (cm^{-2})	Liquid (mL^{-1})	Swab/Surface (cm^{-2})	Liquid (mL^{-1})
ATP[a] results - Corroded Area	1.00E+02	1.00E+02	1.00E+08	1.00E+08	1.00E+08
ATP results - NON-Corroded Area	No data	No data	No data	No data	No data
qPCR[b] results - Corroded Area - Total Bacteria	No data	< 1.00E+04	No data	2.00E+10	No data
qPCR results - Corroded Area - Total Archaea	No data	< 1.00E+04	No data	3.00E+09	No data
qPCR results - NON-Corroded Area - Total Bacteria	No data	No data	No data	No data	No data
qPCR results - NON-Corroded Area - Total Archaea	No data	No data	No data	No data	No data
NGS[c] results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	No data	0.00%	No data	54.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	No data	0.00%	No data	8.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	No data	0.00%	No data	12.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Acetogens (ACE)	No data	0.00%	No data	17.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Fermenters (FER)	No data	0.00%	No data	9.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	No data	35.00%	No data	0.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	No data	0.00%	No data	0.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	No data	0.00%	No data	0.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	No data	60.00%	No data	0.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Others/Unidentified	No data	5.00%	No data	0.00%	No data
NGS results - Corroded Area - Relative Abundance (%) - Total	No data	100.00%	No data	100.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Acetogens (ACE)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Fermenters (FER)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Others/Unidentified	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) - Total	No data	No data	No data	No data	No data
MPN[d] bacteria/mL as per number of bottles - Corroded Area - Sulfate Reducing Bacteria (SRB)	1.00E+01	No data	1.00E+01	No data	1.00E+09
MPN bacteria/mL as per number of bottles - Corroded Area - Acid Producing Bacteria (APB)	1.00E+01	No data	1.00E+01	No data	1.00E+08
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Sulfate Reducing Bacteria (SRB)	No data	No data	No data	No data	No data
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Acid Producing Bacteria (APB)	No data	No data	No data	No data	No data

a Adenosine triphosphate assay (enzymatic assay)
b Quantitative polymerase chain reaction (DNA target quantification)
c Next generation sequencing (DNA sequencing)
d Most probable numbers (culture-based test)

Table A9 Operating, chemistry, and metallurgy/corrosion related parameters included in the case studies provided to the experts – cases 21 thru 25.

Case ID	Case 21	Case 22	Case 23	Case 24	Case 25
Operating related parameters					
Water Wetting (flow information)	Water stagnant at a dead leg with continuous water wetting on the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface	Water stagnant at a dead leg with continuous water wetting on the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface
Temperature (°C)	34 °C	27 °C	34 °C	34 °C	34 °C
Chemistry related parameters					
pH	6.3	3.5	3.5	6.8	3.5
Amount of Total Dissolved Solids in the water (mg/L)	261,456 mg/L	56,964 mg/L	78,456 mg/L	3,456 mg/L	78,456 mg/L
Amount of H_2S dissolved in the gas (mole fraction, %)	3.45%	0.00%	0.00%	3.45%	3.45%
Amount of CO_2 dissolved in the gas (mole fraction, %)	2.34%	12.30%	12.65%	5.60%	12.65%
Metallurgy/corrosion related parameters					
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - Corroded Area	19.00%	No data	11.00%	No data	19.00%
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - NON-Corroded Area	No data	No data	No data	No data	No data
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - Corroded Area	45%	No data	No data	No data	45%
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - NON-Corroded Area	No data	No data	No data	No data	No data
Did Chemical Spot Testing get POSITIVE for Sulfides at the corroded area?	No data	NO	No data	YES	No data
Did Chemical Spot Testing get POSITIVE for Sulfides at the NON-corroded area?	No data	No data	No data	No data	No data
What is the corrosion morphology in the system?	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Isolated pit at 6 o'clock position of the pipe with no uniform corrosion	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline

Table A10 Microbiology-related parameters included in the case studies provided to the experts – 21 thru 25.

Case ID	Case 21	Case 22	Case 23	Case 24	Case 25
Microbiology related parameters					
Microbiological Sample Type (s.u.)	Swab/Surface (cm^{-2})	Liquid (mL^{-1})	Swab/Surface (cm^{-2})	Liquid (mL^{-1})	Swab/Surface (cm^{-2})
ATP[a] results - Corroded Area	1.00E+08	1.00E+08	1.00E+08	1.00E+08	1.00E+02
ATP results - NON-Corroded Area	No data	No data	No data	No data	No data
qPCR[b] results - Corroded Area - Total Bacteria	2.00E+10	No data	2.00E+10	No data	< 1.00E+04
qPCR results - Corroded Area - Total Archaea	3.00E+09	No data	3.00E+09	No data	< 1.00E+04
qPCR results - NON-Corroded Area - Total Bacteria	No data	No data	No data	No data	No data
qPCR results - NON-Corroded Area - Total Archaea	No data	No data	No data	No data	No data
NGS[c] results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	54.00%	No data	54.00%	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	8.00%	No data	8.00%	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	12.00%	No data	12.00%	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Acetogens (ACE)	17.00%	No data	17.00%	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Fermenters (FER)	9.00%	No data	9.00%	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	0.00%	No data	0.00%	No data	35.00%
NGS results - Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	0.00%	No data	0.00%	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	0.00%	No data	0.00%	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	0.00%	No data	0.00%	No data	60.00%
NGS results - Corroded Area - Relative Abundance (%) of Others/Unidentified	0.00%	No data	0.00%	No data	5.00%
NGS results - Corroded Area - Relative Abundance (%) - Total	100.00%	No data	100.00%	No data	100.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Acetogens (ACE)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Fermenters (FER)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Others/Unidentified	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) - Total	No data	No data	No data	No data	No data
MPN[d] bacteria/mL as per number of bottles - Corroded Area - Sulfate Reducing Bacteria (SRB)	No data	1.00E+01	No data	1.00E+01	No data
MPN bacteria/mL as per number of bottles - Corroded Area - Acid Producing Bacteria (APB)	No data	1.00E+08	No data	1.00E+08	No data
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Sulfate Reducing Bacteria (SRB)	No data	No data	No data	No data	No data
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Acid Producing Bacteria (APB)	No data	No data	No data	No data	No data

a Adenosine triphosphate assay (enzymatic assay)
b Quantitative polymerase chain reaction (DNA target quantification)
c Next generation sequencing (DNA sequencing)
d Most probable numbers (culture-based test)

Table A11 Operating, chemistry, and metallurgy/corrosion related parameters included in the case studies provided to the experts – cases 26 thru 30.

Case ID	Case 26	Case 27	Case 28	Case 29	Case 30
Operating related parameters					
Water Wetting (flow information)	Flowing line at stratified flow with continuous contact of water with the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface	Water stagnant at a dead leg with continuous water wetting on the metal surface	No data	Flowing line at stratified flow with continuous contact of water with the metal surface
Temperature (°C)	34 °C	35 °C	34 °C	22 °C	No data
Chemistry related parameters					
pH	3.5	3.5	3.5	6.8	6.9
Amount of Total Dissolved Solids in the water (mg/L)	261,456 mg/L	78,457 mg/L	78,456 mg/L	3,456 mg/L	34,567 mg/L
Amount of H_2S dissolved in the gas (mole fraction, %)	0.00%	0.00%	3.45%	3.45%	3.45%
Amount of CO_2 dissolved in the gas (mole fraction, %)	12.65%	12.65%	12.65%	3.50%	0.00%
Metallurgy/corrosion related parameters					
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - Corroded Area	No data	No data	11.00%	No data	11.00%
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - NON-Corroded Area	No data	No data	No data	No data	11.00%
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - Corroded Area	No data	No data	14%	No data	No data
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - NON-Corroded Area	No data	No data	No data	No data	No data
Did Chemical Spot Testing get POSITIVE for Sulfides at the corroded area?	NO	YES	No data	NO	No data
Did Chemical Spot Testing get POSITIVE for Sulfides at the NON-corroded area?	No data	No data	No data	NO	No data
What is the corrosion morphology in the system?	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	General corrosion uniformly distributed all over the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	General corrosion uniformly distributed all over the pipeline

Table A12 Microbiology-related parameters included in the case studies provided to the experts – cases 26 thru 30.

Case ID	Case 26	Case 27	Case 28	Case 29	Case 30
Microbiology related parameters					
Microbiological Sample Type (s.u.)	Liquid (mL^{-1})	Liquid (mL^{-1})	Swab/Surface (cm^{-2})	No data	Liquid (mL^{-1})
ATP[a] results - Corroded Area	1.00E+02	1.00E+08	1.00E+02	No data	1.00E+02
ATP results - NON-Corroded Area	No data	No data	No data	No data	No data
qPCR[b] results - Corroded Area - Total Bacteria	No data	2.00E+10	< 1.00E+04	No data	No data
qPCR results - Corroded Area - Total Archaea	No data	3.00E+09	< 1.00E+04	No data	No data
qPCR results - NON-Corroded Area - Total Bacteria	No data	No data	No data	No data	No data
qPCR results - NON-Corroded Area - Total Archaea	No data	No data	No data	No data	No data
NGS[c] results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	No data	54.00%	0.00%	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	No data	8.00%	0.00%	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	No data	12.00%	0.00%	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Acetogens (ACE)	No data	17.00%	0.00%	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Fermenters (FER)	No data	9.00%	0.00%	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	No data	0.00%	35.00%	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	No data	0.00%	0.00%	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	No data	0.00%	0.00%	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	No data	0.00%	60.00%	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Others/Unidentified	No data	0.00%	5.00%	No data	No data
NGS results - Corroded Area - Relative Abundance (%) - Total	No data	100.00%	100.00%	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Acetogens (ACE)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Fermenters (FER)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Others/Unidentified	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) - Total	No data	No data	No data	No data	No data
MPN[d] bacteria/mL as per number of bottles - Corroded Area - Sulfate Reducing Bacteria (SRB)	1.00E+01	No data	No data	No data	No data
MPN bacteria/mL as per number of bottles - Corroded Area - Acid Producing Bacteria (APB)	1.00E+01	No data	No data	No data	No data
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Sulfate Reducing Bacteria (SRB)	No data	No data	No data	No data	No data
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Acid Producing Bacteria (APB)	No data	No data	No data	No data	No data

a Adenosine triphosphate assay (enzymatic assay)
b Quantitative polymerase chain reaction (DNA target quantification)
c Next generation sequencing (DNA sequencing)
d Most probable numbers (culture-based test)

Table A13 Operating, chemistry, and metallurgy/corrosion related parameters included in the case studies provided to the experts – cases 31 thru 35.

Case ID	Case 31	Case 32	Case 33	Case 34	Case 35
Operating related parameters					
Water Wetting (flow information)	No data	Water stagnant at a dead leg with continuous water wetting on the metal surface	Water stagnant at a dead leg with continuous water wetting on the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface	Water stagnant at a dead leg with continuous water wetting on the metal surface
Temperature (°C)	33 °C	No data	24 °C	24 °C	12 °C
Chemistry related parameters					
pH	6	3.5	No data	6.2	No data
Amount of Total Dissolved Solids in the water (mg/L)	56,964 mg/L	261,456 mg/L	No data	40,340 mg/L	No data
Amount of H_2S dissolved in the gas (mole fraction, %)	0.00%	No data	3.45%	3.45%	0.00%
Amount of CO_2 dissolved in the gas (mole fraction, %)	4.45%	No data	0.00%	5.22%	0.00%
Metallurgy/corrosion related parameters					
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - Corroded Area	No data	No data	No data	19.00%	No data
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - NON-Corroded Area	No data	No data	No data	No data	No data
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - Corroded Area	No data	No data	No data	No data	No data
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - NON-Corroded Area	No data	No data	No data	No data	No data
Did Chemical Spot Testing get POSITIVE for Sulfides at the corroded area?	No data	YES	No data	No data	No data
Did Chemical Spot Testing get POSITIVE for Sulfides at the NON-corroded area?	No data	No data	No data	No data	No data
What is the corrosion morphology in the system?	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	General corrosion uniformly distributed all over the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Isolated pit at 6 o'clock position of the pipe with no uniform corrosion	General corrosion uniformly distributed all over the pipeline

Table A14 Microbiology-related parameters included in the case studies provided to the experts – cases 31 thru 35.

Case ID	Case 31	Case 32	Case 33	Case 34	Case 35
Microbiology related parameters					
Microbiological Sample Type (s.u.)	Liquid (mL^{-1})	Liquid (mL^{-1})	No data	Liquid (mL^{-1})	Liquid (mL^{-1})
ATP[a] results - Corroded Area	1.00E+02	No data	No data	1.00E+08	1.00E+08
ATP results - NON-Corroded Area	No data	No data	No data	No data	No data
qPCR[b] results - Corroded Area - Total Bacteria	No data	< 1.00E+04	No data	No data	No data
qPCR results - Corroded Area - Total Archaea	No data	< 1.00E+04	No data	No data	No data
qPCR results - NON-Corroded Area - Total Bacteria	No data	< 1.00E+04	No data	No data	No data
qPCR results - NON-Corroded Area - Total Archaea	No data	< 1.00E+04	No data	No data	No data
NGS[c] results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	No data	0.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	No data	0.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	No data	0.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Acetogens (ACE)	No data	0.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Fermenters (FER)	No data	0.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	No data	35.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	No data	0.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	No data	0.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	No data	60.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Others/Unidentified	No data	5.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) - Total	No data	100.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	No data	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	No data	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	No data	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Acetogens (ACE)	No data	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Fermenters (FER)	No data	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	No data	35.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	No data	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	No data	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	No data	60.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Others/Unidentified	No data	5.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) - Total	No data	100.00%	No data	No data	No data
MPN[d] bacteria/mL as per number of bottles - Corroded Area - Sulfate Reducing Bacteria (SRB)	1.00E+01	No data	No data	No data	1.00E+08
MPN bacteria/mL as per number of bottles - Corroded Area - Acid Producing Bacteria (APB)	1.00E+01	No data	No data	No data	1.00E+08
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Sulfate Reducing Bacteria (SRB)	1.00E+01	No data	No data	No data	No data
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Acid Producing Bacteria (APB)	1.00E+01	No data	No data	No data	No data

a Adenosine triphosphate assay (enzymatic assay)
b Quantitative polymerase chain reaction (DNA target quantification)
c Next generation sequencing (DNA sequencing)
d Most probable numbers (culture-based test)

Table A15 Operating, chemistry, and metallurgy/corrosion related parameters included in the case studies provided to the experts – cases 36 thru 40.

Case ID	Case 36	Case 37	Case 38	Case 39	Case 40
Operating related parameters					
Water Wetting (flow information)	Water stagnant at a dead leg with continuous water wetting on the metal surface	No data	Water stagnant at a dead leg with continuous water wetting on the metal surface	No data	Water stagnant at a dead leg with continuous water wetting on the metal surface
Temperature (°C)	34 °C	45 °C	No data	No data	33 °C
Chemistry related parameters					
pH	6.3	No data	6.5	No data	No data
Amount of Total Dissolved Solids in the water (mg/L)	78,456 mg/L	No data	12,856 mg/L	No data	No data
Amount of H_2S dissolved in the gas (mole fraction, %)	No data	3.45%	0.00%	0.00%	0.00%
Amount of CO_2 dissolved in the gas (mole fraction, %)	No data	7.10%	2.40%	4.56%	7.10%
Metallurgy/corrosion related parameters					
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - Corroded Area	19.00%	0.00%	No data	9.00%	0.00%
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - NON-Corroded Area	9.00%	No data	No data	No data	0.00%
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - Corroded Area	45%	0%	No data	No data	0%
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - NON-Corroded Area	5%	No data	No data	No data	0%
Did Chemical Spot Testing get POSITIVE for Sulfides at the corroded area?	No data	No data	YES	No data	No data
Did Chemical Spot Testing get POSITIVE for Sulfides at the NON-corroded area?	No data	No data	No data	No data	No data
What is the corrosion morphology in the system?	Isolated pit at 6 o'clock position of the pipe with no uniform corrosion	General corrosion uniformly distributed all over the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	General corrosion uniformly distributed all over the pipeline

Table A16 Microbiology-related parameters included in the case studies provided to the experts – cases 36 thru 40.

Case ID	Case 36	Case 37	Case 38	Case 39	Case 40
Microbiology related parameters					
Microbiological Sample Type (s.u.)	Swab/Surface (cm^{-2})	No data	Liquid (mL^{-1})	Liquid (mL^{-1})	Swab/Surface (cm^{-2})
ATP[a] results - Corroded Area	No data	No data	1.00E+08	1.00E+08	1.00E+02
ATP results - NON-Corroded Area	No data	No data	1.00E+02	No data	No data
qPCR[b] results - Corroded Area - Total Bacteria	2.00E+10	No data	No data	No data	< 1.00E+04
qPCR results - Corroded Area - Total Archaea	3.00E+09	No data	No data	No data	< 1.00E+04
qPCR results - NON-Corroded Area - Total Bacteria	No data	No data	No data	No data	< 1.00E+04
qPCR results - NON-Corroded Area - Total Archaea	No data	No data	No data	No data	< 1.00E+04
NGS[c] results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	54.00%	No data	No data	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	8.00%	No data	No data	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	12.00%	No data	No data	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Acetogens (ACE)	17.00%	No data	No data	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Fermenters (FER)	9.00%	No data	No data	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	0.00%	No data	No data	No data	35.00%
NGS results - Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	0.00%	No data	No data	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	0.00%	No data	No data	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	0.00%	No data	No data	No data	60.00%
NGS results - Corroded Area - Relative Abundance (%) of Others/Unidentified	0.00%	No data	No data	No data	5.00%
NGS results - Corroded Area - Relative Abundance (%) - Total	100.00%	No data	No data	No data	100.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	No data	No data	No data	No data	0.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	No data	No data	No data	No data	0.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	No data	No data	No data	No data	0.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Acetogens (ACE)	No data	No data	No data	No data	0.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Fermenters (FER)	No data	No data	No data	No data	0.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	No data	No data	No data	No data	35.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	No data	No data	No data	No data	0.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	No data	No data	No data	No data	0.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	No data	No data	No data	No data	60.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Others/Unidentified	No data	No data	No data	No data	5.00%
NGS results - NON-Corroded Area - Relative Abundance (%) - Total	No data	No data	No data	No data	100.00%
MPN[d] bacteria/mL as per number of bottles - Corroded Area - Sulfate Reducing Bacteria (SRB)	No data	No data	No data	1.00E+08	No data
MPN bacteria/mL as per number of bottles - Corroded Area - Acid Producing Bacteria (APB)	No data	No data	No data	1.00E+08	No data
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Sulfate Reducing Bacteria (SRB)	No data	No data	No data	No data	No data
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Acid Producing Bacteria (APB)	No data	No data	No data	No data	No data

a Adenosine triphosphate assay (enzymatic assay)
b Quantitative polymerase chain reaction (DNA target quantification)
c Next generation sequencing (DNA sequencing)
d Most probable numbers (culture-based test)

Table A17 Operating, chemistry, and metallurgy/corrosion related parameters included in the case studies provided to the experts – cases 41 thru 45.

Case ID	Case 41	Case 42	Case 43	Case 44	Case 45
Operating related parameters					
Water Wetting (flow information)	Water stagnant at a dead leg with continuous water wetting on the metal surface	Water stagnant at a dead leg with continuous water wetting on the metal surface	Water stagnant at a dead leg with continuous water wetting on the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface	No data
Temperature (°C)	No data	No data	2 °C	28 °C	29 °C
Chemistry related parameters					
pH	No data	6.3	No data	No data	No data
Amount of Total Dissolved Solids in the water (mg/L)	No data	78,456 mg/L	No data	No data	No data
Amount of H_2S dissolved in the gas (mole fraction, %)	0.00%	0.00%	No data	0.00%	0.00%
Amount of CO_2 dissolved in the gas (mole fraction, %)	4.60%	0.00%	No data	5.90%	0.00%
Metallurgy/corrosion related parameters					
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - Corroded Area	No data	0.00%	9.00%	19.00%	0.00%
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - NON-Corroded Area	No data	0.00%	9.00%	9.00%	No data
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - Corroded Area	No data	No data	No data	No data	0%
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - NON-Corroded Area	No data	No data	No data	No data	No data
Did Chemical Spot Testing get POSITIVE for Sulfides at the corroded area?	No data	No data	No data	No data	No data
Did Chemical Spot Testing get POSITIVE for Sulfides at the NON-corroded area?	No data	No data	No data	No data	No data
What is the corrosion morphology in the system?	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	General corrosion uniformly distributed all over the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline

Table A18 Microbiology-related parameters included in the case studies provided to the experts – cases 41 thru 45.

Case ID	Case 41	Case 42	Case 43	Case 44	Case 45
Microbiology related parameters					
Microbiological Sample Type (s.u.)	No data	Liquid (mL^{-1})	Liquid (mL^{-1})	Swab/Surface (cm^{-2})	No data
ATP[a] results - Corroded Area	No data	1.00E+02	1.00E+02	1.00E+08	No data
ATP results - NON-Corroded Area	No data	No data	1.00E+02	No data	No data
qPCR[b] results - Corroded Area - Total Bacteria	No data	No data	No data	2.00E+10	No data
qPCR results - Corroded Area - Total Archaea	No data	No data	No data	3.00E+09	No data
qPCR results - NON-Corroded Area - Total Bacteria	No data	No data	No data	< 1.00E+04	No data
qPCR results - NON-Corroded Area - Total Archaea	No data	No data	No data	< 1.00E+04	No data
NGS[c] results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	No data	No data	No data	54.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	No data	No data	No data	8.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	No data	No data	No data	12.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Acetogens (ACE)	No data	No data	No data	17.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Fermenters (FER)	No data	No data	No data	9.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	No data	No data	No data	0.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	No data	No data	No data	0.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	No data	No data	No data	0.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	No data	No data	No data	0.00%	No data
NGS results - Corroded Area - Relative Abundance (%) of Others/Unidentified	No data	No data	No data	0.00%	No data
NGS results - Corroded Area - Relative Abundance (%) - Total	No data	No data	No data	100.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	No data	No data	No data	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	No data	No data	No data	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	No data	No data	No data	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Acetogens (ACE)	No data	No data	No data	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Fermenters (FER)	No data	No data	No data	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	No data	No data	No data	35.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	No data	No data	No data	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	No data	No data	No data	0.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	No data	No data	No data	60.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Others/Unidentified	No data	No data	No data	5.00%	No data
NGS results - NON-Corroded Area - Relative Abundance (%) - Total	No data	No data	No data	100.00%	No data
MPN[d] bacteria/mL as per number of bottles - Corroded Area - Sulfate Reducing Bacteria (SRB)	No data	No data	1.00E+01	No data	No data
MPN bacteria/mL as per number of bottles - Corroded Area - Acid Producing Bacteria (APB)	No data	No data	1.00E+01	No data	No data
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Sulfate Reducing Bacteria (SRB)	No data	No data	1.00E+01	No data	No data
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Acid Producing Bacteria (APB)	No data	No data	1.00E+01	No data	No data

a Adenosine triphosphate assay (enzymatic assay)
b Quantitative polymerase chain reaction (DNA target quantification)
c Next generation sequencing (DNA sequencing)
d Most probable numbers (culture-based test)

Table A19 Operating, chemistry, and metallurgy/corrosion related parameters included in the case studies provided to the experts – cases 46 thru 50.

Case ID	Case 46	Case 47	Case 48	Case 49	Case 50
Operating related parameters					
Water Wetting (flow information)	No data	Water stagnant at a dead leg with continuous water wetting on the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface
Temperature (°C)	34 °C	No data	34 °C	2 °C	34 °C
Chemistry related parameters					
pH	No data	3.5	6.3	6.8	5.3
Amount of Total Dissolved Solids in the water (mg/L)	261,456 mg/L	78,456 mg/L	No data	261,456 mg/L	34,567 mg/L
Amount of H_2S dissolved in the gas (mole fraction, %)	No data	3.45%	0.00%	3.45%	0.00%
Amount of CO_2 dissolved in the gas (mole fraction, %)	No data	12.65%	2.34%	6.40%	5.90%
Metallurgy/corrosion related parameters					
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - Corroded Area	No data	No data	19.00%	11.00%	No data
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - NON-Corroded Area	No data	No data	9.00%	11.00%	No data
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - Corroded Area	No data	No data	No data	No data	No data
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - NON-Corroded Area	No data	No data	No data	No data	No data
Did Chemical Spot Testing get POSITIVE for Sulfides at the corroded area?	No data	YES	No data	No data	NO
Did Chemical Spot Testing get POSITIVE for Sulfides at the NON-corroded area?	No data	No data	No data	No data	No data
What is the corrosion morphology in the system?	Isolated pit at 6 o'clock position of the pipe with no uniform corrosion	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Isolated pit at 6 o'clock position of the pipe with no uniform corrosion	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	General corrosion uniformly distributed all over the pipeline

Table A20 Microbiology-related parameters included in the case studies provided to the experts – cases 46 thru 50.

Case ID	Case 46	Case 47	Case 48	Case 49	Case 50
Microbiology related parameters					
Microbiological Sample Type (s.u.)	Liquid (mL^{-1})	Liquid (mL^{-1})	Swab/Surface (cm^{-2})	No data	Swab/Surface (cm^{-2})
ATP[a] results - Corroded Area	1.00E+08	1.00E+02	1.00E+08	No data	1.00E+02
ATP results - NON-Corroded Area	1.00E+08	1.00E+02	No data	No data	No data
qPCR[b] results - Corroded Area - Total Bacteria	No data	No data	2.00E+10	No data	No data
qPCR results - Corroded Area - Total Archaea	No data	No data	3.00E+09	No data	No data
qPCR results - NON-Corroded Area - Total Bacteria	No data	No data	No data	No data	No data
qPCR results - NON-Corroded Area - Total Archaea	No data	No data	No data	No data	No data
NGS[c] results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	No data	No data	54.00%	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	No data	No data	8.00%	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	No data	No data	12.00%	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Acetogens (ACE)	No data	No data	17.00%	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Fermenters (FER)	No data	No data	9.00%	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	No data	No data	0.00%	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	No data	No data	0.00%	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	No data	No data	0.00%	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	No data	No data	0.00%	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Others/Unidentified	No data	No data	0.00%	No data	No data
NGS results - Corroded Area - Relative Abundance (%) - Total	No data	No data	100.00%	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Acetogens (ACE)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Fermenters (FER)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Others/Unidentified	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) - Total	No data	No data	No data	No data	No data
MPN[d] bacteria/mL as per number of bottles - Corroded Area - Sulfate Reducing Bacteria (SRB)	No data	1.00E+01	No data	No data	No data
MPN bacteria/mL as per number of bottles - Corroded Area - Acid Producing Bacteria (APB)	No data	1.00E+01	No data	No data	No data
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Sulfate Reducing Bacteria (SRB)	No data	No data	No data	No data	No data
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Acid Producing Bacteria (APB)	No data	No data	No data	No data	No data

a Adenosine triphosphate assay (enzymatic assay)
b Quantitative polymerase chain reaction (DNA target quantification)
c Next generation sequencing (DNA sequencing)
d Most probable numbers (culture-based test)

Table A21 Operating, chemistry, and metallurgy/corrosion related parameters included in the case studies provided to the experts – cases 51 thru 55.

Case ID	Case 51	Case 52	Case 53	Case 54	Case 55
Operating related parameters					
Water Wetting (flow information)	Water stagnant at a dead leg with continuous water wetting on the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface
Temperature (°C)	27 °C	2 °C	28 °C	28 °C	28 °C
Chemistry related parameters					
pH	No data	No data	6.3	No data	No data
Amount of Total Dissolved Solids in the water (mg/L)	No data	261,456 mg/L	5,897 mg/L	No data	No data
Amount of H_2S dissolved in the gas (mole fraction, %)	3.45%	3.45%	0.00%	0.00%	0.00%
Amount of CO_2 dissolved in the gas (mole fraction, %)	0.00%	0.00%	2.34%	0.00%	8.20%
Metallurgy/corrosion related parameters					
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - Corroded Area	No data	11.00%	No data	No data	No data
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - NON-Corroded Area	No data	11.00%	No data	No data	No data
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - Corroded Area	No data	14%	No data	No data	No data
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - NON-Corroded Area	No data	14%	No data	No data	No data
Did Chemical Spot Testing get POSITIVE for Sulfides at the corroded area?	YES	No data	YES	No data	YES
Did Chemical Spot Testing get POSITIVE for Sulfides at the NON-corroded area?	No data	No data	No data	No data	No data
What is the corrosion morphology in the system?	Isolated pit at 6 o'clock position of the pipe with no uniform corrosion	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Isolated pit at 6 o'clock position of the pipe with no uniform corrosion	Isolated pit at 6 o'clock position of the pipe with no uniform corrosion	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline

Table A22 Microbiology-related parameters included in the case studies provided to the experts – cases 51 thru 55.

Case ID	Case 51	Case 52	Case 53	Case 54	Case 55
Microbiology related parameters					
Microbiological Sample Type (s.u.)	Liquid (mL^{-1})	Swab/Surface (cm^{-2})	No data	Swab/Surface (cm^{-2})	Swab/Surface (cm^{-2})
ATP[a] results - Corroded Area	No data	1.00E+02	No data	1.00E+08	No data
ATP results - NON-Corroded Area	No data	No data	No data	1.00E+01	No data
qPCR[b] results - Corroded Area - Total Bacteria	No data	< 1.00E+04	No data	No data	No data
qPCR results - Corroded Area - Total Archaea	No data	< 1.00E+04	No data	No data	No data
qPCR results - NON-Corroded Area - Total Bacteria	No data	No data	No data	No data	No data
qPCR results - NON-Corroded Area - Total Archaea	No data	No data	No data	No data	No data
NGS[c] results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	No data	0.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	No data	0.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	No data	0.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Acetogens (ACE)	No data	0.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Fermenters (FER)	No data	0.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	No data	35.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	No data	0.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	No data	0.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	No data	60.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Others/Unidentified	No data	5.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) - Total	No data	100.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Acetogens (ACE)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Fermenters (FER)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Others/Unidentified	No data	No data	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) - Total	No data	No data	No data	No data	No data
MPN[d] bacteria/mL as per number of bottles - Corroded Area - Sulfate Reducing Bacteria (SRB)	1.00E+08	No data	No data	No data	1.00E+08
MPN bacteria/mL as per number of bottles - Corroded Area - Acid Producing Bacteria (APB)	1.00E+08	No data	No data	No data	1.00E+08
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Sulfate Reducing Bacteria (SRB)	No data	No data	No data	No data	No data
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Acid Producing Bacteria (APB)	No data	No data	No data	No data	No data

a Adenosine triphosphate assay (enzymatic assay)
b Quantitative polymerase chain reaction (DNA target quantification)
c Next generation sequencing (DNA sequencing)
d Most probable numbers (culture-based test)

Table A23 Operating, chemistry, and metallurgy/corrosion related parameters included in the case studies provided to the experts – cases 56 thru 60.

Case ID	Case 56	Case 57	Case 58	Case 59	Case 60
Operating related parameters					
Water Wetting (flow information)	Flowing line at stratified flow with continuous contact of water with the metal surface	Water stagnant at a dead leg with continuous water wetting on the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface	Water stagnant at a dead leg with continuous water wetting on the metal surface	Flowing line at stratified flow with continuous contact of water with the metal surface
Temperature (°C)	99 °C	34 °C	2 °C	34 °C	2 °C
Chemistry related parameters					
pH	No data	3.5	6.3	6.7	3.5
Amount of Total Dissolved Solids in the water (mg/L)	No data	40,340 mg/L	85,567 mg/L	261,456 mg/L	85,567 mg/L
Amount of H_2S dissolved in the gas (mole fraction, %)	No data	0.00%	3.45%	3.45%	3.45%
Amount of CO_2 dissolved in the gas (mole fraction, %)	No data	12.65%	5.90%	0.00%	12.65%
Metallurgy/corrosion related parameters					
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - Corroded Area	0.00%	19.00%	11.00%	No data	No data
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - NON-Corroded Area	0.00%	9.00%	No data	No data	No data
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - Corroded Area	0%	45%	14%	No data	No data
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - NON-Corroded Area	0%	5%	No data	No data	No data
Did Chemical Spot Testing get POSITIVE for Sulfides at the corroded area?	No data	No data	No data	NO	YES
Did Chemical Spot Testing get POSITIVE for Sulfides at the NON-corroded area?	No data	No data	No data	No data	No data
What is the corrosion morphology in the system?	General corrosion uniformly distributed all over the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline

Table A24 Microbiology-related parameters included in the case studies provided to the experts – cases 56 thru 60.

Case ID	Case 56	Case 57	Case 58	Case 59	Case 60
Microbiology related parameters					
Microbiological Sample Type (s.u.)	Swab/Surface (cm^{-2})	Liquid (mL^{-1})	Liquid (mL^{-1})	Liquid (mL^{-1})	Liquid (mL^{-1})
ATP[a] results - Corroded Area	1.00E+02	1.00E+08	1.00E+08	1.00E+02	1.00E+02
ATP results - NON-Corroded Area	1.00E+02	1.00E+02	No data	No data	No data
qPCR[b] results - Corroded Area - Total Bacteria	< 1.00E+04	2.00E+10	No data	No data	No data
qPCR results - Corroded Area - Total Archaea	< 1.00E+04	3.00E+09	No data	No data	No data
qPCR results - NON-Corroded Area - Total Bacteria	< 1.00E+04	< 1.00E+04	No data	No data	No data
qPCR results - NON-Corroded Area - Total Archaea	< 1.00E+04	< 1.00E+04	No data	No data	No data
NGS[c] results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	0.00%	54.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	0.00%	8.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	0.00%	12.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Acetogens (ACE)	0.00%	17.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Fermenters (FER)	0.00%	9.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	35.00%	0.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	0.00%	0.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	0.00%	0.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	60.00%	0.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) of Others/Unidentified	5.00%	0.00%	No data	No data	No data
NGS results - Corroded Area - Relative Abundance (%) - Total	100.00%	100.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	0.00%	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	0.00%	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	0.00%	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Acetogens (ACE)	0.00%	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Fermenters (FER)	0.00%	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	35.00%	35.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	0.00%	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	0.00%	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	60.00%	60.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Others/Unidentified	5.00%	5.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) - Total	100.00%	100.00%	No data	No data	No data
MPN[d] bacteria/mL as per number of bottles - Corroded Area - Sulfate Reducing Bacteria (SRB)	No data	No data	1.00E+08	1.00E+08	1.00E+01
MPN bacteria/mL as per number of bottles - Corroded Area - Acid Producing Bacteria (APB)	No data	No data	1.00E+08	1.00E+01	1.00E+01
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Sulfate Reducing Bacteria (SRB)	No data	No data	No data	No data	No data
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Acid Producing Bacteria (APB)	No data	No data	No data	No data	No data

a Adenosine triphosphate assay (enzymatic assay)
b Quantitative polymerase chain reaction (DNA target quantification)
c Next generation sequencing (DNA sequencing)
d Most probable numbers (culture-based test)

Table A25 Operating, chemistry, and metallurgy/corrosion related parameters included in the case studies provided to the experts – cases 61 thru 65.

Case ID	Case 61	Case 62	Case 63	Case 64	Case 65
Operating related parameters					
Water Wetting (flow information)	Water stagnant at a dead leg with continuous water wetting on the metal surface	Water stagnant at a dead leg with continuous water wetting on the metal surface	Water stagnant at a dead leg with continuous water wetting on the metal surface	No data	Water stagnant at a dead leg with continuous water wetting on the metal surface
Temperature (°C)	2 °C	2 °C	34 °C	2 °C	2 °C
Chemistry related parameters					
pH	3.5	No data	6.7	No data	No data
Amount of Total Dissolved Solids in the water (mg/L)	261,456 mg/L	No data	78,456 mg/L	No data	78,456 mg/L
Amount of H_2S dissolved in the gas (mole fraction, %)	0.00%	0.00%	3.45%	No data	3.45%
Amount of CO_2 dissolved in the gas (mole fraction, %)	12.65%	5.90%	2.34%	No data	12.65%
Metallurgy/corrosion related parameters					
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - Corroded Area	0.00%	19.00%	No data	No data	11.00%
Energy-dispersive X-ray spectroscopy (EDS) results - Amount of Sulfur present (Mass %) - NON-Corroded Area	0.00%	9.00%	No data	No data	11.00%
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - Corroded Area	0%	45%	No data	No data	No data
X-Ray Diffraction (XRD) results - Amount of Total Iron Sulfides present (Mass %) - NON-Corroded Area	0%	5%	No data	No data	No data
Did Chemical Spot Testing get POSITIVE for Sulfides at the corroded area?	No data	No data	YES	YES	No data
Did Chemical Spot Testing get POSITIVE for Sulfides at the NON-corroded area?	No data	No data	No data	No data	No data
What is the corrosion morphology in the system?	General corrosion uniformly distributed all over the pipeline	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	Isolated pit at 6 o'clock position of the pipe with no uniform corrosion	Pitting uniformly distributed over a large area across 6 o'clock position of the pipeline	General corrosion uniformly distributed all over the pipeline

Table A26 Microbiology-related parameters included in the case studies provided to the experts – cases 61 thru 65.

Case ID	Case 61	Case 62	Case 63	Case 64	Case 65
Microbiology related parameters					
Microbiological Sample Type (s.u.)	Swab/Surface (cm^{-2})	Swab/Surface (cm^{-2})	Liquid (mL^{-1})	Liquid (mL^{-1})	Swab/Surface (cm^{-2})
ATP[a] results - Corroded Area	1.00E+02	1.00E+08	1.00E+08	1.00E+08	1.00E+02
ATP results - NON-Corroded Area	1.00E+02	1.00E+01	1.00E+01	No data	1.00E+02
qPCR[b] results - Corroded Area - Total Bacteria	< 1.00E+04	2.00E+10	No data	No data	< 1.00E+04
qPCR results - Corroded Area - Total Archaea	< 1.00E+04	3.00E+09	No data	No data	< 1.00E+04
qPCR results - NON-Corroded Area - Total Bacteria	< 1.00E+04	< 1.00E+04	No data	No data	No data
qPCR results - NON-Corroded Area - Total Archaea	< 1.00E+04	< 1.00E+04	No data	No data	No data
NGS[c] results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	0.00%	54.00%	No data	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	0.00%	8.00%	No data	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	0.00%	12.00%	No data	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Acetogens (ACE)	0.00%	17.00%	No data	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Fermenters (FER)	0.00%	9.00%	No data	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	35.00%	0.00%	No data	No data	35.00%
NGS results - Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	0.00%	0.00%	No data	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	0.00%	0.00%	No data	No data	0.00%
NGS results - Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	60.00%	0.00%	No data	No data	60.00%
NGS results - Corroded Area - Relative Abundance (%) of Others/Unidentified	5.00%	0.00%	No data	No data	5.00%
NGS results - Corroded Area - Relative Abundance (%) - Total	100.00%	100.00%	No data	No data	100.00%
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Bacteria (SRB)	0.00%	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Sulfate Reducing Archaea (SRA)	0.00%	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Methanogenic Archaea (MA)	0.00%	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Acetogens (ACE)	0.00%	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Fermenters (FER)	0.00%	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Reducing Bacteria (IRB)	35.00%	35.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Iron Oxidizing Bacteria (IOB)	0.00%	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Manganese Oxidizing Bacteria (MnOB)	0.00%	0.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Nitrate Reducing Bacteria (NRB)	60.00%	60.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) of Others/Unidentified	5.00%	5.00%	No data	No data	No data
NGS results - NON-Corroded Area - Relative Abundance (%) - Total	100.00%	100.00%	No data	No data	No data
MPN[d] bacteria/mL as per number of bottles - Corroded Area - Sulfate Reducing Bacteria (SRB)	No data	No data	No data	No data	No data
MPN bacteria/mL as per number of bottles - Corroded Area - Acid Producing Bacteria (APB)	No data	No data	No data	No data	No data
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Sulfate Reducing Bacteria (SRB)	No data	No data	No data	No data	No data
MPN bacteria/mL as per number of bottles - NON-Corroded Area - Acid Producing Bacteria (APB)	No data	No data	No data	No data	No data

a Adenosine triphosphate assay (enzymatic assay)
b Quantitative polymerase chain reaction (DNA target quantification)
c Next generation sequencing (DNA sequencing)
d Most probable numbers (culture-based test)

Appendix B. Translation of Case Study Variables into 16 ANN Input Variables for ANN Training, Validation, and Testing (Chapter 5)

Appendix B: Second set of supplementary data to **Chapter 5**: Tables B1 thru B5.

Table B1 The 16 Input Variables used to Train, Validate, and Test the ANN – 1 thru 15.

# Input Parameter	Case ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	Operating related parameters															
1	Is the liquid water accumulated on the metal surface *STAGNANT* (1), STRATIFIED (0) or NOT TESTED (-1)?	0	1	1	0	1	1	1	0	0	1	0	0	0	1	0
2	Is the operating temperature of the system between $10°C \leq T \leq 95°C$? [YES (1), NO (0), NOT TESTED (-1)]	1	1	1	1	1	1	1	0	1	1	0	1	0	0	0
	Chemistry related parameters															
3	Is the operating pH of the system between $4 \leq pH \leq 9$? [YES (1), NO (0), NOT TESTED (-1)]	1	1	0	1	1	1	1	1	1	1	0	1	0	1	1
4	Is the total dissolved solids (TDS) in the water in the system below 200,000 mg/L? [YES (1), NO (0), NOT TESTED (-1)]	1	1	1	1	1	1	1	1	0	1	0	0	1	1	0
5	Is H_2S present in the system? [YES (1), NO (0), NOT TESTED (-1)]	0	1	0	0	0	1	0	1	0	0	1	1	1	0	0
6	Is CO_2 present in the system? [YES (1), NO (0), NOT TESTED (-1)]	1	1	1	0	0	1	0	1	0	1	1	0	1	1	1
	Metallurgy/corrosion related parameters															
7	Was the chemistry of solids present on the surface analysed by EDS[a] [1], EDS + XRD[b] [2], spot testing [0], or not tested at all [-1]?	2	0	2	0	2	0	2	0	2	0	2	0	2	2	2
8	Did chemical testing of corrosion products identify the presence of **sulfur related species** (sulfur, sulfides)? [YES (1), NO (0), NOT TESTED (-1)]	1	1	0	0	0	1	0	1	0	0	1	1	1	0	0
9	Is the **contrast** of chemical testing results for sulfur related species greater in the corroded area than in the non-corroded area? [MORE (1), SAME (0), NOT CONTRASTED (-1)]	1	0	0	0	0	0	0	0	0	0	0	0	0	0	-1
10	What is the morphology of the corrosion present? [Uniform/General (1), Clustered/Scattered Pits (2), Isolated Pits (3)]	3	2	3	2	3	2	3	2	2	2	2	2	2	1	1

Table B1 (continued)

# Input Parameter	**Case ID**	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	Microbiology related parameters															
11	Are the microbiological related tests (e.g., ATP[c], BART[d], MPN[e], qPCR[f], DNA sequencing) taken from surface/solid samples or liquid samples? [SURFACE (1), LIQUID (0), NEED DATA (-1)]	1	0	1	0	1	0	1	0	1	0	1	0	1	1	1
12	Were abundance and diversity assessed by Molecular Microbiological Methods, MMM[g], (e.g., qPCR, NGS[h]) or culturing methods (e.g., MPN, BART)? [MMM (1), Culturing (0), NEED DATA (-1)]	1	0	1	0	1	0	1	0	1	0	1	0	1	1	1
13	Is the ATP result equal to or greater than 10E6 cells/sample unit? [YES (1), NO (0), NEED DATA (-1)]	1	0	1	0	1	1	1	1	0	1	0	1	0	0	0
14	Is the contrast between the ATP result at the corroded area greater than at uncorroded areas? [YES (1), NO (0), NEED DATA (-1)]	1	0	1	0	1	0	1	1	0	1	0	1	0	0	-1
15	Are MIC related microorganisms present in abundance (e.g., >10E6, 6 bottles) in the system? [YES (1), NO (0), NEED DATA (-1)]	1	0	1	0	1	0	1	1	0	1	0	1	0	0	0
16	Is there a difference between the corroded area and the non corroded area in terms of the diversity and abundance of the MIC related microorganisms present? [YES (1), NO (0), NEED DATA (-1)]	1	0	1	0	1	0	1	1	0	1	0	1	0	0	-1

a Energy-dispersive X-ray spectroscopy
b X-ray diffraction
c Adenosine triphosphate assay (enzymatic assay)
d Biological activity reaction test
e Most probable numbers (culture-based test)
f Quantitative polymerase chain reaction (DNA target quantification)
g Molecular microbiological methods
h Next generation sequencing (DNA sequencing)

Table B2 The 16 Input Variables used to Train, Validate, and Test the ANN – 16 thru 30.

# Input Parameter	Case ID	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
	Operating related parameters															
1	Is the liquid water accumulated on the metal surface *STAGNANT* (1), STRATIFIED (0) or NOT TESTED (-1)?	1	1	1	0	0	1	0	1	0	0	0	0	1	-1	0
2	Is the operating temperature of the system between 10°C ≤ T ≤ 95°C? [YES (1), NO (0), NOT TESTED (-1)]	1	1	1	1	1	1	1	1	1	1	1	1	1	1	-1
	Chemistry related parameters															
3	Is the operating pH of the system between 4 ≤ pH ≤ 9? [YES (1), NO (0), NOT TESTED (-1)]	1	1	1	0	1	1	0	0	1	0	0	0	0	1	1
4	Is the total dissolved solids (TDS) in the water in the system below 200,000 mg/L? [YES (1), NO (0), NOT TESTED (-1)]	0	1	0	1	1	0	1	1	1	1	0	1	1	1	1
5	Is H_2S present in the system? [YES (1), NO (0), NOT TESTED (-1)]	1	1	1	1	1	1	0	0	1	1	0	0	1	1	1
6	Is CO_2 present in the system? [YES (1), NO (0), NOT TESTED (-1)]	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0
	Metallurgy/corrosion related parameters															
7	Was the chemistry of solids present on the surface analysed by EDS[a] [1], EDS + XRD[b] [2], spot testing [0], or not tested at all [-1]?	0	2	0	2	0	2	0	1	0	2	0	0	2	0	1
8	Did chemical testing of corrosion products identify the presence of **sulfur related species** (sulfur, sulfides)? [YES (1), NO (0), NOT TESTED (-1)]	0	1	1	1	1	1	0	1	1	1	0	1	1	0	1
9	Is the **contrast** of chemical testing results for sulfur related species greater in the corroded area than in the non-corroded area? [MORE (1), SAME (0), NOT CONTRASTED (-1)]	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	0
10	What is the morphology of the corrosion present? [Uniform/General (1), Clustered/Scattered Pits (2), Isolated Pits (3)]	2	2	2	3	2	2	2	3	2	2	2	2	1	2	1

Table B2 (continued)

# Input Parameter	Case ID	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
	Microbiology related parameters															
11	Are the microbiological related tests (e.g., ATP[c], BART[d], MPN[e], qPCR[f], DNA sequencing) taken from surface/solid samples or liquid samples? [SURFACE (1), LIQUID (0), NEED DATA (-1)]	0	1	0	1	0	1	0	1	0	1	0	0	1	-1	0
12	Were abundance and diversity assessed by Molecular Microbiological Methods, MMM[g], (e.g., qPCR, NGS[h]) or culturing methods (e.g., MPN, BART)? [MMM (1), Culturing (0), NEED DATA (-1)]	0	1	0	1	0	1	0	1	0	1	0	1	1	-1	-1
13	Is the ATP result equal to or greater than 10E6 cells/sample unit? [YES (1), NO (0), NEED DATA (-1)]	0	0	1	1	1	1	1	1	1	0	0	1	0	-1	0
14	Is the contrast between the ATP result at the corroded area greater than at uncorroded areas? [YES (1), NO (0), NEED DATA (-1)]	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
15	Are MIC related microorganisms present in abundance (e.g., >10E6, 6 bottles) in the system? [YES (1), NO (0), NEED DATA (-1)]	0	0	0	1	1	1	1	1	1	0	0	1	0	-1	-1
16	Is there a difference between the corroded area and the non-corroded area in terms of the diversity and abundance of the microbiologically influenced corrosion (MIC) related microorganisms present? [YES (1), NO (0), NEED DATA (-1)]	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1

a Energy-dispersive X-ray spectroscopy
b X-ray diffraction
c Adenosine triphosphate assay (enzymatic assay)
d Biological activity reaction test
e Most probable numbers (culture-based test)
f Quantitative polymerase chain reaction (DNA target quantification)
g Molecular microbiological methods
h Next generation sequencing (DNA sequencing)

Table B3 The 16 Input Variables used to Train, Validate, and Test the ANN – 31 thru 45.

# Input Parameter	Case ID	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45
	Operating related parameters															
1	Is the liquid water accumulated on the metal surface *STAGNANT* (1), STRATIFIED (0) or NOT TESTED (-1)?	-1	1	1	0	1	1	-1	1	-1	1	1	1	1	0	-1
2	Is the operating temperature of the system between 10°C ≤ T ≤ 95°C? [YES (1), NO (0), NOT TESTED (-1)]	1	-1	1	1	1	1	1	-1	-1	1	-1	-1	0	1	1
	Chemistry related parameters															
3	Is the operating pH of the system between 4 ≤ pH ≤ 9? [YES (1), NO (0), NOT TESTED (-1)]	1	0	-1	1	-1	1	-1	1	-1	-1	-1	1	-1	-1	-1
4	Is the total dissolved solids (TDS) in the water in the system below 200,000 mg/L? [YES (1), NO (0), NOT TESTED (-1)]	1	0	-1	1	-1	1	-1	1	-1	-1	-1	1	-1	-1	-1
5	Is H_2S present in the system? [YES (1), NO (0), NOT TESTED (-1)]	0	-1	1	1	0	-1	1	0	0	0	0	0	-1	0	0
6	Is CO_2 present in the system? [YES (1), NO (0), NOT TESTED (-1)]	1	-1	0	1	0	-1	1	1	1	1	1	0	-1	1	0
	Metallurgy/corrosion related parameters															
7	Was the chemistry of solids present on the surface analysed by EDS[a] [1], EDS + XRD[b] [2], spot testing [0], or not tested at all [-1]?	-1	0	-1	1	-1	2	2	0	1	2	-1	1	1	1	2
8	Did chemical testing of corrosion products identify the presence of **sulfur related species** (sulfur, sulfides)? [YES (1), NO (0), NOT TESTED (-1)]	-1	1	-1	1	-1	1	0	1	1	0	-1	0	1	1	0
9	Is the **contrast** of chemical testing results for sulfur related species greater in the corroded area than in the non-corroded area? [MORE (1), SAME (0), NOT CONTRASTED (-1)]	-1	-1	-1	-1	-1	1	-1	-1	-1	0	-1	0	0	1	-1
10	What is the morphology of the corrosion present? [Uniform/General (1), Clustered/Scattered Pits (2), Isolated Pits (3)]	2	1	2	3	1	3	1	2	2	1	2	1	2	2	2

Table B3 (continued)

# Input Parameter	Case ID	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45
	Microbiology related parameters															
11	Are the microbiological related tests (e.g., ATP[c], BART[d], MPN[e], qPCR[f], DNA sequencing) taken from surface/solid samples or liquid samples? [SURFACE (1), LIQUID (0), NEED DATA (-1)]	0	0	-1	0	0	1	-1	0	0	1	-1	0	0	1	-1
12	Were abundance and diversity assessed by Molecular Microbiological Methods, MMM[g], (e.g., qPCR, NGS[h]) or culturing methods (e.g., MPN, BART)? [MMM (1), Culturing (0), NEED DATA (-1)]	0	1	-1	-1	0	1	-1	-1	0	1	-1	-1	0	1	-1
13	Is the ATP result equal to or greater than 10E6 cells/sample unit? [YES (1), NO (0), NEED DATA (-1)]	0	-1	-1	1	1	-1	-1	1	1	0	-1	0	0	1	-1
14	Is the contrast between the ATP result at the corroded area greater than at uncorroded areas? [YES (1), NO (0), NEED DATA (-1)]	-1	-1	-1	-1	-1	-1	-1	1	-1	-1	-1	-1	0	-1	-1
15	Are MIC related microorganisms present in abundance (e.g., >10E6, 6 bottles) in the system? [YES (1), NO (0), NEED DATA (-1)]	0	0	-1	-1	1	1	-1	-1	1	0	-1	-1	0	1	-1
16	Is there a difference between the corroded area and the non-corroded area in terms of the diversity and abundance of the microbiologically influenced corrosion (MIC) related microorganisms present? [YES (1), NO (0), NEED DATA (-1)]	0	0	-1	-1	-1	-1	-1	-1	-1	0	-1	-1	0	1	-1

a Energy-dispersive X-ray spectroscopy
b X-ray diffraction
c Adenosine triphosphate assay (enzymatic assay)
d Biological activity reaction test
e Most probable numbers (culture-based test)
f Quantitative polymerase chain reaction (DNA target quantification)
g Molecular microbiological methods
h Next generation sequencing (DNA sequencing)

Table B4 The 16 Input Variables used to Train, Validate, and Test the ANN – 46 thru 60.

# Input Parameter	Case ID	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60
	Operating related parameters															
1	Is the liquid water accumulated on the metal surface *STAGNANT* (1), STRATIFIED (0) or NOT TESTED (-1)?	-1	1	0	0	0	1	0	0	0	0	0	1	0	1	0
2	Is the operating temperature of the system between 10°C ≤ T ≤ 95°C? [YES (1), NO (0), NOT TESTED (-1)]	1	-1	1	0	1	1	0	1	1	1	0	1	0	1	0
	Chemistry related parameters															
3	Is the operating pH of the system between 4 ≤ pH ≤ 9? [YES (1), NO (0), NOT TESTED (-1)]	-1	0	1	1	1	-1	-1	1	-1	-1	-1	0	1	1	0
4	Is the total dissolved solids (TDS) in the water in the system below 200,000 mg/L? [YES (1), NO (0), NOT TESTED (-1)]	0	1	-1	0	1	-1	0	1	-1	-1	-1	1	1	0	1
5	Is H_2S present in the system? [YES (1), NO (0), NOT TESTED (-1)]	-1	1	0	1	0	1	1	0	0	0	-1	0	1	1	1
6	Is CO_2 present in the system? [YES (1), NO (0), NOT TESTED (-1)]	-1	1	1	1	1	0	0	1	0	1	-1	1	1	0	1
	Metallurgy/corrosion related parameters															
7	Was the chemistry of solids present on the surface analysed by EDS[a] [1], EDS + XRD[b] [2], spot testing [0], or not tested at all [-1]?	-1	0	1	1	0	0	2	0	-1	0	2	2	2	0	0
8	Did chemical testing of corrosion products identify the presence of **sulfur related species** (sulfur, sulfides)? [YES (1), NO (0), NOT TESTED (-1)]	-1	1	1	1	0	1	1	1	-1	1	0	1	1	0	1
9	Is the **contrast** of chemical testing results for sulfur related species greater in the corroded area than in the non-corroded area? [MORE (1), SAME (0), NOT CONTRASTED (-1)]	-1	-1	1	0	-1	-1	0	-1	-1	-1	0	1	-1	-1	-1
10	What is the morphology of the corrosion present? [Uniform/General (1), Clustered/Scattered Pits (2), Isolated Pits (3)]	3	2	3	2	1	3	2	3	3	2	1	2	2	2	2

Table B4 (continued)

# Input Parameter	Case ID	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60
	Microbiology related parameters															
11	Are the microbiological related tests (e.g., ATP[c], BART[d], MPN[e], qPCR[f], DNA sequencing) taken from surface/solid samples or liquid samples? [SURFACE (1), LIQUID (0), NEED DATA (-1)]	0	0	1	-1	1	0	1	-1	1	1	1	0	0	0	0
12	Were abundance and diversity assessed by Molecular Microbiological Methods, MMM[g], (e.g., qPCR, NGS[h]) or culturing methods (e.g., MPN, BART)? [MMM (1), Culturing (0), NEED DATA (-1)]	-1	0	1	-1	-1	0	1	-1	-1	0	1	1	0	0	0
13	Is the ATP result equal to or greater than 10E6 cells/sample unit? [YES (1), NO (0), NEED DATA (-1)]	1	0	1	-1	0	-1	0	-1	1	-1	0	1	1	0	0
14	Is the contrast between the ATP result at the corroded area greater than at uncorroded areas? [YES (1), NO (0), NEED DATA (-1)]	0	0	-1	-1	-1	-1	-1	-1	1	-1	0	1	-1	-1	-1
15	Are MIC related microorganisms present in abundance (e.g., >10E6, 6 bottles) in the system? [YES (1), NO (0), NEED DATA (-1)]	-1	0	1	-1	-1	1	0	-1	-1	1	0	1	0	1	0
16	Is there a difference between the corroded area and the non-corroded area in terms of the diversity and abundance of the microbiologically influenced corrosion (MIC) related microorganisms present? [YES (1), NO (0), NEED DATA (-1)]	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	1	-1	-1	-1

a Energy-dispersive X-ray spectroscopy
b X-ray diffraction
c Adenosine triphosphate assay (enzymatic assay)
d Biological activity reaction test
e Most probable numbers (culture-based test)
f Quantitative polymerase chain reaction (DNA target quantification)
g Molecular microbiological methods
h Next generation sequencing (DNA sequencing)

Table B5 The 16 Input Variables used to Train, Validate, and Test the ANN – 61 thru 65.

# Input Parameter	Case ID	61	62	63	64	65
	Operating related parameters					
1	Is the liquid water accumulated on the metal surface *STAGNANT* (1), STRATIFIED (0) or NOT TESTED (-1)?	1	1	1	-1	1
2	Is the operating temperature of the system between 10°C ≤ T ≤ 95°C? [YES (1), NO (0), NOT TESTED (-1)]	0	0	1	0	0
	Chemistry related parameters					
3	Is the operating pH of the system between 4 ≤ pH ≤ 9? [YES (1), NO (0), NOT TESTED (-1)]	0	-1	1	-1	-1
4	Is the total dissolved solids (TDS) in the water in the system below 200,000 mg/L? [YES (1), NO (0), NOT TESTED (-1)]	0	-1	1	-1	1
5	Is H_2S present in the system? [YES (1), NO (0), NOT TESTED (-1)]	0	0	1	-1	1
6	Is CO_2 present in the system? [YES (1), NO (0), NOT TESTED (-1)]	1	1	1	-1	1
	Metallurgy/corrosion related parameters					
7	Was the chemistry of solids present on the surface analysed by EDS[a] [1], EDS + XRD[b] [2], spot testing [0], or not tested at all [-1]?	2	2	0	0	1
8	Did chemical testing of corrosion products identify the presence of **sulfur related species** (sulfur, sulfides)? [YES (1), NO (0), NOT TESTED (-1)]	0	1	1	1	1
9	Is the **contrast** of chemical testing results for sulfur related species greater in the corroded area than in the non-corroded area? [MORE (1), SAME (0), NOT CONTRASTED (-1)]	0	1	-1	-1	0
10	What is the morphology of the corrosion present? [Uniform/General (1), Clustered/Scattered Pits (2), Isolated Pits (3)]	1	2	3	2	1

Table B5 (continued)

# Input Parameter	**Case ID**	61	62	63	64	65
	Microbiology related parameters					
11	Are the microbiological related tests (e.g., ATP[c], BART[d], MPN[e], qPCR[f], DNA sequencing) taken from surface/solid samples or liquid samples? [SURFACE (1), LIQUID (0), NEED DATA (-1)]	1	1	0	0	1
12	Were abundance and diversity assessed by Molecular Microbiological Methods, MMM[g], (e.g., qPCR, NGS[h]) or culturing methods (e.g., MPN, BART)? [MMM (1), Culturing (0), NEED DATA (-1)]	1	1	-1	-1	1
13	Is the ATP result equal to or greater than 10E6 cells/sample unit? [YES (1), NO (0), NEED DATA (-1)]	0	1	1	1	0
14	Is the contrast between the ATP result at the corroded area greater than at uncorroded areas? [YES (1), NO (0), NEED DATA (-1)]	0	1	1	-1	0
15	Are MIC related microorganisms present in abundance (e.g., >10E6, 6 bottles) in the system? [YES (1), NO (0), NEED DATA (-1)]	0	1	-1	-1	0
16	Is there a difference between the corroded area and the non-corroded area in terms of the diversity and abundance of the microbiologically influenced corrosion (MIC) related microorganisms present? [YES (1), NO (0), NEED DATA (-1)]	0	1	-1	-1	-1

a Energy-dispersive X-ray spectroscopy
b X-ray diffraction
c Adenosine triphosphate assay (enzymatic assay)
d Biological activity reaction test
e Most probable numbers (culture-based test)
f Quantitative polymerase chain reaction (DNA target quantification)
g Molecular microbiological methods
h Next generation sequencing (DNA sequencing)

Appendix C. Complete Standard Deviation Tables for 5- and 3-Output Classifications (Chapter 5)

Appendix C: Third set of supplementary data to **Chapter 5**: Tables C1 thru C6.

Table C1 List of case responses (targets), model predicted classes, and the standard deviation results associated with each of the training and validation cases for the 5-output classification – 1 thru 28.

General			5 Output Classes[a]								
Case Number	Case Data Type[b]	Number of Case Replications	Model Prediction	Expert Response A	Expert Response B	Expert Response C	Expert Response D	Expert Response E	Expert Response F	Average Expert Response	Expert Standard Deviation
1	Fully	6	1	1	1	1	1	1	1	1.0	0.0
2	Fully	5	4	3	4	3	3	2	-	3.0	0.7
3	Fully	6	2	1	1	2	3	4	1	2.0	1.3
4	Fully	5	3	4	3	5	3	4	-	3.8	0.8
5	Fully	6	1	3	1	1	2	4	1	2.0	1.3
6	Fully	6	4	4	4	4	3	5	3	3.8	0.8
7	Fully	4	1	2	2	2	1	-	-	1.8	0.5
8	Fully	5	4	2	4	4	4	4	-	3.6	0.9
9	Fully	6	5	5	4	3	3	5	5	4.2	1.0
10	Fully	5	2	2	3	2	2	2	-	2.2	0.4

Table C1 (continued)

General			5 Output Classes[a]								
Case Number	Case Data Type[b]	Number of Case Replications	Model Prediction	Expert Response A	Expert Response B	Expert Response C	Expert Response D	Expert Response E	Expert Response F	Average Expert Response	Expert Standard Deviation
11	Fully	5	5	5	4	5	4	3	-	4.2	0.8
12	Fully	6	2	3	3	1	3	2	2	2.3	0.8
13	Fully	5	5	5	2	5	5	5	-	4.4	1.3
14	Fully	5	5	5	5	5	5	5	-	5.0	0.0
15	Partially	5	5	5	5	5	5	5	-	5.0	0.0
16	Partially	5	3	3	4	3	5	3	-	3.6	0.9
17	Partially	6	5	2	5	3	2	4	5	3.5	1.4
18	Partially	5	3	4	4	3	3	2	-	3.2	0.8
19	Partially	5	1	1	2	2	3	1	-	1.8	0.8
20	Partially	6	3	1	3	2	3	3	3	2.5	0.8
21	Partially	6	2	2	1	2	2	1	2	1.7	0.5
22	Partially	6	3	2	3	3	5	2	3	3.0	1.1

Table C1 (continued)

General			5 Output Classes[a]								
Case Number	Case Data Type[b]	Number of Case Replications	Model Prediction	Expert Response A	Expert Response B	Expert Response C	Expert Response D	Expert Response E	Expert Response F	Average Expert Response	Expert Standard Deviation
23	Partially	6	1	1	4	1	2	3	1	2.0	1.3
24	Partially	5	3	3	2	4	3	2	-	2.8	0.8
25	Partially	5	5	2	5	5	4	3	-	3.8	1.3
26	Partially	5	3	5	5	3	3	2	-	3.6	1.3
27	Partially	4	1	1	3	2	1	-	-	1.8	1.0
28	Partially	6	5	5	5	4	5	5	5	4.8	0.4

a "1" represents output class 'MIC high confidence'. "2" represents output class 'MIC low confidence'. "3" represents output class 'need more data'. "4" represents output class 'no MIC low confidence'. "5" represents output class 'no MIC high confidence'.

b "Fully" refers to cases where all layers of evidence included are fully populated. "Partially" refers to cases where all layers of evidence included are fully populated, but the corrosion and microbiological related results associated to the non-corroded area (allowing for no contrast). "Missing" refers to cases with missing data at various levels across the 4 information groups.

Table C2 List of case responses (targets), model predicted classes, and the standard deviation results associated with each of the training and validation cases for the 5-output classification – 29 thru 56.

General			5 Output Classes[a]								
Case Number	Case Data Type[b]	Number of Case Replications	Model Prediction	Expert Response A	Expert Response B	Expert Response C	Expert Response D	Expert Response E	Expert Response F	Average Expert Response	Expert Standard Deviation
29	Missing	5	3	3	3	3	3	3	-	3.0	0.0
30	Missing	5	3	3	3	4	5	3	-	3.6	0.9
31	Missing	5	3	3	3	3	3	5	-	3.4	0.9
32	Missing	6	4	4	4	5	5	4	4	4.3	0.5
33	Missing	5	3	3	3	3	3	3	-	3.0	0.0
34	Missing	5	3	3	3	3	3	2	-	2.8	0.4
35	Missing	5	3	2	3	3	4	3	-	3.0	0.7
36	Missing	6	1	1	1	2	1	2	1	1.3	0.5
37	Missing	4	5	4	5	4	4	-	-	4.3	0.5
38	Missing	5	3	2	3	3	3	2	-	2.6	0.5
39	Missing	5	2	2	2	3	3	1	-	2.2	0.8
40	Missing	5	5	5	5	5	5	3	-	4.6	0.9

Table C2 (continued)

General				5 Output Classes[a]							
Case Number	Case Data Type[b]	Number of Case Replications	Model Prediction	Expert Response A	Expert Response B	Expert Response C	Expert Response D	Expert Response E	Expert Response F	Average Expert Response	Expert Standard Deviation
41	Missing	6	3	3	3	3	3	3	3	3.0	0.0
42	Missing	5	3	3	3	3	3	4	-	3.2	0.4
43	Missing	6	4	4	3	4	3	5	4	3.8	0.8
44	Missing	5	1	3	2	1	1	2	-	1.8	0.8
45	Missing	6	3	3	3	3	3	3	3	3.0	0.0
46	Missing	6	3	3	3	3	3	3	3	3.0	0.0
47	Missing	6	5	4	3	5	5	5	3	4.2	1.0
48	Missing	5	1	1	1	1	2	1	-	1.2	0.4
49	Missing	5	5	5	5	4	4	3	-	4.2	0.8
50	Missing	6	4	4	4	4	3	4	3	3.7	0.5
51	Missing	6	2	2	3	2	1	2	2	2.0	0.6
52	Missing	4	4	5	4	4	4	-	-	4.3	0.5

Table C2 (continued)

General						5 Output Classes[a]					
Case Number	Case Data Type[b]	Number of Case Replications	Model Prediction	Expert Response A	Expert Response B	Expert Response C	Expert Response D	Expert Response E	Expert Response F	Average Expert Response	Expert Standard Deviation
53	Missing	6	3	3	3	3	3	2	3	2.8	0.4
54	Missing	5	3	3	3	2	2	2	-	2.4	0.5
55	Missing	6	2	2	1	3	3	2	2	2.2	0.8
56	Missing	6	4	4	5	4	5	4	4	4.3	0.5

a "1" represents output class 'MIC high confidence'. "2" represents output class 'MIC low confidence'. "3" represents output class 'need more data'. "4" represents output class 'no MIC low confidence'. "5" represents output class 'no MIC high confidence'.

b "Fully" refers to cases where all layers of evidence included are fully populated. "Partially" refers to cases where all layers of evidence included are fully populated, but the corrosion and microbiological related results associated to the non-corroded area (allowing for no contrast). "Missing" refers to cases with missing data at various levels across the 4 information groups.

Table C3 List of case responses (targets), model predicted classes, and the standard deviation results associated with each of the training and validation cases for the 3-output classification – 1 thru 28.

General				3 Output Classes[a]							
Case Number	Case Data Type[b]	Number of Case Replications	Model Prediction	Expert Response A	Expert Response B	Expert Response C	Expert Response D	Expert Response E	Expert Response F	Average Expert Response	Expert Standard Deviation
1	Fully	6	1	1	1	1	1	1	1	1.0	0.0
2	Fully	5	2	2	3	2	2	1	-	2.0	0.7
3	Fully	6	1	1	1	1	2	3	1	1.5	0.8
4	Fully	5	2	3	2	3	2	3	-	2.6	0.5
5	Fully	6	1	2	1	1	1	3	1	1.5	0.8
6	Fully	6	2	3	3	3	2	3	2	2.7	0.5
7	Fully	4	1	1	1	1	1	-	-	1.0	0.0
8	Fully	5	3	1	3	3	3	3	-	2.6	0.9
9	Fully	6	3	3	3	2	2	3	3	2.7	0.5
10	Fully	5	1	1	2	1	1	1	-	1.2	0.4
11	Fully	5	3	3	3	3	3	2	-	2.8	0.4
12	Fully	6	1	2	2	1	2	1	1	1.5	0.5

Table C3 (continued)

General				3 Output Classes[a]							
Case Number	Case Data Type[b]	Number of Case Replications	Model Prediction	Expert Response A	Expert Response B	Expert Response C	Expert Response D	Expert Response E	Expert Response F	Average Expert Response	Expert Standard Deviation
13	Fully	5	3	3	1	3	3	3	-	2.6	0.9
14	Fully	5	3	3	3	3	3	3	-	3.0	0.0
15	Partially	5	3	3	3	3	3	3	-	3.0	0.0
16	Partially	5	3	2	3	2	3	2	-	2.4	0.5
17	Partially	6	3	1	3	2	1	3	3	2.2	1.0
18	Partially	5	3	3	3	2	2	1	-	2.2	0.8
19	Partially	5	1	1	1	1	2	1	-	1.2	0.4
20	Partially	6	2	1	2	1	2	2	2	1.7	0.5
21	Partially	6	1	1	1	1	1	1	1	1.0	0.0
22	Partially	6	1	1	2	2	3	1	2	1.8	0.8
23	Partially	6	1	1	3	1	1	2	1	1.5	0.8
24	Partially	5	2	2	1	3	2	3	-	2.2	0.8

Table C3 (continued)

General				3 Output Classes[a]							
Case Number	Case Data Type[b]	Number of Case Replications	Model Prediction	Expert Response A	Expert Response B	Expert Response C	Expert Response D	Expert Response E	Expert Response F	Average Expert Response	Expert Standard Deviation
25	Partially	5	3	1	3	3	3	2	-	2.4	0.9
26	Partially	5	2	3	3	2	2	1	-	2.2	0.8
27	Partially	4	1	1	2	1	1	-	-	1.3	0.5
28	Partially	6	3	3	3	3	3	3	3	3.0	0.0

a "1" represents output class 'MIC'; "2" represents output class 'need more data'; "3" represents output class 'no MIC'.

b "Fully" refers to cases where all layers of evidence included are fully populated. "Partially" refers to cases where all layers of evidence included are fully populated, but the corrosion and microbiological related results associated to the non-corroded area (allowing for no contrast). "Missing" refers to cases with missing data at various levels across the 4 information groups.

Table C4 List of case responses (targets), model predicted classes, and the standard deviation results associated with each of the training and validation cases for the 3-output classification – 29 thru 56.

General				3 Output Classes[a]							
Case Number	Case Data Type[b]	Number of Case Replications	Model Prediction	Expert Response A	Expert Response B	Expert Response C	Expert Response D	Expert Response E	Expert Response F	Average Expert Response	Expert Standard Deviation
29	Missing	5	2	2	2	2	2	2	-	2.0	0.0
30	Missing	5	2	2	2	3	3	2	-	2.4	0.5
31	Missing	5	2	2	2	2	2	3	-	2.2	0.4
32	Missing	6	3	3	3	3	3	3	3	3.0	0.0
33	Missing	5	2	2	2	2	2	2	-	2.0	0.0
34	Missing	5	2	2	2	2	2	1	-	1.8	0.4
35	Missing	5	2	1	2	2	3	2	-	2.0	0.7
36	Missing	6	1	1	1	1	1	1	1	1.0	0.0
37	Missing	4	3	3	3	3	3	-	-	3.0	0.0
38	Missing	5	2	1	2	2	2	1	-	1.6	0.5
39	Missing	5	1	1	1	2	2	1	-	1.4	0.5
40	Missing	5	3	3	3	3	3	2	-	2.8	0.4

Table C4 (continued)

General				3 Output Classes[a]							
Case Number	Case Data Type[b]	Number of Case Replications	Model Prediction	Expert Response A	Expert Response B	Expert Response C	Expert Response D	Expert Response E	Expert Response F	Average Expert Response	Expert Standard Deviation
41	Missing	6	2	2	2	2	2	2	2	2.0	0.0
42	Missing	5	2	2	2	2	2	3	-	2.2	0.4
43	Missing	6	3	3	2	3	2	3	3	2.7	0.5
44	Missing	5	1	2	1	1	1	1	-	1.2	0.4
45	Missing	6	2	2	2	2	2	2	2	2.0	0.0
46	Missing	6	2	2	2	2	2	2	2	2.0	0.0
47	Missing	6	3	3	2	3	3	3	2	2.7	0.5
48	Missing	5	1	1	1	1	1	1	-	1.0	0.0
49	Missing	5	3	3	3	3	3	2	-	2.8	0.4
50	Missing	6	3	3	3	3	2	3	2	2.7	0.5
51	Missing	6	1	1	2	1	1	1	1	1.2	0.4
52	Missing	4	3	3	3	3	3	-	-	3.0	0.0

Table C4 (continued)

General			3 Output Classes[a]								
Case Number	Case Data Type[b]	Number of Case Replications	Model Prediction	Expert Response A	Expert Response B	Expert Response C	Expert Response D	Expert Response E	Expert Response F	Average Expert Response	Expert Standard Deviation
53	Missing	6	2	2	2	2	2	1	2	1.8	0.4
54	Missing	5	1	2	2	1	1	1	-	1.4	0.5
55	Missing	6	1	1	1	2	2	1	1	1.3	0.5
56	Missing	6	3	3	3	3	3	3	3	3.0	0.0

a "1" represents output class 'MIC'; "2" represents output class 'need more data'; "3" represents output class 'no MIC'.

b "Fully" refers to cases where all layers of evidence included are fully populated. "Partially" refers to cases where all layers of evidence included are fully populated, but the corrosion and microbiological related results associated to the non-corroded area (allowing for no contrast). "Missing" refers to cases with missing data at various levels across the 4 information groups.

Table C5 List of case responses (targets), model predicted classes, and the standard deviation results associated with each of the testing cases for the 5-output classification – 57 thru 65.

General			5 Output Classes[a]						
Case Number	Case Data Type[b]	Number of Case Replications	Model Prediction	Expert Response A	Expert Response B	Expert Response C	Expert Response D	Average Expert Response	Expert Standard Deviation
57	Fully	2	4	1	4	-	-	2.8	2.1
58	Fully	4	3	3	4	4	2	3.3	1.0
59	Partially	3	3	2	3	3	-	2.8	0.6
60	Partially	3	5	3	5	5	-	4.2	1.2
61	Partially	4	5	5	5	5	5	4.8	0.0
62	Missing	4	1	1	4	2	1	2.2	1.4
63	Missing	2	3	3	2	-	-	2.5	0.7
64	Missing	4	3	3	3	3	3	3.2	0.0
65	Missing	3	5	5	4	5	-	4.4	0.6

a "1" represents output class 'MIC high confidence'. "2" represents output class 'MIC low confidence'. "3" represents output class 'need more data'. "4" represents output class 'no MIC low confidence'. "5" represents output class 'no MIC high confidence'.

b "Fully" refers to cases where all layers of evidence included are fully populated. "Partially" refers to cases where all layers of evidence included are fully populated, but the corrosion and microbiological related results associated to the non-corroded area (allowing for no contrast). "Missing" refers to cases with missing data at various levels across the 4 information groups.

Table C6 List of case responses (targets), model predicted classes, and the standard deviation results associated with each of the training and validation cases for the 3-output classification – 57 thru 65.

General			3 Output Classes[a]						
Case Number	Case Data Type[b]	Number of Case Replications	Model Prediction	Expert Response A	Expert Response B	Expert Response C	Expert Response D	Average Expert Response	Expert Standard Deviation
57	Fully	2	1	1	3	-	-	1.8	1.4
58	Fully	4	3	2	3	3	1	2.7	1.0
59	Partially	3	1	1	2	2	-	1.8	0.6
60	Partially	3	3	2	3	3	-	2.8	0.6
61	Partially	4	3	3	3	3	3	3.2	0.0
62	Missing	4	1	1	3	1	1	1.8	1.0
63	Missing	2	2	2	1	-	-	1.8	0.7
64	Missing	4	2	2	2	2	2	2.3	0.0
65	Missing	3	3	3	3	3	-	3.0	0.0

a "1" represents output class 'MIC'; "2" represents output class 'need more data'; "3" represents output class 'no MIC'.

b "Fully" refers to cases where all layers of evidence included are fully populated. "Partially" refers to cases where all layers of evidence included are fully populated, but the corrosion and microbiological related results associated to the non-corroded area (allowing for no contrast). "Missing" refers to cases with missing data at various levels across the 4 information groups.

Appendix D. Sensitivity Analysis Calculations – Weights and Biases of ANN (Chapter 5)

Appendix D: Fourth set of supplementary data to **Chapter 5**: Tables D1 thru D10.

Table D1 Weight matrix of hidden layer (10×16) for the 5-output classification.

$W_{ij,5}$	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	0.227	-0.367	-0.265	-0.841	-1.291	-0.605	0.423	0.634	-0.311	1.343	-0.333	-0.832	1.127	0.436	0.852	0.104
2	0.768	0.331	0.323	-1.062	0.299	0.294	-0.050	-0.069	-0.413	0.045	-0.097	-0.272	-0.269	-0.097	1.058	0.578
3	0.264	-0.672	1.105	-0.273	0.095	-0.082	-0.533	0.126	-0.378	1.063	-0.597	0.416	-0.340	0.245	0.220	-0.426
4	-0.247	0.453	0.080	-0.052	0.929	1.159	0.099	0.753	-0.148	0.947	0.297	0.521	0.543	0.182	0.671	-0.406
5	0.020	0.351	0.436	-0.313	-0.621	0.388	0.085	-0.921	0.429	-0.187	-0.526	0.586	0.722	-0.039	0.428	0.206
6	0.032	-0.786	-1.145	-0.218	-0.245	0.465	1.274	-0.182	-0.007	0.603	0.147	0.529	-0.167	-0.181	-0.332	-1.067
7	0.270	0.004	0.142	-0.020	0.222	-0.793	-0.234	0.811	0.068	0.866	-0.594	0.676	0.487	0.875	-0.080	-0.017
8	-0.060	-0.593	-0.267	0.606	-0.307	-0.759	0.284	0.486	-0.142	-1.183	-0.558	1.421	-0.372	0.452	0.619	0.259
9	-0.605	0.442	-0.297	0.569	0.043	-0.418	-0.466	-0.550	0.193	1.548	-0.226	-0.936	-0.128	-0.264	0.242	-0.290
10	0.401	-0.321	0.195	0.316	-0.478	-0.015	-0.529	-1.053	-0.172	-1.039	0.231	-0.620	-0.050	0.294	-1.173	0.266

Table D2 Weight matrix of output layer (5×10) for the 5-output classification.

$\Theta_{ij,5}$	1	2	3	4	5	6	7	8	9	10
1	0.5233	-0.3623	-0.0505	-0.0440	0.9672	-0.4230	1.3817	-0.0037	0.4017	-2.5675
2	0.2101	0.5753	0.3447	1.7469	0.1379	0.3631	0.4654	-0.3573	0.9036	0.0277
3	-0.4771	-0.3850	-0.1382	-0.7127	-0.1932	-0.1945	0.3951	-1.7764	0.7817	0.3984
4	-0.9841	-0.5762	-1.4018	-0.2359	-0.3968	-1.2371	0.5598	0.9602	-1.4924	0.3152
5	-1.8503	-0.7353	-0.0323	0.8960	0.8048	1.2766	0.0847	1.7584	-0.0331	1.3023

Table D3 Ten Bias vectors of first hidden layer (10×1) for the 5-output classification.

$W_{i1,5}$	1
1	0.8386
2	-1.5837
3	0.9590
4	0.5602
5	-0.6830
6	0.2300
7	0.4190
8	-1.1462
9	-1.6515
10	2.1039

Table D4 Five Bias vectors of output layer (5×1) for the 5-output classification.

$\Theta_{1j,5}$	1
1	-0.5147
2	0.0908
3	1.3623
4	0.8419
5	0.1487

Table D5 Relative weights for the 16 input variables of the 5-output classification.

$R_{Ij,5}$	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Relative Weight	4.2%	5.9%	6.0%	5.9%	5.9%	6.8%	5.4%	7.8%	3.2%	11.8%	5.1%	9.2%	5.7%	4.2%	7.8%	5.1%

Table D6 Weight matrix of hidden layer (10×16) for the 3-output classification.

$W_{ij,3}$	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	0.212	0.175	-0.248	0.084	0.077	-0.091	-0.516	-0.441	-0.475	-0.263	-0.462	0.194	-0.428	0.869	0.272	0.003
2	0.001	-0.533	0.705	-0.153	0.040	0.378	0.310	1.043	0.615	0.227	-0.474	0.539	-0.248	-0.547	-0.373	-0.214
3	-0.537	0.046	0.489	0.065	0.727	0.810	-0.274	-0.25	0.412	-0.211	-0.040	-0.401	-0.343	-0.441	0.212	-0.245
4	-0.420	0.342	0.766	-0.271	-0.200	-0.783	-0.17	0.146	0.622	-0.692	-0.562	-0.341	-0.398	-0.377	-0.367	0.092
5	0.518	0.667	-0.267	-0.438	0.236	0.865	-0.000	0.075	-0.722	1.704	-0.046	0.489	0.794	0.409	0.164	0.12
6	0.197	0.224	-0.005	-0.422	0.704	0.443	0.029	0.813	0.024	-1.204	-0.887	1.414	0.406	-0.130	0.965	0.289
7	0.067	-0.526	-0.145	0.678	-0.081	-0.917	0.424	-1.575	0.222	0.576	-0.948	-0.887	0.137	-0.241	-0.372	0.186
8	-0.371	-0.770	0.254	0.734	0.594	-0.260	-0.168	-0.036	0.627	-1.496	-0.614	-0.518	-0.139	-0.507	-1.454	0.443
9	0.078	0.030	0.688	-0.335	-0.049	-0.166	-0.417	0.397	0.518	0.845	-0.701	0.234	-0.648	0.314	1.263	0.168
10	-0.141	-0.556	-0.203	0.133	-0.259	-0.028	-0.787	1.037	0.997	0.659	-1.196	-0.810	-0.290	0.093	0.445	0.273

Table D7 Weight matrix of output layer (3×10) for the 3-output classification.

$\Theta_{ij,3}$	1	2	3	4	5	6	7	8	9	10
1	0.4302	1.4562	0.5185	-0.7253	1.0789	-1.5370	-0.0914	-1.3752	0.4961	0.2639
2	-0.2930	0.1733	0.1172	0.2562	0.3036	-0.9838	1.1920	0.2782	-1.2185	0.2478
3	0.2531	0.1006	-0.8012	-0.5256	-1.8525	1.1889	-0.7712	2.2359	-0.6615	-0.9801

Table D8 Ten Bias vectors of first hidden layer (10×1) for the 3-output classification.

$W_{i1,3}$	1
1	-2.07424
2	-1.25781
3	1.258245
4	0.611601
5	-0.19441
6	0.699818
7	-0.28913
8	1.672056
9	-1.33494
10	1.166353

Table D9 Three Bias vectors of output layer (3×1) for the 3-output classification.

$\Theta_{1j,3}$	1
1	0.408727
2	0.388524
3	-0.72564

Table D10 Relative weights for the 16 input variables of the 3-output classification.

$R_{Ij,3}$	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Relative Weight	3.8%	5.2%	5.8%	4.4%	4.2%	6.9%	4.7%	8.2%	7.6%	10.5%	8.2%	7.9%	5.7%	6.2%	8.0%	2.8%