Dynamic Corrosion Risk Assessment in the Oil and Gas Production and Processing Facility

by

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Dedicated to

my parents and wife

for their patience and faith

ABSTRACT

Corrosion is a major cause of process equipment deterioration in the oil and gas industry. It represents a significant threat to asset integrity and process safety. Corrosion can lead to leakage, which subsequently, leads to contamination by the spill of hazardous materials, vapour cloud explosions or toxic releases, depending on the geolocation and nature of the fluid carried inside the process equipment. For metal structures, the deteriorative process caused by corrosion reduces the residual ultimate strength leading to structural failure when exceeding the total stress. Localized corrosion is reported to be the most hazardous form of corrosion leading to catastrophic failures. Among corrosion modes, microbiologically influenced corrosion (MIC) is particularly complex to predict, detect and mitigate. Hence, significant attention should be given to prediction of the occurrence of MIC and assessment of the associated risks. Several studies by microbiologists and corrosion scientists focused on the understanding of MIC initiation and development mechanisms. However, in-depth assessment of MIC susceptibility and risk quantification is still lacking.

This thesis advances the understanding of MIC susceptibility and risk assessment by providing enhanced probabilistic models developed to fit the complexity of the microbiological corrosive process. Bayesian analysis was employed to assess the potential of having MIC while considering: chemical, physical, biological and molecular variables. A new modelling tool based on Stochastic Petri-nets enhanced with Bayesian updating capabilities was developed to address the main shortcomings of traditional Bayesian networks. This work also proposes an MIC risk assessment framework using Bow-Tie

analysis and a corrosion resilience model based on Stochastic Petri-nets. The application of the proposed methods is demonstrated using different case studies.

The outcomes of this research provide advanced probability-based methods adapted to the corrosion field. Application of the proposed methods enhances the prediction and remediation of localized corrosion processes, especially MIC.

ACKNOWLEDGEMENTS

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INTRODUCTION

1.1 Overview

Corrosion is defined as an irreversible interfacial reaction of a material (metal, ceramic, polymer) with its environment that results in the consumption of the material in dissolution into the material of a component of the environment [1]. In metals, the corrosive process is an electrochemical reaction that occurs between the metal surface and its environment leading to physical deterioration and/or alteration of properties. Traditionally, corrosion is classified as uniform corrosion and localized corrosion. In uniform or general corrosion, the anodic reaction occurs uniformly over the entire exposed surface. Uniform corrosion reduces the thickness of the material; it is the cause for iron rusting on large surfaces [2]. Localized corrosion manifests in a form of accelerated attack on a passive metal in a corrosive environment at discrete sites where the otherwise protective film is damaged [3].

Among different localized corrosion mechanisms, microbiologically influenced corrosion (MIC) is the most challenging to identify and assess due to its biological parameters and complex electrochemical mechanisms varying from one microbiological species to another (e.g. sulfate reducing bacteria versus acid producing bacteria). In addition, the sessile micro-organisms are difficult to assess and mitigate, and they are the ones causing MIC, not the planktonic population floating with the process fluid flow.

Currently, there is a significant need for advanced models capable of predicting MIC and assessing its location and potential impact on the process system in terms of deterioration of the asset and substantial hazards by loss of containment.

1.2 Corrosion risk assessment

Corrosion is a major cause of deterioration and equipment failure in the oil and gas production and processing facilities. Pipeline systems are particularly more vulnerable to localized forms of corrosion [4]. In pipeline systems, internal corrosion is due to contact of an aggressive fluid with a vulnerable metal surface. The corrosive process occurs under specific operating conditions and within a pH range favourable to one or more corrosion mechanisms (e.g. microbiologically influenced corrosion - MIC). The vulnerability of the metal surface, evaluated in terms of water wettability, surface roughness and micro-cracks presence, is an important factor when it comes to initiation and settlement of localized corrosion. The rate of localized corrosion can grow faster and cause premature corrosion-induced failure of the asset. Failure refers typically to a leak, which leads to contamination by a hazardous materials spill, vapour cloud explosion, or toxic releases, depending on the geolocation and nature of the carried fluid inside the pipeline.

Shabarchin and Tesfamariam [5] developed an approach to assess the risk of internal corrosion in pipelines using Bayesian networks [6]. The approach extracted some data from analytical models and combined it expert judgement to populate the conditional probability tables. The multiple sources of the collected data generated a significant uncertainty in the output parameters. Sadiq et al. [7] assessed the risk of corrosion associated failure in a probabilistic form using Monte Carlo simulation. The work focused on the failure prediction when the factor of safety is smaller than 1. This study focused on the probability of failure and did not consider consequences. Several other studies [8]–[10] attempted to assess the risk of corrosion by considering the component of corrosion occurrence without any consideration to the consequences analysis part. A study by Pursell et al. [11], examined both the likelihood and consequences of corrosion. The likelihood of corrosion was estimated based on De Waard & Milliams Method [12] with a correction factor. Where the consequences were assessed in terms of number of persons harmed by a failure, based on the population exposed and likelihood of harm from the failure. Assessing the risk of corrosion in a conventional way requires case-specific consideration with limited flexibility. The proposed methodology overcomes this practicality issue by providing a generic method largely applicable to different process systems and corrosion mechanisms. Among different corrosion mechanisms, MIC is the most challenging to identify and assess due to high dependency on operating conditions and highly localized nature [13], [14]. Risk assessment of corrosion in general, and MIC specifically, has proven to be a complicated task [15]. To address these challenges, probabilistic methods such as Bow-Tie and Bayesian networks are promising tool to handle the uncertainty and the large number of influencing factors.

1.3 Microbiologically Influenced Corrosion

MIC is a result of interactions between micro-organisms attached to a metal surface, abiotic corrosion products, and microbiological metabolites. In most cases, MIC does not manifest as a single mechanism of corrosion and is often poorly understood among corrosion professionals. The presence of micro-organisms, at certain concentrations and forms, in offshore systems has been reported as an accelerant for the corrosion rate, leading to system failures and loss of production. MIC is not only caused by bacteria but can also be initiated by other micro-organisms such as methanogenic archaea and fungi.

MIC is in part a result of the development of biofilms on metal surfaces. Biofilms are communities of micro-organisms attached to metal surface in a consortium [4]. MIC development can be seen as a sequence of microbiological metabolic reactions, where some micro-organisms are taking electrons crucial to microbiological activities from the metal. However, the threat that can be generated by the microorganisms is not limited to the corrosive process. The proliferation of microorganisms in oil reservoirs, especially the sulphate-reducing prokaryotes (SRPs), can cause reservoir souring [5,6]. In processing systems, it can cause filter plugging which may lead to a loss of production [7,8].

The significance of MIC stems from the fact that corrosion induces processing equipment failures, like pipeline leakage and loss of containment. These failures lead to catastrophic consequences and cause high financial and reputational losses. The presence of biofilm or microbiological products has been reported in many cases where corrosion has caused failures [3,9]. However, the degree of microbiological involvement in initiating or accelerating the corrosive process is still difficult to predict or determine.

1.4 Motivations

As discussed earlier, MIC has been identified by most researchers as the most complex form of localized corrosion. There have been several attempts to predict the susceptibility of process systems to this type of corrosion and subsequently, assess the risk associated with MIC. These attempts were made by either microbiologists or corrosion scientists. Microbiologists have focused on the biological part in terms of microbiological growth rate, whereas the corrosion scientists have focused on the fluid chemistry and electrochemical reactions happening on the metal surface. The motivation of this thesis is to bridge the main modelling gaps between the existing methods using probability-based models [16]–[18] and to develop a proper corrosion risk assessment model. The main modelling gaps are identified as follows:

a. Limited understanding of MIC mechanism and its link to corrosion risk assessment;
b. Time and space dependence of MIC;
c. The synergy between influencing factors is not taken into account. This synergy plays a significant role in MIC occurrence and the effectiveness of mitigative strategies;
d. Susceptibility of MIC in causing failures;
e. A lack of risk assessment framework for MIC to incorporate both the assessment of MIC likelihood and consequences.

1.5 Scope and Objectives

The proposed models in this thesis perform the required corrosion threats evaluation with application to MIC by answering these questions:

1- What is the probability of having corrosion in a particular process system? And how does the uncertainty in input data affect the estimated probability?

2- What factors cause corrosion in the system at a particular time?

3- If corrosion occurs in a system, what is the probability of a corrosion-induced failure? And what will be the effect of improving corrosion prevention, detection or mitigation capabilities have on the likelihood of corrosion and its consequences?

4- How resilient is a pipeline to the corrosive process? And how does the change in input parameters affect the useful life of the pipeline system?

To answer these questions, the following research objectives are identified for this research (illustrated in Figure 1.1):

1- To develop a probability-based corrosion potential assessment model considering uncertainty in input data and uncertainty propagation;

2- To develop a dynamic model for corrosion diagnosis considering the time-varying root-causes and time of observations (i.e. evidences);

3- To develop a systematic framework for corrosion risk assessment considering the likelihood and consequences of the corrosive process;

4- To develop a corrosion resilience assessment model for pipelines based on the monitoring and prediction of pipe wall thickness.

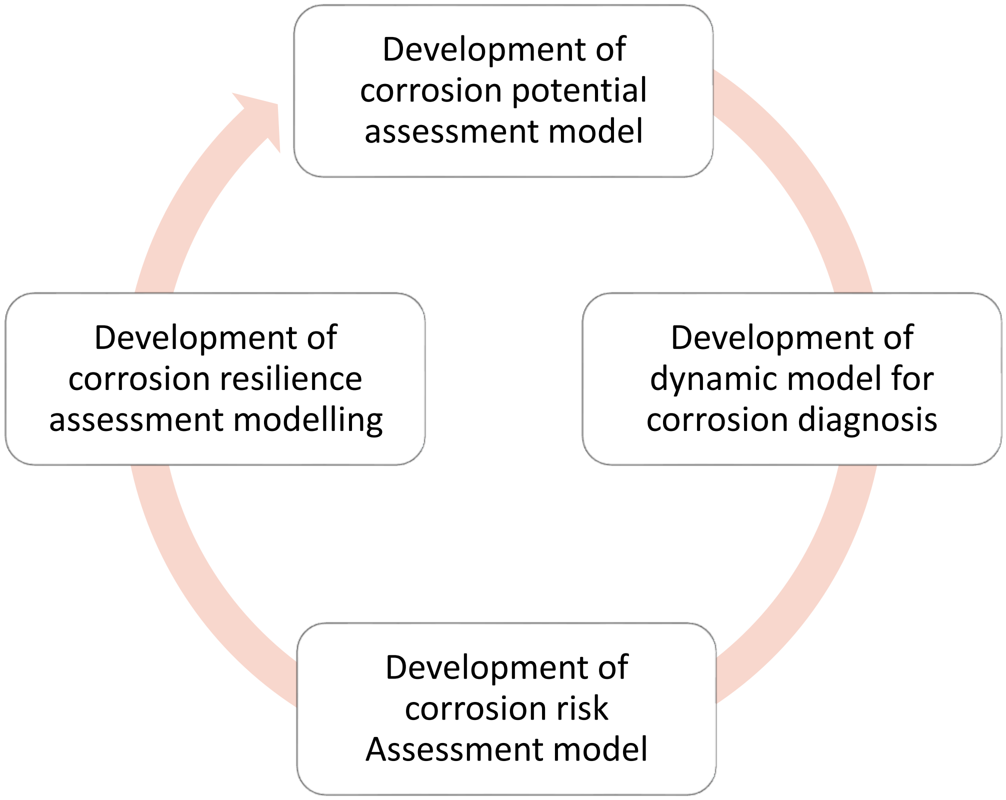

Figure 1. 1 Research deliverables of this thesis

The scope of this research covers corrosion susceptibility and risk-based evaluation of MIC in process facilities, which may result in loss of containment of hazardous chemicals leading to human, environmental and equipment damage. The models developed in this work are suited for the evaluation of localized corrosion. The applications were mostly on MIC due to its complexity as a localized corrosion process.

1.6 Contribution and Novelty

This section highlights the contributions and significance among existing research work in the field of corrosion susceptibility and risk assessment. A detailed description of each contribution is provided in the following sections:

1.6.1 MIC Potential Assessment

The ability to predict the potential or susceptibility of having an MIC in a process system is key to preserving the integrity of the system [13]. The challenge that the current MIC susceptibility models are facing is to correlate the diverse chemical, biological and process parameters that influence MIC potential, while handling uncertainty in input parameters. Chapter 2 of this thesis proposes a probability-based network model to take into consideration the uncertainties associated with input data and their propagation to the output parameter. In the proposed model, an extension of Bayesian network called Object Oriented Bayesian Networks (OOBN) is employed to handle the inter-dependency between 60 contributing factors to MIC settlement in a process circuit. The model was tested and verified using real data from a pipeline leakage incident that was the result of MIC.

1.6.2 Dynamic Model for MIC Diagnosis

MIC diagnosis requires a powerful modelling tool able to capture the time-dependency and dynamic changes in terms of microbiological growth, biofilm maturity, nutrient diffusion and changes in the conditions of operation. One of the contributions of this thesis is to develop a new modelling tool able to meet these requirements. The Bayesian stochastic Petri nets (BSPN) is graphical and uses the advanced modelling features of stochastic Petri nets with predicates such as the coding of mathematical variables to perform data updating functions [19]. Chapter 3 of this thesis introduces the new modelling tool with an illustrative application on a simple failure scenario.

1.6.3 Corrosion Risk Assessment

The majority of existing corrosion risk assessment studies evaluate the risk of corrosion by considering the component of corrosion occurrence without any consideration of the consequences analysis part. Other studies focused on predicting the corrosion rate and assigned the risk qualitatively based on the predicted corrosion rate. These models are, in majority, case-specific and lack a systematic and clear methodology to assess the risks of corrosion. The novelty of this proposed methodology, presented in Chapter 4, is the assessment of both likelihood and consequences of corrosion using an enhanced Bow-Tie (BT) approach. The proposed methodology puts emphasis on the verification of the probabilistic model against the collected field data of corrosion and its related failures.

1.6.4 Corrosion Resilience Modelling

There have hardly been any studies conducted to qualify or quantify the resilience of a process system against the corrosive process. Chapter 5 of this thesis proposes a dynamic approach to quantify the resilience of pipeline systems under varying conditions. The approach uses Stochastic Petri-nets (SPN) coupled with Monte Carlo simulation to model and analyze resilience metrics. The absorptive capacity (AB) depicts the ability of the pipeline to absorb the disruption (i.e. pit nucleation) and decelerate the corrosive process. The adaptive capacity (AD) is the gain in pipeline lifetime due to the adoption of proper corrosion control actions. At this stage, the pipeline survives while operating on low performance. The restorative capacity (RS) in the case of pipeline corrosion is mainly represented in terms of pipeline repair or replacement.

1.7 Organization of the Thesis

This thesis is written in a manuscript-based format. Overall, the outcomes of this thesis are four published and one submitted peer-reviewed journal papers and three conference papers. Figure 1.2 shows the structure of this PhD thesis. As shown in this figure, Chapters 2 to 5 of this thesis are developed based on the paper submissions to peer-reviewed journals.

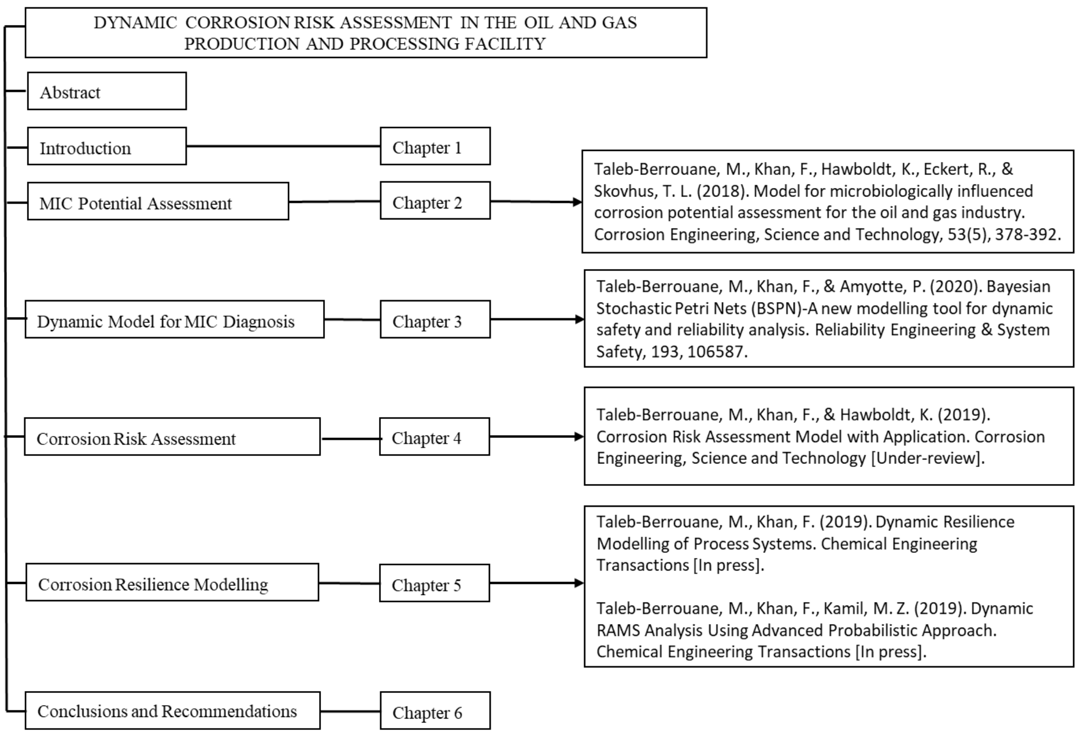

Figure 1. 2 Structure of the PhD thesis and related publications

1.8 Statement of Co-Authorship for Journal Articles

Authors have worked with a team of researchers (or varied expertise) to complete the agreed research tasks. The outcome of these research tasks are published in peer reviewed journals with co-authors who have directly contributed to the work. Below are details of the contribution.

Paper 1 (Chapter 2): Taleb-Berrouane, M., Khan, F., Hawboldt, K., Eckert, R., & Skovhus, T. L. (2018). Model for microbiologically influenced corrosion potential assessment for the oil and gas industry. Corrosion Engineering, Science and Technology, 53(5), 378-392.

Mohammed Taleb-Berrouane: Lead author, developed the research problem, conduct the study and wrote the first draft of the maunscript. Faisal Khan: assisted in developing the model and analysis of results; reviewed the draft and make revisions. Kelly Hawboldt: analyzed results and help review and revise the draft. Torben Lund Skovhus: analyzed results, review and revised the draft. Richard Eckert: provdied data, analyzed results, review and revised the draft.

Paper 2 (Chapter 3): Taleb-Berrouane, M., Khan, F., & Amyotte, P. (2020). Bayesian Stochastic Petri Nets (BSPN)-A new modelling tool for dynamic safety and reliability analysis. Reliability Engineering & System Safety, 193, 106587.

Mohammed Taleb-Berrouane: Lead author, developed the research problem, conduct the study and wrote the first draft of the maunscript. Faisal Khan: assisted in developing the model and analysis of results; reviewed the draft and make revisions. Paul Amyotte: analyzed results and help review and revise the draft.

Paper 3 (Chapter 4): Taleb-Berrouane, M., Khan, F., & Hawboldt, K. (2019). Corrosion Risk Assessment Model with Application. Corrosion Engineering, Science and Technology [Under-review].

Mohammed Taleb-Berrouane: Lead author, developed the research problem, collected the data, conduct the study and wrote the first draft of the maunscript. Faisal Khan:

assisted in developing the model and analysis of results; reviewed the draft and make revisions. Kelly Hawboldt: analyzed results and help review and revise the draft.

Paper 4 (Chapter 5): Taleb-Berrouane, M., Khan, F. (2019). Dynamic Resilience Modelling of Process Systems. Chemical Engineering Transactions [In press].

Mohammed Taleb-Berrouane: Lead author, developed the research problem, conduct the study and wrote the initial draft of the maunscript. Faisal Khan: assisted in developing the model, analysising the results and providing revisions.

Paper 5 (Chapter 5): Taleb-Berrouane, M., Khan, F., Kamil, M. Z. (2019). Dynamic RAMS Analysis Using Advanced Probabilistic Approach. Chemical Engineering Transactions [In press].

Mohammed Taleb-Berrouane: Lead author, developed the research problem, collected the data, conduct the study and wrote the first draft of the maunscript. Faisal Khan: assisted in developing the model and analysis of results; reviewed the draft and make revisions. Zaid Kamil: analyzed results and help in reviewing the draft.

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2. MODEL FOR MICROBIOLOGICALLY INFLUENCED CORROSION POTENTIAL ASSESSMENT FOR THE OIL AND GAS INDUSTRY

Preface

A version of this manuscript has been published in the Journal of Corrosion Engineering, Science and Technology [https://doi.org/10.1080/1478422X.2018.1483221]. I am the primary author of this paper. Along with the co-authors, Faisal Khan, Kelly Hawboldt, Torben Lund Skovhus and Richard Eckert, I developed the conceptual model. I carried out most of the literature review, data collection and the model verification. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' feedback. The co-author Faisal Khan helped in developing and testing the concepts/models, reviewed and corrected the models and results, and contributed in preparing, reviewing and revising the manuscript. The co-authors Kelly Hawboldt and Torben Lund Skovhus contributed through support in the development, testing and improvement of the models. Richard Eckert also assisted in reviewing and revising the manuscript.

Abstract

Corrosion is one of the major causes of failure in onshore and offshore oil and gas operations. Microbiologically influenced corrosion (MIC) is inherently more complex to predict, detect and measure because, for instance, the presence of biofilm and/or bacterial products is not sufficient to indicate active microbiological corrosion. The major challenge for current MIC models is to correlate factors that influence corrosion (i.e. chemical,

physical, biological and molecular variables) with the potential of having MIC. Previous work has proposed the potential for MIC as a simple product of multiple factors, without fully considering the synergy or the interference among the factors. The present work proposes a network-based approach to analyze and predict MIC potential considering the complex interactions among a total of 60 influencing factors and 20 screening parameters (SPs). The proposed model has the ability to capture the complex interdependencies and the synergic interactions of the factors used to assess MIC potential and uses an Object-Oriented approach based on a Bayesian Network (BN). The model has been tested and verified using real data from a pipeline leakage incident that was a result of MIC. The proposed model constitutes a significant step in deepening the understanding of when MIC occurs and its predictability.

*Keywords***:** Microbiologically Influenced Corrosion, Metal vulnerability, Synergy analysis, Object-Oriented Bayesian Network, Corrosion, Risk modelling, Susceptibility, Bio-corrosion.

2.1 Introduction

2.1.1. Overview of MIC and other microbiological threats

MIC is a result of synergistic interactions between the metal surface, abiotic corrosion products, and microorganisms and their metabolites [1,2]. MIC is not a single corrosion mechanism and is often poorly understood among corrosion professionals [2]. The presence of microorganisms, at certain concentrations and forms, in offshore systems has been reported as accelerator in the corrosion rate, leading to system failures and loss of production [3]. MIC is not only caused by bacteria but can also be initiated by other microorganisms such as methanogenic archaea and fungi.

MIC is in part a result of the development of biofilms on metal surfaces. The biofilms are communities of microorganisms attached to the metal surface in a consortium [4]. MIC development can be seen as sequences of microbiological metabolic reactions; where some microorganisms are taking electrons crucial to microbiological activities, from the metal. However, the threat that can be generated by the microorganisms is not limited to the corrosive process. The proliferation of microorganisms in oil reservoirs, especially the sulfate-reducing prokaryotes (SRP), can cause reservoir souring [5,6]. In processing systems, it can cause filter plugging that may lead to a loss of production [7,8]. Additionally, in domestic water pipelines, the hydrogen sulfide (H_2S) produced by SRP can cause toxicity and safety issues for humans**.** The significance of MIC stems from the fact that corrosion induces processing equipment failures; for example, pipeline leakage. These failures lead to catastrophic consequences and high financial losses. The presence of biofilm or microbiological products has been reported in many cases where corrosion has caused failures [3,9] . However, the degree of microbiological involvement in initiating or accelerating the corrosive process is still difficult to predict or determine.

Microbiological diversity [10] and the ability of certain microorganisms to subsist over a wide range of conditions make it complex and challenging to predict the MIC potential. Moreover, the complex nature of various factors influencing MIC occurrence and development adds more complexity.

2.1.2. Objectives and scope of this work

The limiting factor in MIC surveillance is not only the quality of the microbiological data, but also the conversion of data into a reliable risk assessment [11]. Based on the aforementioned statement, this work aims to relate the different factors that influence MIC to determine the potential of MIC occurring with an acceptable level of certainty.

While preserving the ease of use and maintaining an inherent flexibility, the proposed model incorporates various MIC related factors, ranging from the operating data to the molecular analysis. In this work, the MIC potential is taken from the microbiological perspective in the ability of microorganisms to chemically attack the metal surface. This ability can be measured by multiple parameters, such as specific species presence and activity, molecular microbiological methods (MMM) and quantification, and analysis of bio-corrosion chemical products. The vulnerability of the metal is assessed through parameters such as the operating history, environmental conditions, and the surface proprieties. A better understanding and quantification of the interactional processes of MIC influencing factors allow a better deployment of the corrosion management methods. The proposed model takes into consideration various factors affecting the potential of MIC. These factors are grouped in sub-networks (instance nodes) based on their nature and their dependencies on one another. This model can be implemented as a part of an overall MIC management system. The model aims to preserve asset integrity by preventing corrosion during the operational life cycle of a system. The model can be performed as a key part of the MIC threats assessment phase. This assessment constitutes the first phase in the process of managing corrosion as shown in Figure 2.1.

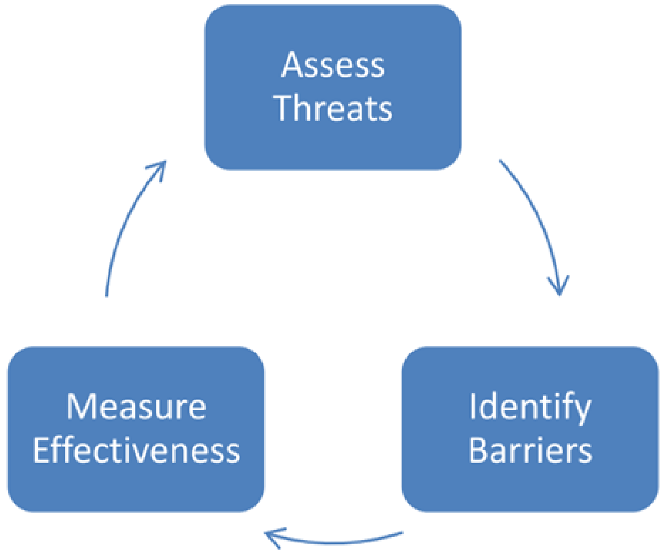

Figure 2. 1 Fundamental process of managing corrosion. [12]

2. 2 Summary of Existing Models

For years the first step in identifying MIC was to establish the presence of bacteria recognised as a source of MIC or those associated with corrosion products [13]. MIC modelling started in the early nineties with the Checworks predictive model [14]. This model is based on a mathematical equation giving a ranking of MIC susceptibility from 0 (very low potential) to 10 (high potential). This model takes into consideration chemical and physical parameters such as temperature, flow nature and use of biocides, and provides qualitative results; however, it does not incorporate any biological parameters.

Table 2. 1 Summary of the MIC susceptibility prediction models

Model	Output				Species considered					Factors considered				Reference
	Qualitative	Quantitative	Measure	Modelling Approach used	SRB	APB	Methanogens	Others	Not specified	Chemical	Physical/process	Biological	Molecular (MMM)	
Checworks predictive model	√		MIC susceptibility (ranking from 0 to 10)	Ranking based approach					√	√	√			[14]
Union Electric Callaway	√		Probability of MIC occurrence on a scale (0 to 100)	Indexing based approach	√	√		CD, GN			√	√		[15]
Luttery/Stein MIC Index	√		MIC susceptibility Index	Indexing based approach	√	√		MeOB, MnOB			√	√		[16]
Pots MIC model		√	MIC rate	Analytical approach	√					√	√			[17]
Maxwell and Campbell model		√	MIC rate - Risk of MIC occurrence (Biofilm initiation)	Analytical approach	√					√	√	√	√	[18]
Sooknah Model	√		Internal MIC Risk Factor (RF)	Ranking based approach					√	√	√			[4]
Allison Model	√		MIC Potential	Ranking based approach	√			√		√		√		[19]

MIC Managem-ent Model		√	IMRF, PPGR	Analytical approach	√		√	SRA				√	√	[7,11]
Taxén Model		√	MIC Potential	Data simulation Approach	√					√		√		[20]
Kaduková Model	√		Risk of External MIC in pipelines	Risk matrix (Ranking approach)					√	√	√			[21]
Skoss Model		√	MIC development rate	Monte Carlo simulation (Friday 13th)						√		√		[22]
Skovhus Model	√		Ranking of PoF for RBI	Logical modelling approach	√		√	Specifed groups		√	√	√	√	[23]
Singh and Pokhrel model		√	MIC rate, optimum time for inspection	Fuzzy logic framework	√	√	√			√	√			[24]

*CD: Clostridia, GN: Gallionella, MeOB: Metal oxidizing bacteria, MnOB: Manganese oxidizing bacteria, SRA: Sulfate-reducing archaea, PoF: Probability of failure, SRB: Sulfate-reducing bacteria, APB: Acid producing bacteria, IMRF: Integrated MIC risk factor, PPGR: Potential pit generation rate.

Quantitative modelling of MIC susceptibility has proven to be challenging because of the complex nature of the biotic and abiotic interactions in both enhancing and inhibiting MIC. The work of Pots et al. [17] was the first attempt to quantitatively assess MIC rate as a function of a factor (F). Here, "F" is the product of five factors; the presence of water, the water wetting, pH, salinity or total dissolved solids, and temperature. This model was improved later by Maxwell and Campbell [18] by introducing biological parameters such as number of bacteria per area and bacteria kinetics. Other MIC modelling attempts such as the work of Allison et al. [19] and Taxén et al. [20], tend to oversimplify the system and incompletely screen the MIC influencing factors. Kaduková et al. [21] used a risk matrix to assess external MIC corrosion risk. However, this risk matrix was based on an oversimplification of the MIC occurrence using an incomplete inventory of the chemical and environmental factors.

The use of molecular techniques to track the microorganisms responsible for the MIC occurrence was first introduced in the work of Larsen et al. [25]. This work demonstrated that the cultivation-independent techniques can provide fast results from within a few hours to a few days as compared to most probable number (MPN) techniques, resulting in a fast and accurate response. An early MMM study, for MIC and reservoir souring, Larsen et al. [26], used molecular tools to investigate the similarities and differences among MIC bacterial populations obtained from produced water and bacteria found in corrosion spots in a X-mas tree from a producing well. Skovhus et al. [7] showed how microbiological numbers were estimated based on DNA enumeration can contribute to assessing the general

MIC threat. For a full summary of the MIC susceptibility prediction models, the reader is referred to Table 2.1

2.3 The Proposed Probabilistic Modelling Approach to MIC Potential

In probabilistic modelling, the approach for dealing with interactions of multivariate factors that have complex interdependency are network-based models such as, Bayesian networks (BN), neural networks, Petri nets and Markov chains [27]. These network-based approaches demonstrate higher modelling capability than the mathematical equations or logical diagrams such as fault tree [28], event tree [29], and reliability block diagrams. In this work, the Bayesian network approach [30] was selected as the most appropriate modelling tool for this study. Compared to other quantitative risk analysis methods, the Bayesian networks provide multi-levels and allow multi-state dependencies to be taken into consideration. Additionally, their architecture is easily traceable to ensure the structural dependencies among the components. In the case where a feature is noted to be missing, it can be easily added to, and implemented, in the network. Similarly, the implementation of new information such as data from one or more additional parameters, can be done on mathematical basis, consistent with Bayes rule [31].

In BN modelling, dependency is presented in two ways: vertical dependency where the intermediate nodes depend on the basic or the root cause nodes, and horizontal dependency where the basic nodes depend on each other. This horizontal dependency is what differentiates the BN from the logic diagram methods such as fault tree and event tree, where the structure is based on basic event independency. These dependencies, vertical and horizontal, are all dictated in the form of a conditional probabilities table based on the domain expert knowledge. To consider the uncertainties, the conditional probability tables are built on the concept of noisy-OR and leaky noisy-OR gates [32,33].

The object-oriented Bayesian network (OOBN) provides a simple graphical interface, where the complexity is hidden within the objects. The objects are instance nodes that contain sub-structures (sub-networks) formed by interconnections of usual chance node (input and output nodes). The nodes are connected to each other, within and without the sub-structures. An instance node can be seen as a virtual node representing an instance of another network. Following standard object-oriented terminology, an object-oriented network is often referred to as a class. Describing a BN network in a hierarchical model often makes the network much less crowded, and thus provides a much better understanding of the graphical structure. An instance node can contain another instance node inside the subnet, an object-oriented network can be viewed as a hierarchical description (or model) of a problem domain.

2.3.1 The Proposed Model

The proposed model takes into consideration factors affecting the potential for MIC. These factors are grouped, based on nature and their implications with other factors resulting in seven object-oriented sub-networks:

- Operating parameters
- Fluid chemistry
- Settlement parameters
- Material parameters
- Operating history

- Mitigation parameters
- MIC presence symptoms

The sub-networks contain MIC influencing factors and MIC SPs connected to the MIC potential. The MIC SPs are metrics used to capture the performances of different components of the system, from the design to the mitigation strategy. The MIC presence symptoms are those factors whom their concomitant presence in a specific layout can be interpreted as a strong sign of MIC occurrence such as, the concentration of microbiological activity products, and the biofilm content and geometry.

2.3.2 MIC Influencing factors and screening parameters

The decision-making process for MIC diagnosis and management lacks the availability of practical tools. The proposed model provides 20 SPs to help the analyst/operator assess the MIC potential. SPs are probabilistic metrics used to measure real-time conditions and trends. These metrics assist the operator in identifying the weakest elements (or links) within the system that impact MIC potential. Based on the SPs assessment, the mitigation strategy can target then those identified factors to reduce the potential for MIC. Measuring these variables or factors in real-time would provide an on-line systematic screening tool to support the decision-making process. If monitoring of the SPs cannot be performed in real-time, a regular update could be defined based on the periodicity of laboratory analysis, for example. Some parameters, such as metallurgical and design parameters, are not practically modifiable if determined as a major contributor to MIC potential. However, most of the SPs, such as deposition and mitigation parameters, have dynamic variation and relatively easy to adapt if determined as active contributors.

Table 2. 2 Nodes functions in sub-networks and overall Bayesian model

Nodes functions	**Input nodes**	**Intermediate nodes**	**Output (child) nodes**
Sub-networks	● Leaf or marginal nodes representing the MIC Influencing factors (Input data)	● Connect the marginal nodes to the final node ● Can represent an SP	● Subnetwork output (output data) ● Can represent an SP
Overall BN model	● Object-oriented subnetwork inputs. ● Connect the object-oriented subnetworks (Emitting the information)	● Connection inter-subnetworks and/or private nodes ● Representation of the target node.	● Object-oriented subnetwork output. ● Connect the object-oriented subnetworks (Receiving the information)

MIC influencing factors are basic variables that can be monitored and recorded. In the proposed model, these influencing factors are presented as leaf nodes where direct input is required. As can be seen from Table 2.2, the SPs are the outcome of these inputs after processing. The SPs are summarized in Table 2.3. In the model, they represent intermediate nodes; however, not all the intermediate nodes are SPs, only those that have a physical meaning are used as SPs. At the last stage of the modelling, the output will be the probability of MIC occurrence (MIC potential) and the impact assessment of the MIC SPs. All the OOBN modelling is run using HUGIN software [34].

2.3.3 OOBN sub-networks

In the OOBN figures (Figure 2.2 to Figure 2.8), the nodes with grey and dotted bounding are OOBN input nodes, and the nodes with a continuous grey bounding are OOBN output nodes. The OOBN input and output nodes allow the communication among instance nodes

(OOBN sub-networks). Detailed structures of the sub-networks are illustrated below in Figures 2.2 to 2.8.

- **Operating parameter sub-network**

The proposed sub-network considers nine operating factors, including four process variables: temperature, pressure, flow and pH; and two SPs : deposition, and flowing parameters.

Table 2. 3 Summary of MIC screening parameters

Nº	Description	Nature of factors considered					Measuring	Figure
		Chemical	Design	Process	Physical	Biological		
SP1	Deposition parameter			√	√		The ability to accumulate deposits on the metal surface	Fig1.2
SP2	Flowing parameter			√			The impact of flow on deposition on the metal surface	Fig1.2
SP3	Nutritional parameter	√					The availability of nutrients favourable for the microbiological growth.	Fig1.3
SP4	Redox potential	√					The availability of electron donors and acceptors.	Fig1.3
SP5	Surface parameter		√	√			The predisposition of the metal surface for the sessile microbiological attachment.	Fig1.4
SP6	Metallurgy parameter		√				The characteristics of metal and metal surface	Fig1.4
SP7	Design parameter		√		√		The geometry affecting the fluid dynamics	Fig1.4
SP8	Operating history			√	√		The impact of process system history and the way that the system was maintained on MIC potential	Fig1.5
SP9	Microbiological activity products	√					The levels of chemical components produced by certain microorganisms	Fig1.6
SP10	Microbiological activity				√	√	Tracking of the microbiological activity in sessile and planktonic forms	Fig1.6
SP11	Biofilm solidity Parameter				√		The potential of the biofilm for hosting MIC considering the physical structure (firmness and strength) of the biofilm.	Fig1.6
SP12	Sessile microbiological Presence					√	The density of sessile microorganisms implicated in MIC. (enhancing and inhibiting).	Fig1.6
SP13	Reactive mitigation Parameter				√		Rate the mitigation actions performed in reacting to detection of MIC or its relevant symptoms.	Fig1.7
SP14	Proactive mitigation Parameter	√			√		Rate the mitigation actions performed in response to some predictions or indications of a predisposition to MIC.	Fig1.7

SP15	Preventive mitigation Parameter			√	√		Rate the mitigation actions performed regularly to prevent the system from developing an MIC process.	Fig1.7
SP16	Microbiological monitoring Parameter	√		√	√	√	Track the microbiological development and the mitigation efficiency based on biological monitoring and inspection techniques.	Fig1.7
SP17	water wetting parameter		√		√		The ability of water to maintain contact with the metal surface.	Fig1.8
SP18	Anchorage ability		√		√		Rate the ability of attachment as the first step in the microbiological settlement process on the metal surface.	Fig1.8
SP19	Biofilm degradation Parameter	√		√	√		Rate the ability to destroy the biofilm structure based on availability of the mitigation methods	Fig1.9
SP20	Attachment parameter	√	√	√	√		Rate the ability of microorganisms to attach to the metal surface	Fig1.9

Table 2. 4 Leaf nodes description for the operating parameter sub-network presented in Figure 2.2

Class	Subclass	Influencing factors	Variance (node's states)				Relevance/impact
			Low/Medium/ High	**Low/ High**	**Yes/ No**	**Specific**	
Opera-ting Para-meter	**Flowing Parameter**	Flow velocity	]0, 1[, [1, 2.5], above 2.5 m/s				Impacts the microbiological deposition and migration. Low velocity is the best condition for the microbiological growth.
		Flow type				Stagnant, Intermittent, Continuous	
	Deposits Presence Parameter	Debris presence		X			Their accumulation promotes the biofilm settlement
		Sand presence		X			
		Deposit Elimination	None, [1-3] per year, over 3 times/year				Counters the accumulation process of the deposits on the metal surface.
	-	Operating temperature				[15, 70[ºC, [71-120] ºC, others	Major role in intensifying or restraining the microbiological growth based on the range.
		Operating pressure	[0-3[, [3-103[, Above 130 MPa				Impacts the microbiological activity. Most microorganisms are killed at high pressure
		Operating pH	[0-5], [5-9.5[, [9.5-14]				A pH range between 5 to 9.5 is the optimum range for the microbiological growth. However, the impact of the operating pH is depending upon the maturity of the biofilm consortium.
		Multiphase fluid			X		A multiphase fluid offers weak spots for corrosion

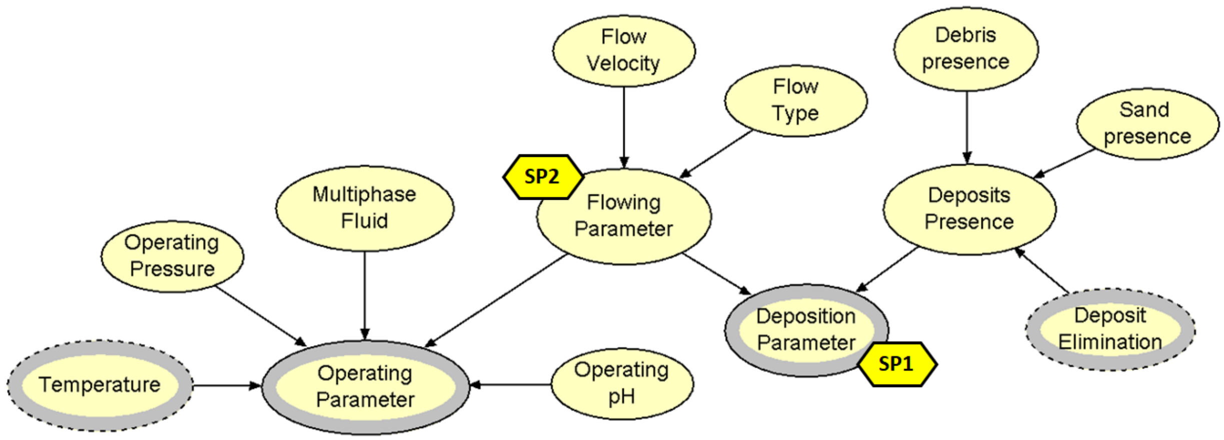

Figure 2. 2 OOBN sub-network of the operating factors that influence the MIC potential and their interactions

Figure 2.2 presents the OOBN sub-network of the operating factors that influence the MIC potential and their interactions, and Table 2.4 summarizes the variance and relevance of each factor. The operating temperature has a significant impact on the microbiological growth, and therefore a major role in enhancing or inhibiting MIC [35]. MIC related microorganisms grow best in the range from 15 ºC to 70 ºC. The range from 71 ºC to 120 ºC is moderately favourable for the growth of common MIC related microorganisms. In general, at temperatures below 15 ºC and higher than 120 ºC, there is less potential for microbiological growth [36]. In this sub-network, dependencies among factors are considered, for example, the flow impact is assessed based on the flow velocity (i.e high, medium or low) and the flow type (i.e continuous, intermittent or stagnant). The flow impact is assessed in form of the SP, defined as "flowing parameter".

- ***Fluid chemistry sub-network***

The proposed fluid chemistry sub-network considers sixteen factors, most of which are measurable. Two SPs are considered; the nutritional parameter and redox potential.

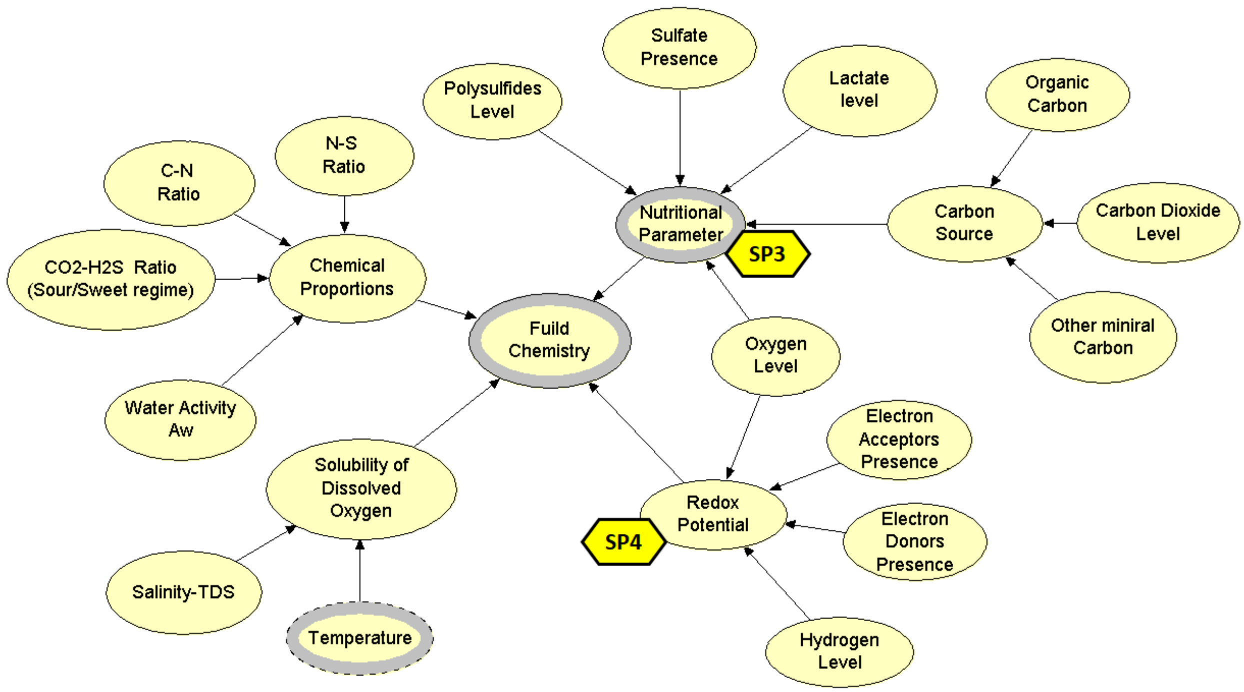

Figure 2. 3 OOBN sub-network of the fluid chemical factors that influence the MIC potential and their interactions

Table 2. 5 Leaf nodes description for fluid chemistry sub-network presented in Figure 2.3

Class	Subclass	Influencing factors	Variance (node's states)			Relevance/impact
			Low/Med./High	Avail/ not-avail.	Specific	
Fluid Chem-istry	**Nutritio-nal parame-ter**	Carbon dioxide level	X			Corrosive gas. Common factor in corrosion and presence of microbiological growth
		Organic carbon		Threshold : 20mg/l		Important nutrients for microorganisms
		Other mineral carbon	X			Nutrients for microorganisms

		Polysulfides Level	X			Essential nutrient for MIC related microorganisms
		Oxygen Level	X			Corrosive gas. If present in naturally anaerobic environments, can promote microbiological activity
		Lactate level	X			Rich source of organic carbon for MIC related microorganisms
		Sulfate presence		Threshold : 10mg/l		Electron acceptor for MIC related microorganisms
	Redox Potential	Electron acceptors presence		X		Enhance activity of MIC related microorganisms
		Electron Donors presence		X		
		Oxygen Level	X			See above.
		Hydrogen Level	X			Major electron donor, essential for the electrochemical activity of the MIC related microorganisms
	Solubi-lity of Dissolved Oxygen	Salinity or TDS*		Threshold : 60 g/l		Impacts the form of the microbiological growth (type of microorganisms)
		Temperature			[15, 70[, [71-120], others	Key factor in inhibiting or enhancing the microbiological growth and corrosion
	Chemical Propor-tions	C:N ratio		Threshold : 10		Ratio key in microbiological growth
		Water activity (Aw)	[0-0.59], [0.6-0.89], [0.89-1]			A boundary for microbiological life. At low water activity (below 0.6) microorganisms cannot survive
		N-S ratio		Threshold : 1		Ratio key in microbiological growth
		CO2-H2S ratio (Sour/Sweet regime)		Threshold : pCO2/pH2S= 20		Ratio is indicator for degree of souring and microbiological growth

*TDS: total dissolved solids

Figure 2.3. outlines the OOBN sub-network of the fluid chemical factors that influence the MIC potential and their interactions, and Table 2.5 summarizes the variance and relevance of each factor. In order to highlight the importance of the carbon dioxide, as a dominant mineral source of carbon and active component in the electrochemical reactions, it has been separated from the other mineral carbon sources. The impact of the fluid salinity or the total dissolved solids and the temperature are required to assess the solubility of the dissolved oxygen.

- **Material parameter sub-network**

The proposed material parameter sub-network considers nine factors and three SPs covering the metallurgy and design aspects, where the third parameter encompasses the surface features such as the roughness and the presence of welding marks.

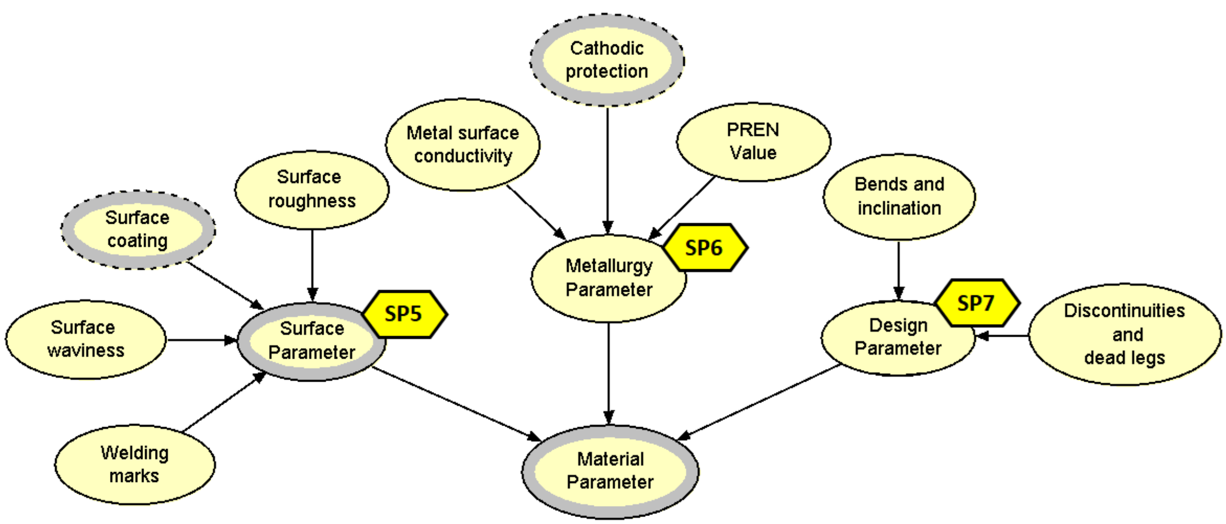

Figure 2. 4 OOBN sub-network of the metallurgy and the surface factors that influence the MIC potential and their interactions

Table 2. 6 Leaf nodes description for the material parameter sub-network presented in Figure 2.4

Class	Subclass	Influencing factors	Variance (node's states)			Relevance/impact
			Low/Medium /High	Applied/ Not-applied	Specific	
Material Parameter	**Surface Parameter**	Welding marks	X			Indicator of predisposition for microbiological attachment to metal surface
		Surface Waviness	X			
		Surface roughness	X			
		Surface coating			Not existing, damaged, non-damaged	Protects metal surface
	Metallurgy Parameter	Metal surface conductivity			[-50, +150] mV, other	Plays a major role in the electro-chemical activity of the metal surface
		Cathodic protection		X		Reduces the conductivity on the metal surface
		PREN Value	[0-32], [33-38], higher than 38			Indicator of estimate of the corrosion resistance. The PREN-value is proportional to the corrosion resistance of the steel
	Design Parameter	Bends and inclination	X			Weak spots where the MIC is most likely to manifest
		Discontinuities and dead legs	X			

* Pitting resistance equivalent number.

Figure 2.4 presents the OOBN sub-network of the metallurgy and surface factors that influence the MIC potential and their interactions, and Table 2.6 summarizes the variance and relevance of each factor. The Pitting resistance equivalent number (PREN) value is given by the formula as follows:

$$PREN = \%Cr + 3.3 \times \%Mo + 16 \times \%N \quad (1)$$

A general review of literature in which MIC is cited as the cause of corrosion shows that as the PREN value increases, the frequency of MIC decreases [37].

- ***Operating history sub-network***

The proposed operating history network considers six influencing factors and one screening parameter "operating history".

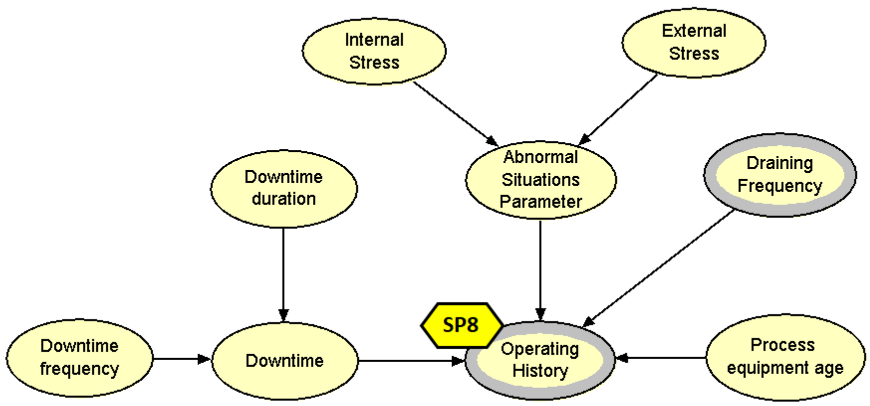

Figure 2. 5 OOBN sub-network of the operating history factors that influence the MIC potential and their interactions

Table 2. 7 Leaf nodes description for the operating history sub-network presented in Figure 2.5

Class	Subclass	Influencing factors	Variance (node's states)		Relevance/Impact
			Low/Medium /High	Specific	
Operating History	**Downtime**	Downtime duration	X		Downtime provides suitable conditions for the microbiological growth
		Downtime frequency	X		
	Abnormal Situations	Internal stress	X		shifts the electrochemical potential by increasing the internal energy level of the metal
		External stress	X		
		Draining frequency		None, [1-3] per year, over 3 times/year	Counters the accumulation process of the deposits on the metal surface.

		Process equipment age		[0-5] years, [5-15] years, Over 15 years	The wearing and deterioration process provides weak spots favourable for the microbiological growth

Figure 2.5 presents the OOBN sub-network of the operating history factors that influence the MIC potential and their interactions, and Table 2.7 summarizes the variance and relevance of each factor. Intermittent operations or downtime are mostly due to emergency shut-down or scheduled shut-down for inspection and maintenance; both duration and frequency of the downtime are considered in the model. The record of the draining frequency for the last five years of operations is also considered in this model. Some abnormal situations such as the excessive internal and external stress are also considered as factors affecting the MIC occurrence. The stress, either generated by applied loads or residual stress, can cause a shift of the electrochemical potential by increasing the internal energy level of the metal. Another mechanism that can be observed more likely on long transmission pipelines, is the generation of micro-cracks on the metal surface, or damage to the protective surface coating. The generated spots can potentially host the early microbiological deposits to form the biofilm consortium.

- ***MIC-presence symptoms sub-network***

The proposed MIC presence symptoms network considers twelve factors and four SPs. Microorganisms are presented in two categories. The planktonic Microorganisms are floating microorganisms in the process fluid. The sessile microorganisms are the microorganisms attached to the metal surface in a biofilm structure.

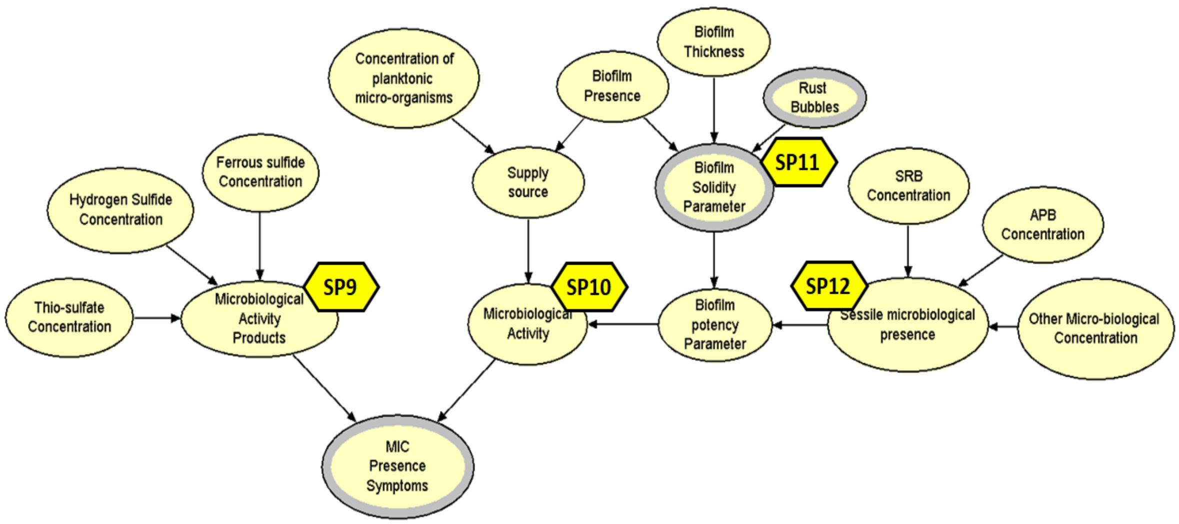

Figure 2. 6 OOBN sub-network of the MIC presence symptoms and their interactions

Table 2. 8 Leaf nodes description for the MIC symptoms sub-network presented in Figure 2.6

<table>
<tr><th rowspan="2">Class</th><th rowspan="2">Subclass</th><th rowspan="2">Influencing factors</th><th colspan="3">Variance (node's states)</th><th rowspan="2">Relevance/Impact</th></tr>
<tr><th>Low/ Med./ High</th><th>High/Low</th><th>Specific</th></tr>
<tr><td rowspan="6">MIC Presence Symptoms</td><td rowspan="3">Microbiological Activity Products</td><td>Ferrous sulfide Concentration</td><td></td><td>X</td><td></td><td rowspan="3">Indicators of the activity of the MIC related microorganisms</td></tr>
<tr><td>Thio-sulfate Concentration</td><td></td><td>X</td><td></td></tr>
<tr><td>Hydrogen Sulfide Concentration</td><td></td><td>X</td><td></td></tr>
<tr><td rowspan="3">Microbiological Activity</td><td>Concentration of planktonic microorganisms</td><td></td><td>X</td><td></td><td>Acts as a regeneration source for the sessile microorganisms</td></tr>
<tr><td>Biofilm Presence</td><td>X</td><td></td><td></td><td>Creates an environment where the MIC process is hosted</td></tr>
<tr><td>Biofilm Thickness</td><td></td><td>X</td><td></td><td>Indicates the stability and maturity of the biofilm structure</td></tr>
</table>

		SRB Concentration		X		Play a major role as MIC related microorganisms.
		APB Concentration	X			
		Other Microbiological Presence			Can promote/ inhibit MIC, other	Have a role in either promoting or inhibiting MIC

Figure 2.6 presents the OOBN sub-network of the MIC symptoms and their interactions, and Table 2.8 summarizes the variance and relevance of each factor. The MIC symptoms are divided into two classes. In the class of the microbiological activity products, it is very challenging to distinguish the origin of some products, either from the process fluid or the microbiological activity. The microbiological activity class considers the physical presence of microorganisms in sessile and planktonic forms.

- ***Mitigation parameter sub-network***

The proposed mitigation parameter sub-network considers twelve factors and four parameters. The mitigation can be preventive, proactive, or reactive. On top of that, the microbiological monitoring parameter, through inspection and advanced monitoring, is a critical parameter to assess the effectiveness of mitigation.

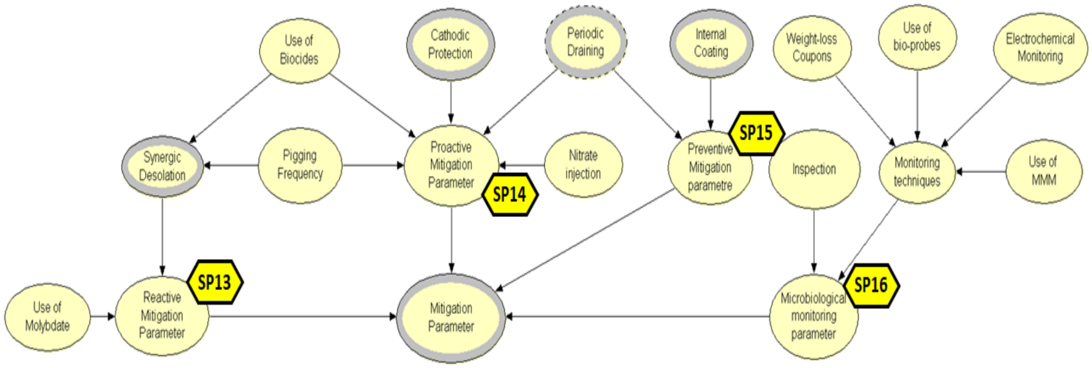

Figure 2. 7 OOBN sub-network of the mitigation strategies and factors that influence the MIC potential and their interactions

Table 2. 9 Leaf nodes description for the mitigation parameter sub-network presented in Figure 2.7

Class	Subclass	Influencing factors	Variance (node's states) Low/Med. /High	Variance (node's states) Specific	Relevance/Impact
Mitigation Parameter	**Reactive Mitigation Parameter**	Pigging Frequency	None, [1, 6], above 6 times/year		Most common method for mechanical mitigation against biofilm development
		Use of Biocides	X		Chemical treatment method to prevent/mitigate biofilm development
		Use of Molybdate	X		
	Proactive Mitigation Parameter	Cathodic Protection		X	Reduces conductivity on the metal surface
		Nitrate Injection	X		Anti-souring treatment. Enhance growth of nitrate-reducing bacteria (NRB) to outcompete SRB
		Pigging Frequency	None, [1, 6], above 6 times/year		See above

		Use of Biocides	X		See above
		Periodic draining	None, [1-3] per year, over 3 times/year		See above
	Preventive Mitigation Parameter	Internal Coating		Damaged, non-damaged	Protects the metal surface
		Periodic draining	None, [1-3] per year, over 3 times/year		Counters the accumulation of deposits on the metal surface
	Microbio-logical monitoring parameter	Inspection		Periodic, non-periodic	Provides a clear picture of the wall characteristics, pits and biofilm presence
		Use of bio-probes	None, annually, over 1 time/year		System monitoring to capture any change in the corrosive process and corrosion rate
		Weight-loss Coupons	None, annually, over 1 time/year		
		Electro-chemical Monitoring		Periodic, non-periodic	
		Use of MMM		Applicable, not-applicable	tracks the microorganisms considered responsible for the MIC potential

Figure 2.7 presents the OOBN sub-network of the mitigation strategies and factors that influence the MIC potential and their interactions, and Table 2.9 summarizes the variance and relevance of each factor. The MMMs have been introduced recently to gauge the microbiological activity with higher accuracy. Nitrate is injected into the process system to control souring by promoting bio-competition between SRB and NRB, in favour of NRB.

However, nitrate has the potential to also cause corrosion as demonstrated by heavy corrosion in an oil installation in the North Sea [38].

- ***Settlement parameter sub-network***

The proposed settlement parameter sub-network considers six factors, and two SPs: water wetting parameter and anchorage ability. The water wetting parameter is a critical element that directly affects the MIC potential.

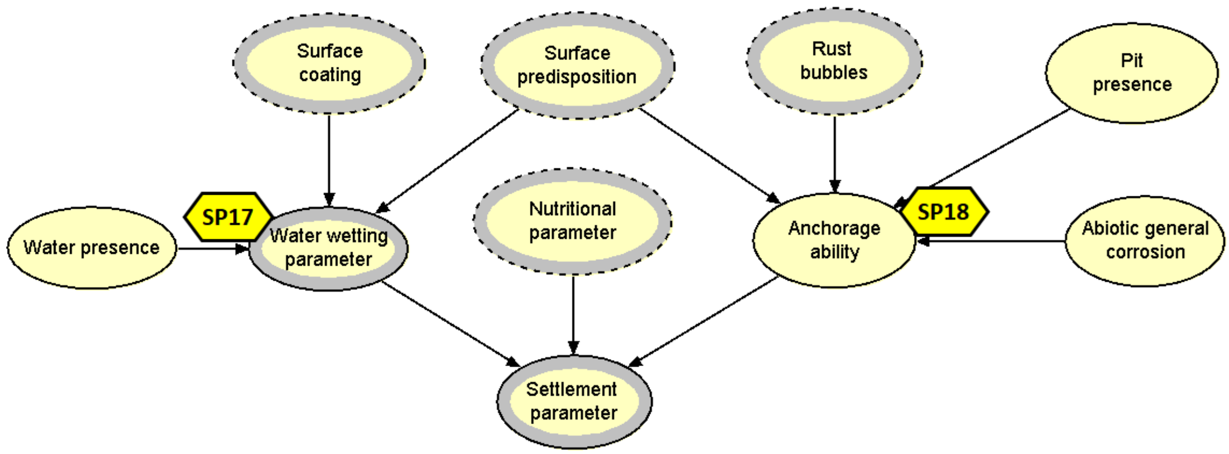

Figure 2. 8 OOBN sub-network of the settlement factors that influence the MIC potential and their interactions

Table 2. 10 Leaf nodes description for the settlement parameter sub-network presented in Figure 2.8

Class	Subclass	Influencing factors	Variance (node's states)			Relevance/Impact
			Low/Med. /High	High/Low	Specific	
Settlement Parameter	**Water wetting parameter**	Water presence	X			Essential and limiting element for the microbiological growth
		Surface predisposition	X			See "Surface Parameter sub-class" in Table 2.6
		Surface coating			Not applicable,	Protects the metal surface

					damaged, non-damaged	
	Anchorage ability	Rust bubble Presence		X		Provides surface for the microbiological attachment on the metal surface
		Abiotic general corrosion	X			
		Pit presence		X		
		Surface predisposition	X			See “Surface Parameter sub-class” in Table 2.6
		Nutritional parameter			Favorable, Non-favorable	Essential and limiting parameter for microbiological growth

Figure 2.8 presents the OOBN sub-network of the settlement factors that influence the MIC potential and their interactions, and Table 2.10 summarizes the variance and relevance of each factor. The microbiological anchorage can be promoted by material related factors, such as the surface roughness and welding marks, or corrosion related factors such as the presence of pit and rust bubbles.

- ***The overall MIC potential network***

The structure of the proposed MIC potential model is provided in Figure 2.9 showing the connections among the seven sub-networks. The overall OOBN in Figure 2.9 presents the structural aspect of the OOBN. The network structure is showing the different level of dependencies and factors affiliations.

2.4 Testing and Verification of the Model

The proposed model was applied to a case study of a liquid hydrocarbon pipeline. This case study investigated a hydrocarbon leak and determined that the failure was due to MIC [9]. It is worth noting that the same case study has been used by Sooknah et al. [39] to validate a MIC susceptibility model. In this pipeline most of the water had been removed before the hydrocarbon entered the pipeline; however, some water carried over and collected at the bottom of the pipeline under low flow conditions. High number of SRB and APB were present in the water as well, examination of the pipeline also revealed a few other pits that were similar to but smaller than the one that leaked.

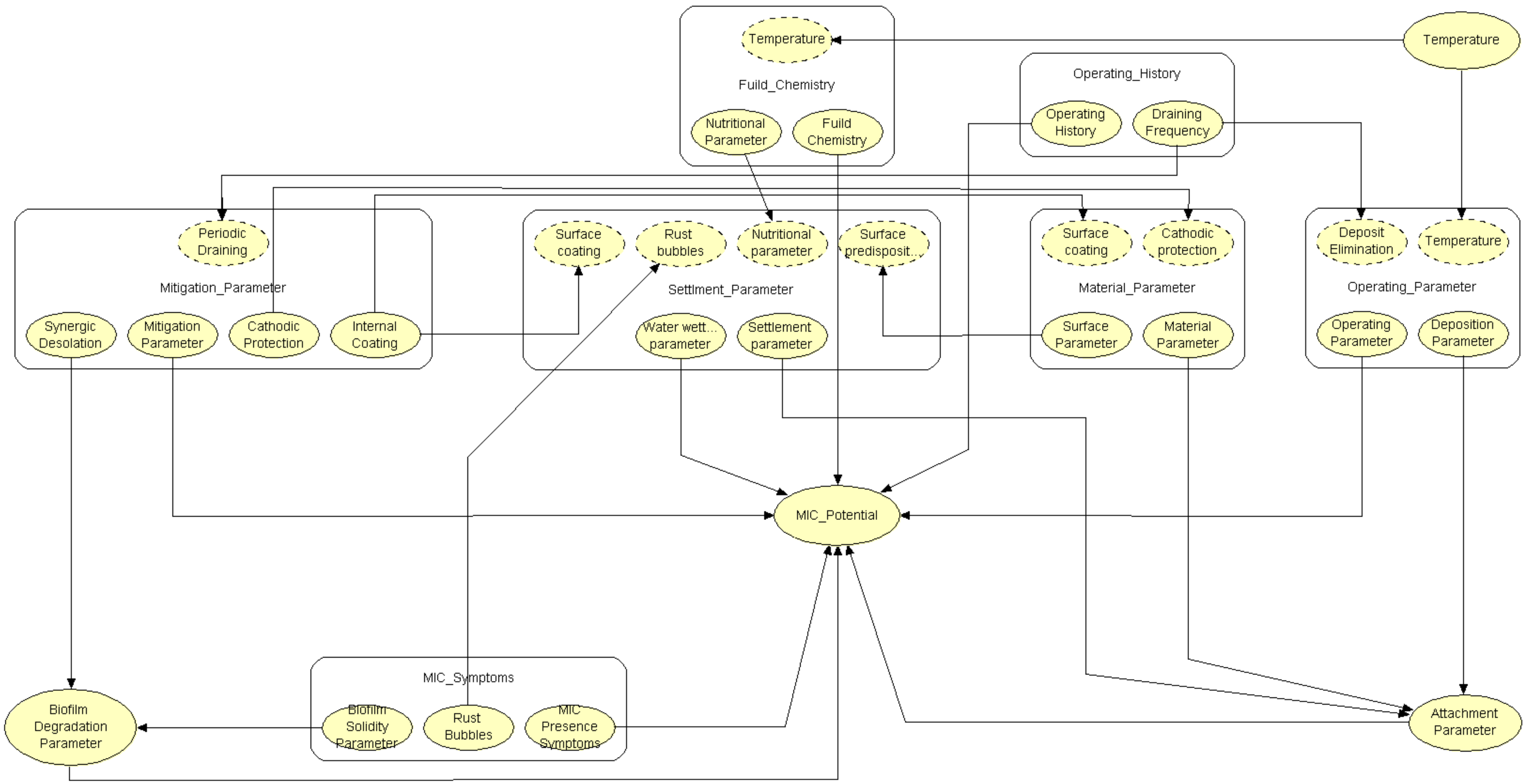

Figure 2. 9 The overall OOBN model for the MIC potential assessment showing the interactions among the sub-network

At the end of the investigation, the experts' diagnosis concluded that MIC caused the damage. For this reason and the data availability, in this case, the model validation was built based on data from this case study. Table 2.11 summarizes the main field and laboratory parameters for this case and the pieces of evidence used to validate the model. For more details about this case study, the reader is referred to [9].

Table 2. 11 Records of the field and laboratory parameters

Case study	Main parameters	Evidence (for verification)
Liquid hydrocarbon line [9]	Operating temperature: 21 ºC Operating pressure: 100 psi (0.69 MPa) pH: 6.8 Fluid nature: liquid hydrocarbon Operating mode: Continuous Steel type: Carbon steel Debris presence: Low Water presence: 1% Start operating: 1986 (never replaced) SRB presence: Yes APB presence: Yes Pit presence: Yes Pipeline piggable: Partially Internal coating: No General corrosion: No	- Status: MIC confirmed - Failure occurred: yes - Failure type: leak - Failure location: non-pigged potion - Clock position in the pipe: 6 O'clock - **Biofilm samples:** Sulfide: High pH: 3.4 Sessile SRB cell number: >100,000 CFU/mL Sessile APB cell number: 10,000 CFU/mL Bacterial activity: Viable - **Experts' diagnosis:** MIC

The available field and laboratory data were input to the OOBN model and the generated results are presented in Table 2.12 and Table 2.13. The data from the case study was provided in detail; however, some data necessary for the model were not specified, for example, the biofilm thickness, usage of biocides, etc. In those cases where the information is not available, the model assumes equal probability distribution of all the node states of the missing information. For example, a node with two states will have a 50% chance of being in state 1 and a 50% chance of being in state 2. The same rule is applied to a node with three states where the chances are eventually divided among the states. For example, the information about the biofilm thickness is not available in this case. The model assumes a 33% chance of having a biofilm with a high thickness, a 33% chance of a medium biofilm thickness, and a 33% chance of a low biofilm thickness. The equally distributed probability is considered as uncertainty in the model. Thereby, the results of the case, in Table 2.13, are built using this averaging method. To quantify the impact of these uncertainties, the model calculates a lower limit, the "Ideal case", where the unavailable information is assumed at the levels that cause the lowest chance of MIC potential. The upper limit, the "worst case", considers the unavailable information is assumed at the levels that cause the highest chance of MIC potential. Consequently, the more information that is available for the model, the narrower the difference is between the upper and lower limits, which reflects the accuracy of the model.

Table 2. 12 Results – MIC potential and sub-networks

Sub-network	Ideal case (Lower limit)	Practical case (Average)	Worst case (Upper limit)
Operating parameter	94%	99%	99%
Fluid chemistry	75%	86%	95%
Material parameter	62%	76%	85%
Operating history	69%	83%	99%
Settlement parameter	78%	87%	91%
Mitigation parameter	28%	18%	4%

MIC symptoms	69%	84%	98%
MIC potential	**71%**	**82%**	**96%**

The results in Table 2.12 show the MIC potential in this case study to be 82% with the worst-case scenario to be 96%. Comparing these results with the field data, where the MIC process has been identified with certainty to be the main cause confirms that the 82% reflects a high likelihood of MIC which was confirmed as the source of failure by [9].

2.5 Sensitivity Analysis of the Screening Parameters

The SPs were further analyzed for their sensitivities towards MIC potential assessment. The results of their sensitivity analysis are shown in Table 2.12. The SPs in each of the categories are further analyzed in Figure 2.10 and Figure 2.11.

Table 2. 13 Screening parameters and their lower and upper limits

SPs	Reference	Ideal case (Lower limit)	Practical case (Average)	Worst case (Upper limit)
Deposition parameter	SP1	65%	79%	90%
Flowing parameter	SP2	82%	82%	82%
Nutritional parameter	SP3	70%	84%	86%
Redox potential	SP4	40%	72%	95%
Surface parameter	SP5	50%	71%	90%
Metallurgy parameter	SP6	60%	68%	75%
Design parameter	SP7	60%	80%	80%

Operating history	SP8	69%	83%	99%
Microbiological activity products	SP9	25%	56%	95%
Microbiological activity	SP10	81%	91%	98%
Biofilm solidity parameter	SP11	30%	71%	99%
Sessile microbiological presence	SP12	90%	96%	99%
Reactive mitigation parameter	SP13	19%	18%	8%
Proactive mitigation parameter	SP14	60%	52%	20%
Preventive mitigation	SP15	0%	0%	0%
Microbiological monitoring parameter	SP16	50%	25%	3%
Water wetting parameter	SP17	99%	99%	99%
Anchorage ability	SP18	68%	80%	92%
Biofilm degradation parameter	SP19	10%	5%	2%
Attachment parameter	SP20	85%	90%	94%

Abiotic parameters are represented by process variables and operations, design, and fluid chemistry aspects. Biotic parameters are the microbiological-related parameters. The mitigation inefficiency assesses all the different types of mitigation strategies along with the microbiological monitoring and the biofilm degradation parameter. It is worth noting that the microbiological monitoring can be performed by using different techniques; the most efficient method reported in the literature is the MMM such as the qPCR [40].

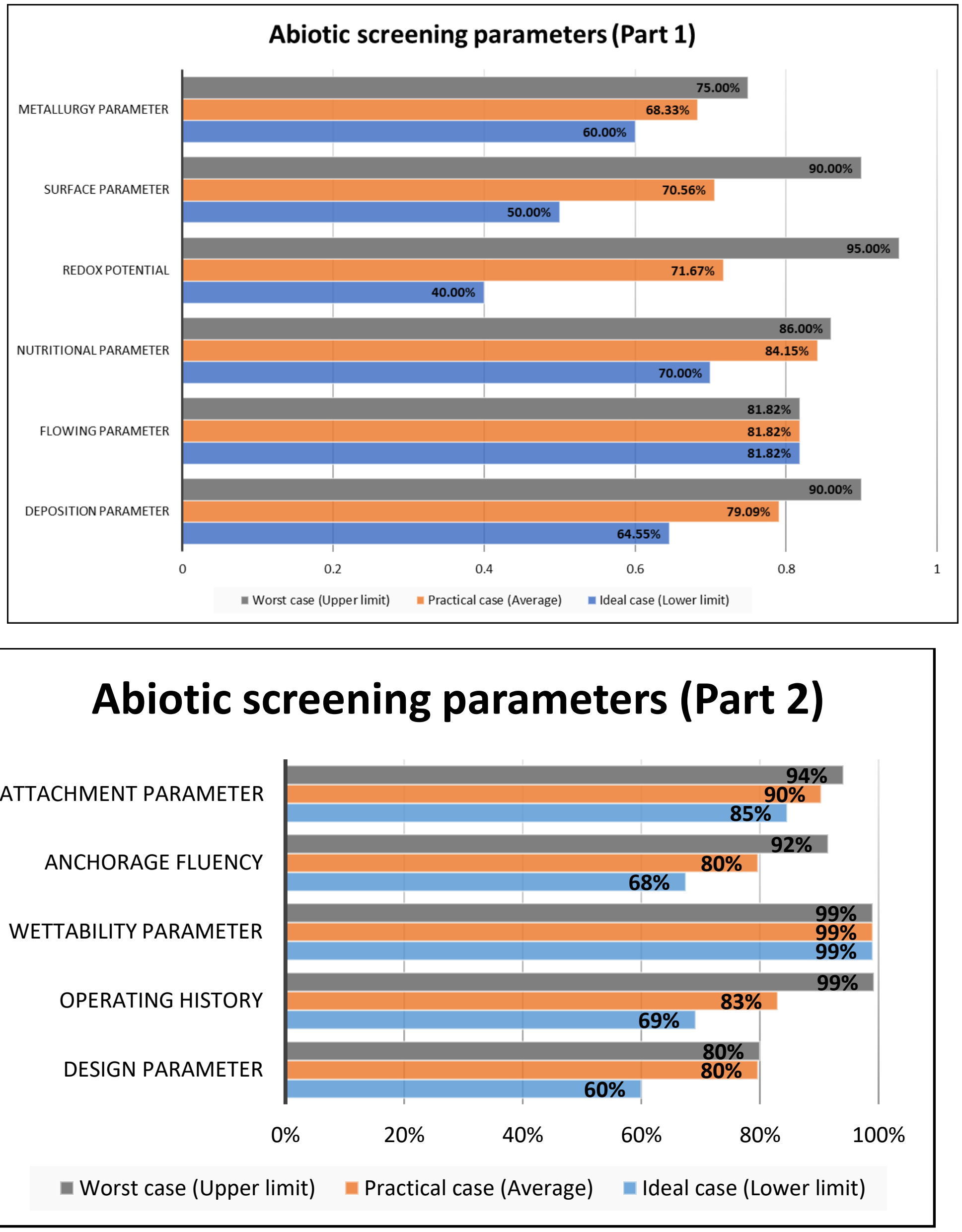

Figure 2. 10 Percentages of the abiotic SPs favourable to MIC potential (Part 1 and Part 2)

Figure 2.10 part 1 and part 2 show the percentages of the abiotic SPs being favourable to MIC potential. From those figures, the critical parameters can be extracted as follows:

1- The water wetting parameter (99 % favourable to MIC occurrence). The water wetting can be mainly improved by applying a coating to the metal surface and reducing the presence of water by water purging or draining.

2- The attachment parameter (90% favourable to MIC occurrence). The microbiological attachment is mainly due to the ability of the microorganisms causing MIC to settle and remain attached to the metal surface. Acting to minimize the deposition process by periodic draining and pre-treatment along with water filtration and pigging could be appropriate strategies to lower the microbiological attachment capability.

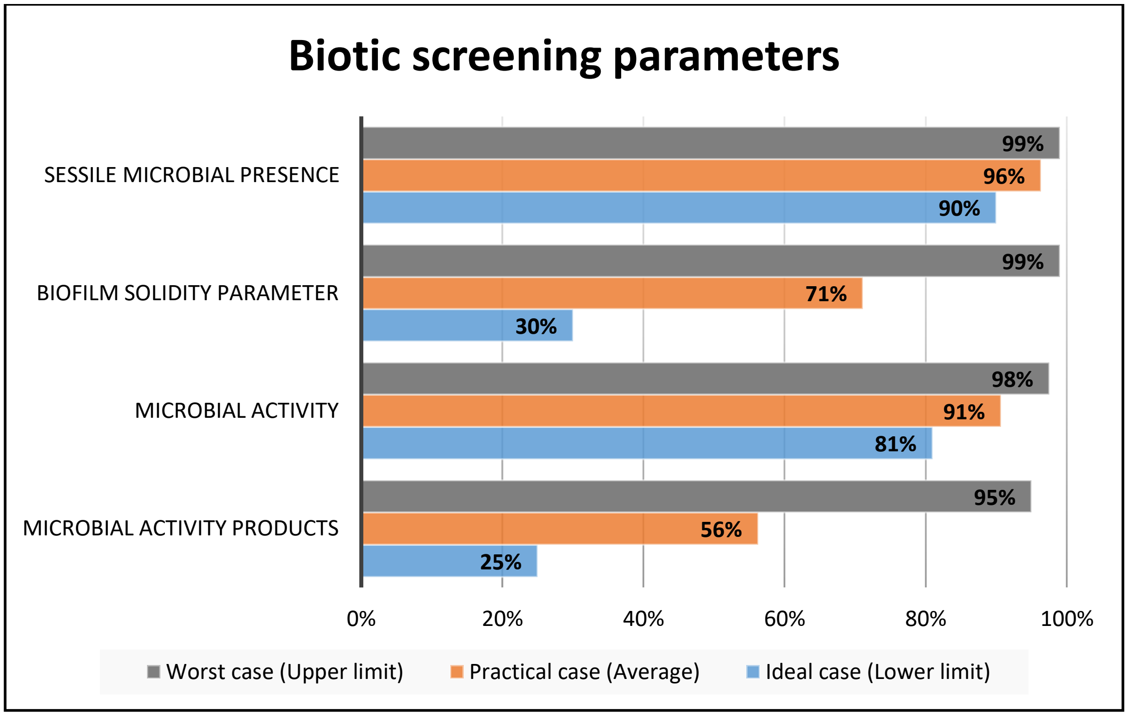

Figure 2. 11 Percentages of the microbiological SPs favourable to MIC occurrence

Figure 2.11 shows the percentages of the microbiological SPs being favourable to the MIC occurrence. From this figure, the critical parameters can be extracted as follows:

1- Sessile microbiological presence (96 % favourable to MIC occurrence). Targeting the biofilm structure hosting the sessile microorganisms would be the appropriate strategy to lower the sessile microbiological presence.
2- Microbiological activity (91 % favourable to MIC occurrence). The microbiological activity can be reduced by targeting the microbiological regeneration in sessile and planktonic forms.

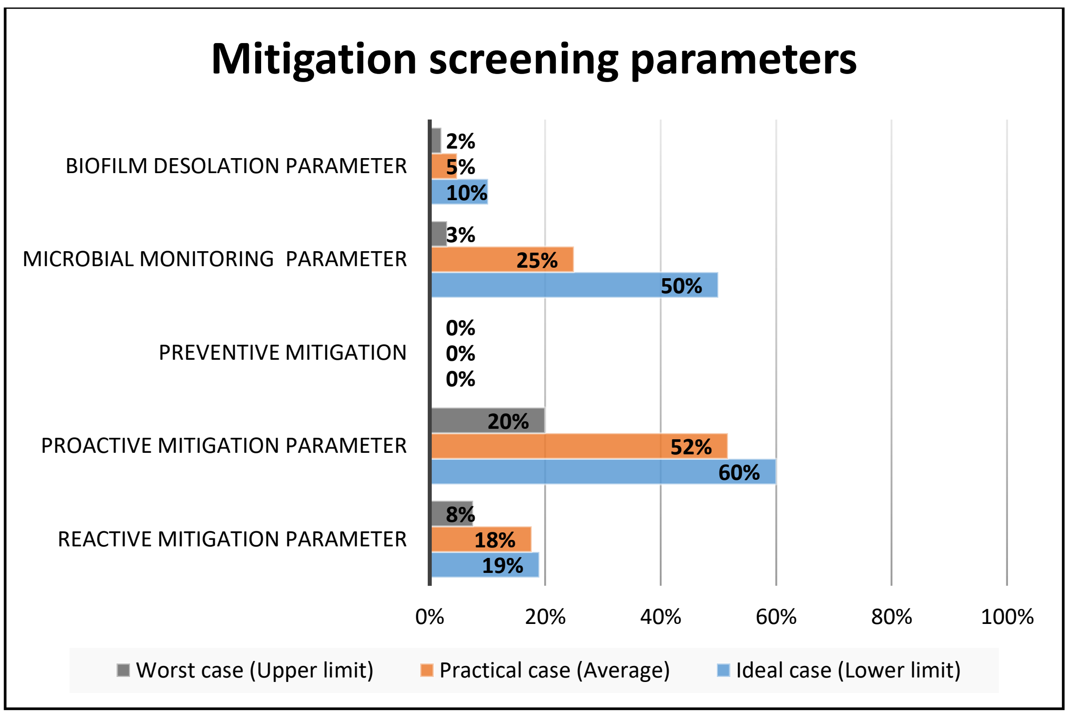

Figure 2. 12 Efficiency of the mitigation practices for MIC attenuation

Figure 2.12 shows the percentages of the mitigation SPs being efficient in attenuating the MIC. The lower in the efficiency of the mitigation, the more critical this parameter becomes. The critical parameters are:

1- Preventive mitigation parameter (0 % efficiency). The preventive mitigation can be improved by applying an internal coating and performing period draining to the pipeline.
2- Biofilm degradation parameter (5 % efficiency). The success of the biofilm degradation depends on two factors; (i) assessment of the location and solidity of the biofilms, (ii) a proper correlation between the mechanical mitigation (pigging) and the chemical mitigation (use of biocides). Thereby, the improvement of the biofilm degradation parameter should be based on a proper analysis of those three factors as a systematic strategy to struggle the biofilm development.

2.6 Conclusions

This chapter presented a new model for assessing the potential for MIC. The model is built upon 60 influencing factors that form 20 SPs. The synergies and dependencies among the parameters are considered in modelling the MIC potential. The model is developed in an object-oriented Bayesian framework that is adaptive and easy to follow. The graphical illustration of the model as interconnected instance nodes provides a clear understanding of interactions of factors and SPs. The conditional dependency of parameters in a node is defined considering the opinion of subject matter experts and past studies.

The model was tested against most cited MIC induced failure of a pipeline study available in the public domain. The model estimated MIC potential of the given case study (using the available data) was 82% with the worst scenario being 96%. This provided initial validity of the model and projects its usability in real life situations. This model will be further tested and validated against several types of environmental archetypes such as:

- Crude systems
- Produced water re-injection (PWRI) – systems
- Seawater
- Multiphase
- Storage
- Transmission

The accuracy of the model is highly dependent on the reliability of data from the field and the laboratory tests. Nevertheless, the model is able to adapt to missing data and also able to consider new data as evidence to update an earlier prediction. Application of the model will help promote better understanding and management of MIC in onshore and offshore process operations. Based on the promising findings of this work, efforts related to the evaluation of the impact of the MIC on processing systems is continuing and will be presented in future papers.

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3. Bayesian Stochastic Petri Nets (BSPN) - A New Modelling Tool for Dynamic Safety and Reliability Analysis

Preface

A version of this manuscript has been published in the Journal of Reliability Engineering & System Safety [https://doi.org/10.1016/j.ress.2019.106587]. I am the primary author of this paper. Along with the co-authors, Faisal Khan, and Paul Amyotte, I developed the conceptual model. I carried out most of the literature review, data collection and the model development. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' feedback and also the peer review process. The co-author Faisal Khan helped in developing and testing the concepts/models, reviewed and corrected the model and results, and contributed in preparing, reviewing and revising the manuscript. Paul Amyotte assisted in reviewing and revising the manuscript.

- Publication: Taleb-Berrouane, M., Khan, F., & Amyotte, P. (2020). Bayesian Stochastic Petri Nets (BSPN)-A new modelling tool for dynamic safety and reliability analysis. *Reliability Engineering & System Safety*, 193, 106587.

Abstract

An efficient formalism for safety analysis should be: (i) able to consider the failure behaviour of complex engineering systems, and (ii) dynamic in nature to capture changing conditions and have wider applicability. The current formalisms used for safety analysis are lacking in one of the above-listed criteria. Bayesian network (BN) allows the modelling of failure of systems where the inter-nodal dependencies are represented exclusively by constant conditional probabilities. Stochastic Petri nets (SPN) enable the study of the dynamic behaviour of complex systems; however, they lack the ability to adapt to changes in the data and operating conditions. This chapter proposes a hybrid formalism that strengthens SPN with BN capabilities. The proposed formalism is graphical and uses advanced modelling features of SPN with predicates such as the codding of mathematical variables to perform the data updating functions. This ability enables the analysis of continuous input data without the necessity of time-slice discretization process. The emergent formalism is termed “Bayesian Stochastic Petri Nets” (BSPN). It provides a dynamic assessment of safety by capturing additional sets of data rends. In BSPN, the conditional probability is captured as a time-dependent function to allow consideration of the cumulative effect of the failure scenario (e.g. fatigue). The BSPN implementation is demonstrated with an example illustrating the modelling capabilities. An extensive comparative analysis is performed against other probabilistic techniques.

Keywords: Petri Nets, Bayesian network, Dynamic modelling, Data updating, Hybrid formalism, Risk analysis.

3.1 Introduction

Process systems are subject to deterioration over time due to natural and human-made causes [41], [55]. During service, this deterioration can manifest suddenly as a failure of one or more components. Primary component failures can trigger a series of events with an increasing degree of complexity. If safety barriers fail to control the hazard, the failure mechanism can lead to an accident with potential harm to humans, the environment, and asset integrity. Despite the technological evolution of complex process systems, failure and associated risk continue to increase.

Safety analysis aims to investigate and predict the failure of process systems and its repercussions on operations and safety of systems. Uncertainty in the output of safety analysis studies is mainly due to initial assumptions and limited knowledge about the failure mechanisms and sub-systems interactions. This results in: (i) misrepresentation of dynamic behaviours, (ii) ignorance of dependencies, (iii) and over-simplification system structure. Several models have been proposed to perform safety analysis. One of the early studies on safety analysis using a Petri nets (PN) approach is the work of Leveson and Stolzy [56]. This work focused on the use time Petri nets to design and analyze a safety critical system such as the modelling of faults and failures. Nyvlt et al. [57] used SPN with predicates to model the sequence of complex accidents. The proposed methodology proved to be efficient and superior compared to an event tree based approach.

Conventional safety analysis techniques such as fault tree analysis (FTA) [58]–[61], event tree analysis (ETA) [62], failure mode and effects analysis (FMEA), and reliability block diagrams (RBD) suffer from severe limitations of static structures, and basic event's independency, or simplified dependency. These techniques have undergone many improvements over the last decades, such as dynamic fault tree [63], dynamic event tree [64]–[66], and fault tree driven Markov process [41], [67]–[69]. However, despite these improvements, logical diagrams still suffer from poor handling of uncertainty [70]. To understand the features of the main categories of failure analysis techniques, a review of the modelling capabilities of FTA, BN and SPN is given in Table 3.1.

Table 3. 1 Review of the modelling capabilities of FTA, BN and SPN

Technique	Questions to answer	Strong points	Limitations
Fault Tree Analysis (FTA)	What are all the possible scenarios leading to the undesired event?	Traceable logical diagram	Cannot handle the multi-state variables; and provides simplified sequences
	What is the probability that the top event occurs?	Ease of computation	Connections are limited to simple logical gates
	What is the most probable sequence leading to this top event?	Qualitative and quantitative results	Subject to multiple assumptions
Bayesian Network (BN)	What is the probability of an event to occur?	Conditional dependencies considered	Limited knowledge about transitional mechanism
	How are the elements of a system conditionally dependent?	Numerically presented in tables (CPT)	Based on estimated absolute values
	What is the impact of data evidence on the other variables?	Founded on mathematical base (Bayes' rule)	Absence of a standard approach for CPTs and input data implementation
Stocha-stic Petri Nets (SPN)	What is the behaviour of the system?	Ample capacity to closely imitate the real behaviour of complex systems	Need extensive data
	What are the possible failure mechanisms?	Fewer assumptions compared to other formalisms	Difficult to track large sized models
	When do we expect an event to happen and what are the probabilities?	Handling deterministic and stochastic events	Need to be coupled with Monte Carlo simulation to provide accurate results

Table 3.1 shows how the current failure analysis techniques answer relevant questions of safety analysis. However, the range of limitations challenges their accuracy and practicability. FTA is the easiest and most commonly used technique in safety analysis [59], [71]. FTA is a top-down deductive method that aims to compute the top event probability as a function of basic events probabilities. The latter represent the likelihood of

component failures. Representing the probability of these events by a constant probability will lead to a misjudgement of top event likelihood [41].

3.2 Background and Novel Contributions

Several researchers prefer to use BN as an alternative to the conventional logical diagram methods. BN, also called Bayesian belief network, have been widely used in recent years as a powerful data mining technique for handling uncertainty and incomplete data sets. The use of BN in safety analysis has recently increased; this is due to the abovementioned benefits, the ease of use that these formalisms provide for the analyst, and the nature of their input data. The inputs are originally subjective and based on domain expert knowledge, making them less exposed to the criticisms of accuracy and validation. Many researchers have used BN to express the causal relationships among the different components of a system. In reliability analysis, Wilson et al. [44] showed the capability of BN for modelling interference from multilevel data in cases of unknown conditional probabilities and the impact of implementing new information on the reliability model. With respect to safety analysis, Boudali and Duga [72] proposed a formalism for reliability analysis based on temporal Bayesian networks to solve dynamic fault trees, they concluded that BN could be used as an alternative solution for dynamic fault tree without resorting to the Markov chain generation. Langseth et al. [73] focused on the difficulties encountered while using discrete BN, and how the hybrid Bayesian networks, through coupling discrete and continuous BN, can solve part of those issues. Weber et al. [74] presented a complete overview on the use of BN in dependability, maintenance, and risk assessment. Recently, Deyab et al. [75] used BN to perform failure analysis of offshore systems based on a novel sensitivity analysis framework. Taleb-Berrouane et al. [12] used an extended BN, called object-oriented Bayesian networks (OOBN), to estimate the likelihood of a complex corrosion process, known as microbiologically influenced corrosion, for the oil and gas industry.

Petri nets [76], through a variety of their extended formalisms such as timed, stochastic and coloured PN, are widely used as modelling tools in several technical fields including computer engineering, electronics and control systems. The wide range of PN application is due to their unique modelling characteristics including concurrency, conflict management, synchronization, and resources sharing [41], [76]–[79]. However, even though they have shown excellent modelling capabilities for safety and risk analysis, they are not as widely used as the logical diagram methods (FTA, ETA and RBD) or BN because of their non-explicit graphical presentation.

In recent years, some hybrid techniques have been developed and described in the literature. One of those techniques is the Bayesian Neural Network (BNN) [80]. The idea behind the development of BNNs is to recast the task of training a network as a problem of inference, which is solved using Bayes' theorem [81]. As a probabilistic formalism, it is a robust method. However, BNN suffers from poor uncertainty handling and requires large data sets. Elidan [82] proposed another kind of hybrid model, called the Copula Bayesian Network (CBN), which combines the modelling capacity of complex distributions provided by the Copula function and the conditional probability distribution provided by BN.

Prior studies have paid considerable attention to the comparison between BN and SPN, as seen in the work of Halim et al. [83] and Weber et al. [74]. In the latter study, the authors have identified the incapability of integrating evidence as one of the severe weaknesses of SPN use in risk analysis. This fact encouraged the authors to undertake this step and develop a hybrid modelling tool that embeds the modelling power of BN into the SPN formalism. It is worth noting that the authors failed to discover any attempt to combine the modelling features of both Petri nets and BNs. In this chapter, the authors aim to explore the integration of Bayes theorem to SPN. The detailed approach is presented here and demonstrated through several cases of dependent structures. The objective is to propose and test an efficient formalism for dynamic safety analysis with potential application to dynamic reliability, availability, maintainability and safety analysis (i.e. RAMS analysis).

The current work is developing a new hybrid concept following innovative considerations. The novelties listed are as follows:

- The Bayes theorem rules are coded as mathematical variables for SPN with predicates formalism. This enables full use of the data updating capability on an SPN with predicates model.
- The BSPN is capable of generating time-dependent functions of the conditional probabilities and posterior probabilities. The benefit of these generated data is highlighted in detail in step 3 of sub-section 3.1.
- Compared to the dynamic capabilities of the SPN, the BSPN conditional probability functions and posterior probability functions can be resultant of dynamic processes while considering the parallelism, concurrency and synchronization of the events.
- The BSPN uses the block based-modelling technique where the system is divided into several sub-systems (i.e. SPN blocks) physically separated. The changes in the

predicates and assertions (mathematical variables) convey the message among the SPN blocks. This feature is explained in detail in step 6 of the BSPN framework in section 3 of the chapter

For this work, the authors have used a performant modelling software called GRIF [84]. Its Petri nets module developed by SATODEV and TOTAL [85] covers the requirements of the presented formalism. This tool uses stochastic Petri nets with predicates and assertions incorporated with a Monte Carlo simulation engine. Relevant applications of this formalism can be found in Taleb-Berrouane et al. [41] and Nývlt et al. [57].

The remaining of this chapter is organized as follows: Section 3 is dedicated to the framework and the step-by-step development of the Bayesian stochastic Petri nets formalism from the input data acquisition to the analysis of generated output data. Section 4 deals with a comparison between the modelling capabilities of the BSPN formalism and the currently used techniques for safety analysis such as FTA, DBN, and SPN. Section 5 summarizes the main features of this work and draws conclusions and recommendations for future work.

3.3 Model Building: Bayesian Stochastic Petri Nets (BSPN)

The building of a BSPN to model the behaviour of a process system comprises multiple steps. The BSPN formalism is an extended SPN with additional features of BN, such as conditional probability, and the capability to generate posterior probabilities. The steps to build a BSPN model are presented in Figure 3.1 For illustration purpose, the steps in building a BSPN are illustration on a pump failure scenario starting from a FT. The same analogy can be applied on different failure scenarios.

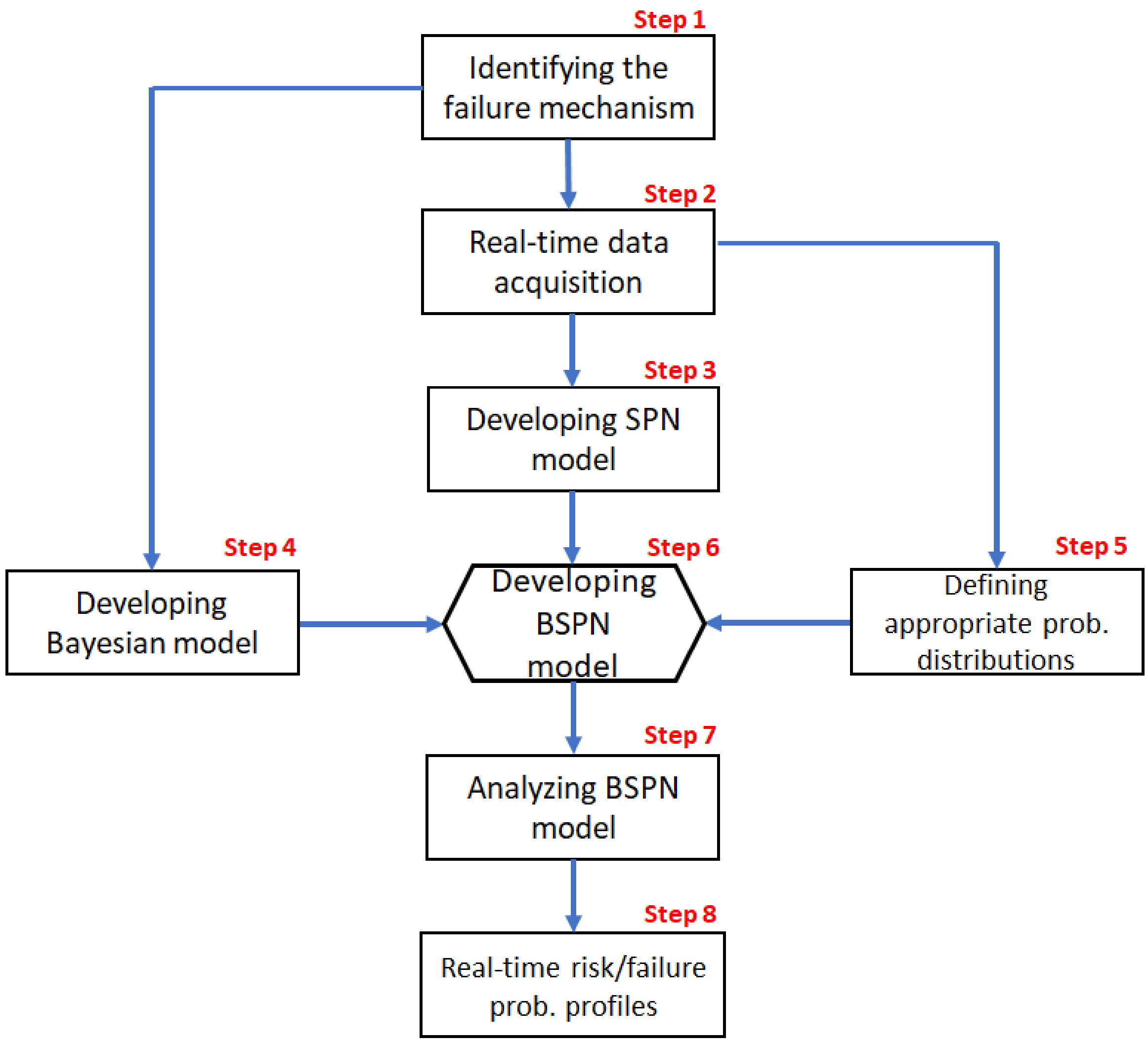


Figure 3. 1 Framework of the BSPN

- Step 1: Failure mechanism identification

The first step in building the BSPN model is to identify the failure mechanism subject to study. This step may be achieved using a hazard identification technique such as HAZOP

[86], HAZID [87], or FMEA [88]. In this work, a pump failure scenario is taken as an example to illustrate the capabilities of the proposed BSPN formalism.

In process systems, failure of a circulation pump can lead to a significant disturbance of the process operations. This disturbance could escalate and cause a hazardous situation affecting the system safety. Figure 3.2 depicts, in a simplified fault tree, some potential sequences leading to failure scenarios of circulation pump trained by electrical power. Table 3.2 provides the meaning of the symbols used in the FTA and their assumed probabilities based on expert opinion.

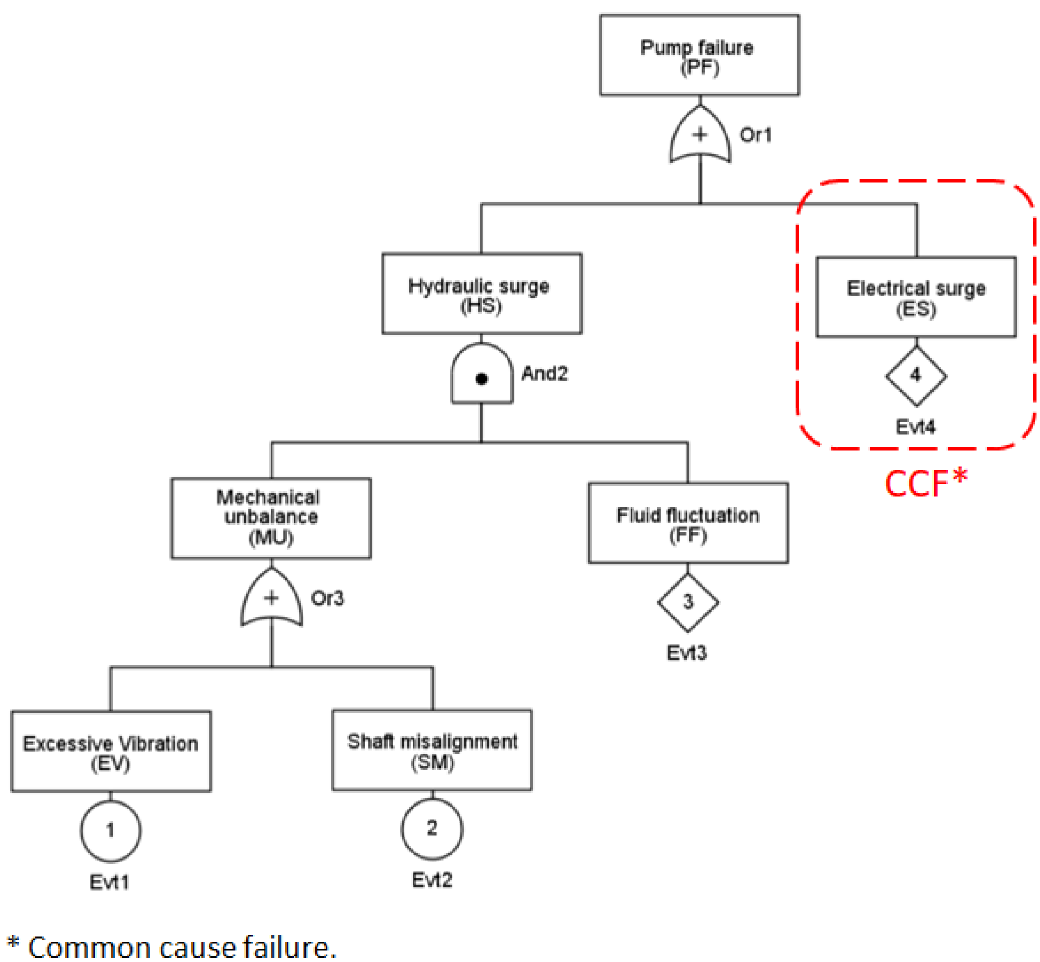


Figure 3. 2 Illustrative fault tree for pump failure scenario

Table 3. 2 Summary of the events, symbols and failure probabilities over the first ten years of operation

	Events	Symbol	Probability of failure
Inputs	Excessive vibration	EV	0.2
	Shaft misalignment	SM	0.1
	Fluid fluctuation	FF	0.2
	Electrical surge	ES	0.05
Outputs	Mechanical unbalance	MU	0.28
	Hydraulic surge	HS	0.056
	Pump failure	PF	0.103

Figure 3.2 shows that a pump can fail by a combination of mechanical unbalance and fluid fluctuation, or by an electrical surge as a common cause failure (CCF). The mechanical unbalance may be caused by excessive vibration or misalignment of the pump shaft.

- Step 2: Real-time data acquisition

Once the potential failure mechanisms are expressed in an FT structure, the basic causes should be monitored in real-time. This real-time data acquisition will draw a time-varying function that can be plotted into a probability distribution.

- Step 3: Stochastic Petri nets development

The basic understanding of SPN model is required to follow the transition to the new concept of BSPN formalism. Compared to conventional Petri nets, when SPN transitions are enabled at a specific marking "m", the tokens remain in the input places during the firing time delay. At the end of the firing time, the tokens move from input places to output places, and the number of tokens in a flow depends on the input and output functions [89].

The same concept is extended to include two notations; immediate transitions with no delay required for the firing, and inhibitor arcs where the absence of tokens enables transition instead of their presence [90]. An SPN is considered for the description of concurrency and synchronization [91]. In a recent extension of SPN, the activation of a transition can be conditioned by one or more mathematical variables through the use of predicates and assertions [92]. The predicates or guards, as defined by IEC 61508-6 [93], are conditions which may be true or false, and control the transition firing, as is shown in Figure 3.3 Assertions or assignments are the mathematical variables that receive predefined updates such as incrementation or state switching as consequences of the transition firing. The simple SPN with predicates and assertions in Figure 3.3 illustrates the abovementioned firing mechanism. The transition “t” in the depicted state is only fired if the variable “A” is true, denoted as “?A”. As a consequence, the variable “A” changes to the state “false” denoted as “!Ac”. The behaviour of these mathematical variables can be monitored and used as outcomes of SPN modelling using instantaneous, average by time intervals, transition firing frequencies, or mean time in a place.

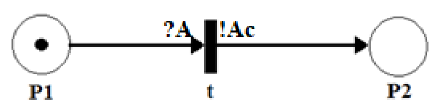


Figure 3. 3 Simple example of SPN with predicates and assertions

To deal with systems involving stochastic and deterministic events in an efficient way, a simulation-based approach can be adopted. Monte Carlo simulation is a powerful tool dedicated to these situations. It is based on the use of random numbers to animate system behaviour. According to the standard IEC 61508-6 [93], SPN formalism provides very efficient support for performing Monte Carlo simulation. The latter produces a large statistical sample from which statistical results are obtained.

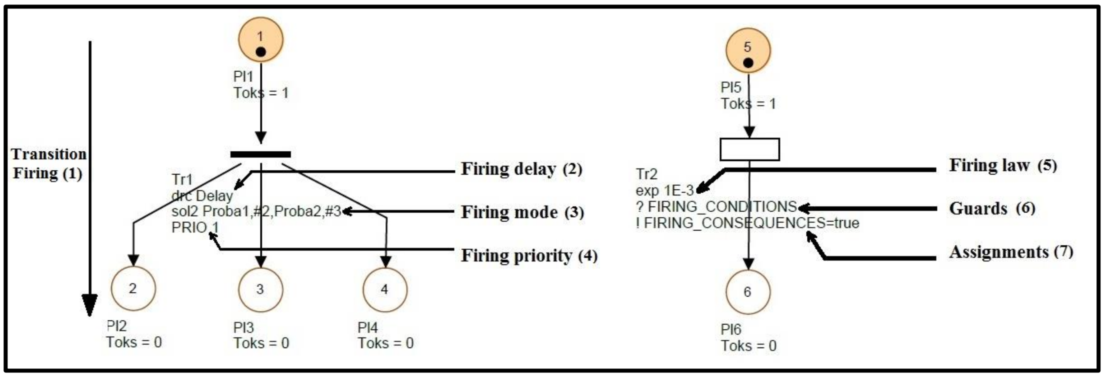


Figure 3. 4 Display of the characteristics of the SPN with predicates and assertions

In SPN modelling, tokens that move from one place to another must pass through a transition; this movement is termed transition firing, as showing in Figure 3.4 and denoted as (1). This movement obeys a firing law, denoted as (5), which defines the transition distribution such as exponential, Weibull, and lognormal distributions. It can also obey a timing through determination of firing delay (2). The firing mode (3) affects the downstream places. It can be either equitably or on demand where each downstream place has its specific probability law. Guards (6) are Boolean expressions that condition transition firing. Assignments (7) are mathematical variables that receive predefined changes. In this article, the authors used SPN with predicates and assertions. For more details, readers can refer to our previous work, Taleb-berrouane et al. [41].

The imitation process from BN to SPN with predicates starts by imitating the nodes as shown in Figure 3.5 The probabilities, noted in this example as C1a, C1b, C1c and C1d, are represented in the SPN equivalent model by the downstream places 2, 3, 4 and 5. The firing law noted as "sol2" shows the probability attributions to the downstream places as the following: the probability of being in place 2 (noted as #2) is 0.4, 0.3 for place #3, 0.2 for place #4, and place #5 will take the remaining probability, in a way that the sum of the probabilities should be equal to 1.

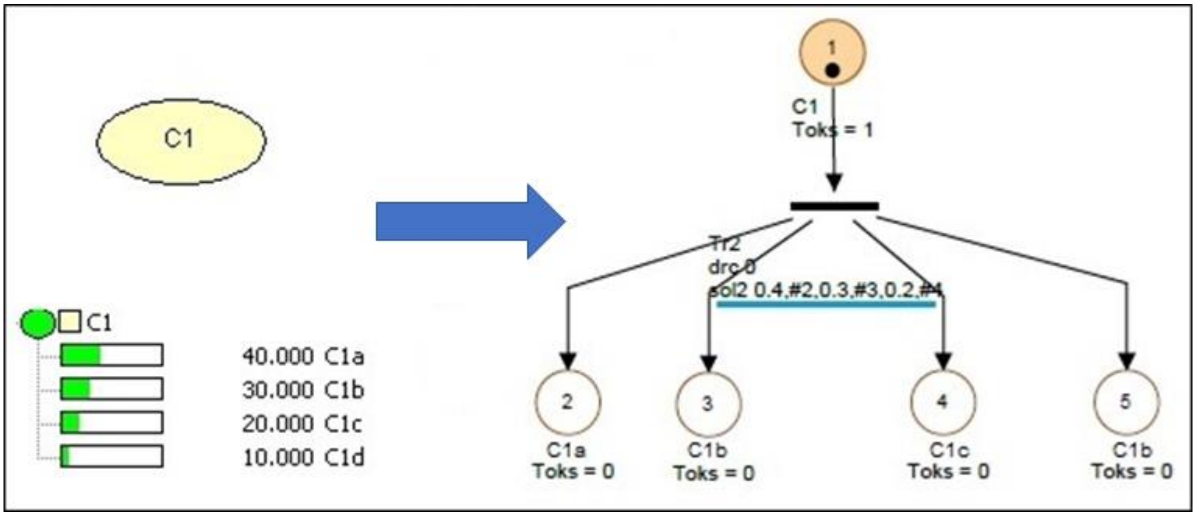


Figure 3. 5 Bayesian single node imitation to an SPN model

After imitating the single nodes, the next step is to imitate the BN with connections considering each ascendance of nodes as a step. This distinction between the ascendance levels is important for the SPN part where each level should be executed with a different firing priority based on the function "PRIOR" as shown in Figure 3.6. In this chapter, all BNs are modelled using the HUGIN software [48].

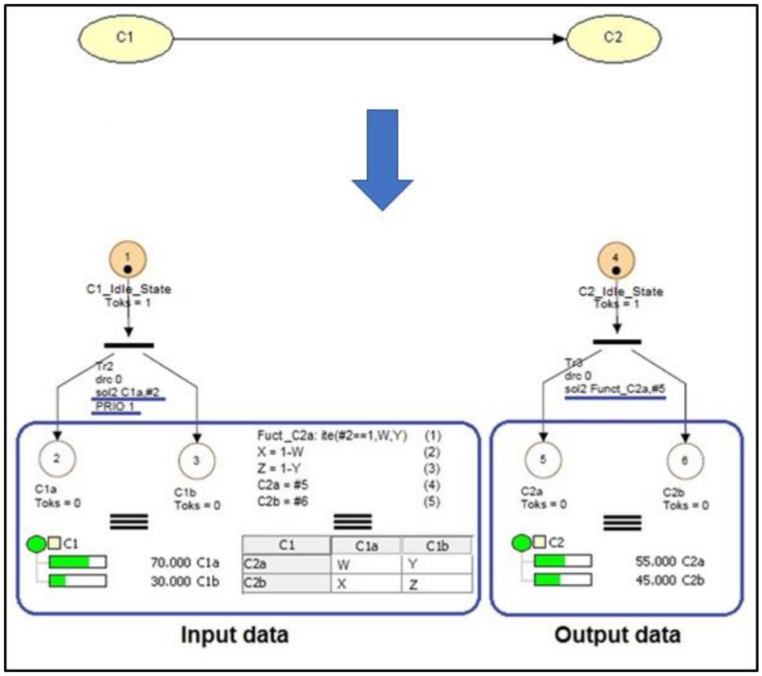


Figure 3. 6 BN connection imitation to an SPN model

Figure 3.6 demonstrates the conversion of a BN to the equivalent SPN model starting with the node imitations as described earlier in Figure 3.5. The ascendant level should have a higher firing priority to ensure proper execution of the SPN simulation. The CPT is replaced by a mathematical variable type called "ite", for "if, then, else". Equation (1) in Figure 3.6 can be read as "if the place 2 has one token, then the function "Funct_C2a" will take the value (W), otherwise it will take the value (Y)", which has the same meaning as the conditional probabilities "C2a|C1a = W and C2a|C1b = Y". The variables (X) and (Z) complete the other cases, where "C2b|C1a = X and C2b|C1b = Z". Equations (4) and (5) in Figure 3.6 are used to extract the output data from places 5 and 6 respectively. Here, the probabilities of C2a and C2b are simply the probabilities of a token being in place 5 and 6 respectively.

- Step 4: Bayesian model development

The Bayesian model is developed in every inter-nodal connection of the network based on Bayes theorem [94]. It allows data updating as shown in (Equation 1).

$$P(X|E) = \frac{P(E|X) \times P(X)}{P(E)} \quad (1)$$

Where P(X) is the prior probability (i.e. prior believe), P(E) is the probability of an observation (i.e. evidence) and P(X|E) is the posterior probability of the event X given the evidence of presence of event E. The probability P(E|X) is the likelihood of the event E given the presence of event X. Using the conditional independence assumptions of BN, the joint probability distribution of a set of random variables {X_1,X_2,X_3,…,X_(n-1),X_n }, can be determined using a chain rule as equation 2:

$$P(X_1, X_2, X_3, \ldots, X_{n-1}, X_n) = \prod_{i=1}^{n} P(X_i|Parents(X_i)) \quad (2)$$

Table 3. 3 Explanation of probability in BN modelling

Tool	Corresponding nodes	Symbol	Examples
Marginal probability (MP)	Orphan nodes (Nodes without parent nodes)	P(A)	P(V), P(MA), P(PO), P(EF)
Conditional probability table (CPT)	Child nodes (nodes having parent nodes)	P(A|Pi)	P(MD|V,MA), P(PF|MPF,EF)
Joint probability (JP)	All nodes	P(A,B)	P(MPF,MD,PO)

Table 3.3 provides an explanation of the different kinds of probabilities used in BN modelling. The conditional dependency is shown in the CPTs and JPTs. Estimation of the CPT was fully considered for the first time by Spiegelhalter and Lauritzen [95], who demonstrated the feasibility of posterior data acquisition. The updated or posterior data can be obtained over the parameter-space in closed form solution.

In the Bayesian approach, a CPT offers a comprehensive specification of conditional dependency as shown in table 3.4. This feature has great significance in the sense of providing the ability to model probabilistic dependency as a unique constant value between 0 to 1 [94].

Table 3. 4 Conditional probability table for mechanical unbalance based on the BN in Figure 3.12

EV		**EVT**		**EVF**	
SM		**SMT**	**SMF**	**SMT**	**SMF**
MU	**MUT**	MUT|EVT,SMT	MUT|EVT,SMF	MUT|EVF,SMT	MUT|EVF,SMF
	MUF	MUF|EVT,SMT	MUF|EVT,SMF	MUF|EVF,SMT	MUF|EVF,SMF

- Occurrence probability of a mechanical unbalance:

$$\mathrm{P(MUT)} = \sum_{i}^{n} \mathrm{P(MUT, EVi, SMi)} \tag{3}$$

- The generated posterior probabilities:

$$\mathrm{P(EVT|MUT)} = \frac{\mathrm{P(EVT\,, MUT)}}{\mathrm{P(MUT)}} = \frac{\mathrm{P(MUT|EVT)} \times \mathrm{P(EVT)}}{\mathrm{P(MUT)}} \tag{4}$$

$$\mathrm{P(SMT|MUT)} = \frac{\mathrm{P(SMT\,, MUT)}}{\mathrm{P(MUT)}} = \frac{\mathrm{P(MUT|SMT)} \times \mathrm{P(SMT)}}{\mathrm{P(MUT)}} \tag{5}$$

Where,

P(MUT |EVT) = [P(MUT, EVT, SMT) + P(MUT, EVT, SMF)] / P(EVT) (6)

P(MUT |SMT) = [P(MUT, EVT, SMT) + P(MUT,EVF, SMT)] / P(SMT) (7)

The nodes V and MA are independents, so:

$$P\ (MUT, EVT, SMT) = P(MUT|EVT, SMT) \times P(EVT) \times P(SMT) \quad (8)$$

$$P\ (MUT,EVF, SMT) = P(MUT|EVF, SMT) \times P(EVF) \times P(SMT) \quad (9)$$

$$P\ (MUT, EVT, SMF) = P(MUT|EVT, SMF) \times P(EVT) \times P(SMF) \quad (10)$$

Bayes theorem is applied to calculate updated (i.e. posterior) probabilities when new information becomes available [96]. The evidence on a given node means that the actual node's state is known. In other words, "there is a belief in that" so the probability of this state will be 1, and 0 for the other states. This evidence can update the probabilities of the ascendant nodes. This change is called data updating and the resultant probabilities are termed posterior probabilities. This data updating represents a prediction.

- Step 5: Definition of appropriate probability distributions

The trends of the real-time data taken during system operations should be fitted to a probability distribution function such as Weibull, exponential or log-normal. For illustration purposes and for the pump failure scenario, we have simulated the variation of the obtained data into Weibull probability distributions. For more details about fitting data into probability distributions, the reader is referred to the work of Delignette-Muller and Dutang [97].

- Step 6: Bayesian stochastic Petri nets model development

The BSPN formalism is an extended SPN with additional features of BN, such as conditional probabilities and posterior probabilities. The BSPN model is developed based on the imitation process described below.

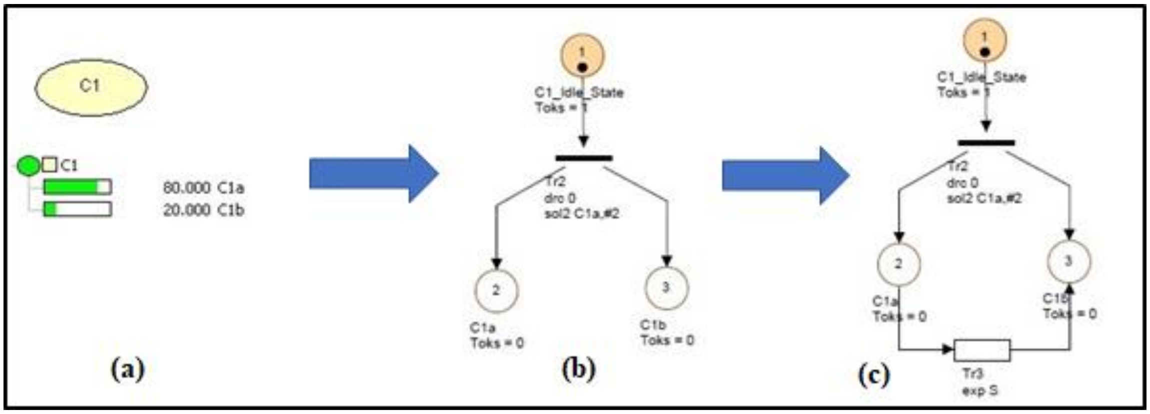


Figure 3. 7 Mapping process from a binary state of BN to SPN, and SPN to BSPN models

Figure 3.7 presents a two-step mapping process from a binary state BN to SPN, then from the resultant SPN to a BSPN model. In addition to the imitation capability, the BSPN through the guards and assignments can handle the timing (e.g., instantaneous or delayed actions), the sequential order, and any other condition of firing. The BSPN can model multi-state variables with different configurations. A three-states illustrative example is demonstrated in Figure 3.8.

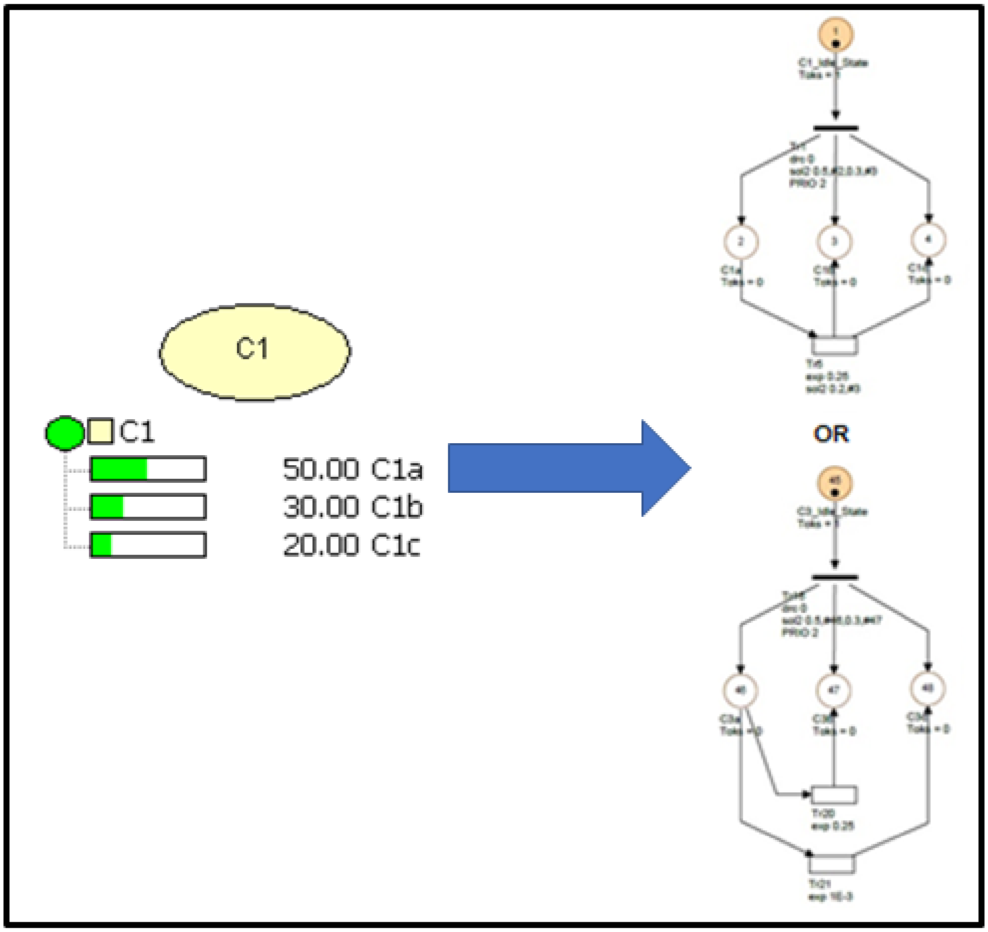


Figure 3. 8 BN mapping to BSPN in different cases of multi-states variables

Figure 3.8 presents the possible dependency configurations between three-state output. The first case models the case where the evolution of the states (b) and (c) is dependent on state (a) following a regular sharing rule type "sol2" without competition. However, case 3 can be used where competition exists between two states following one or two different distributions.

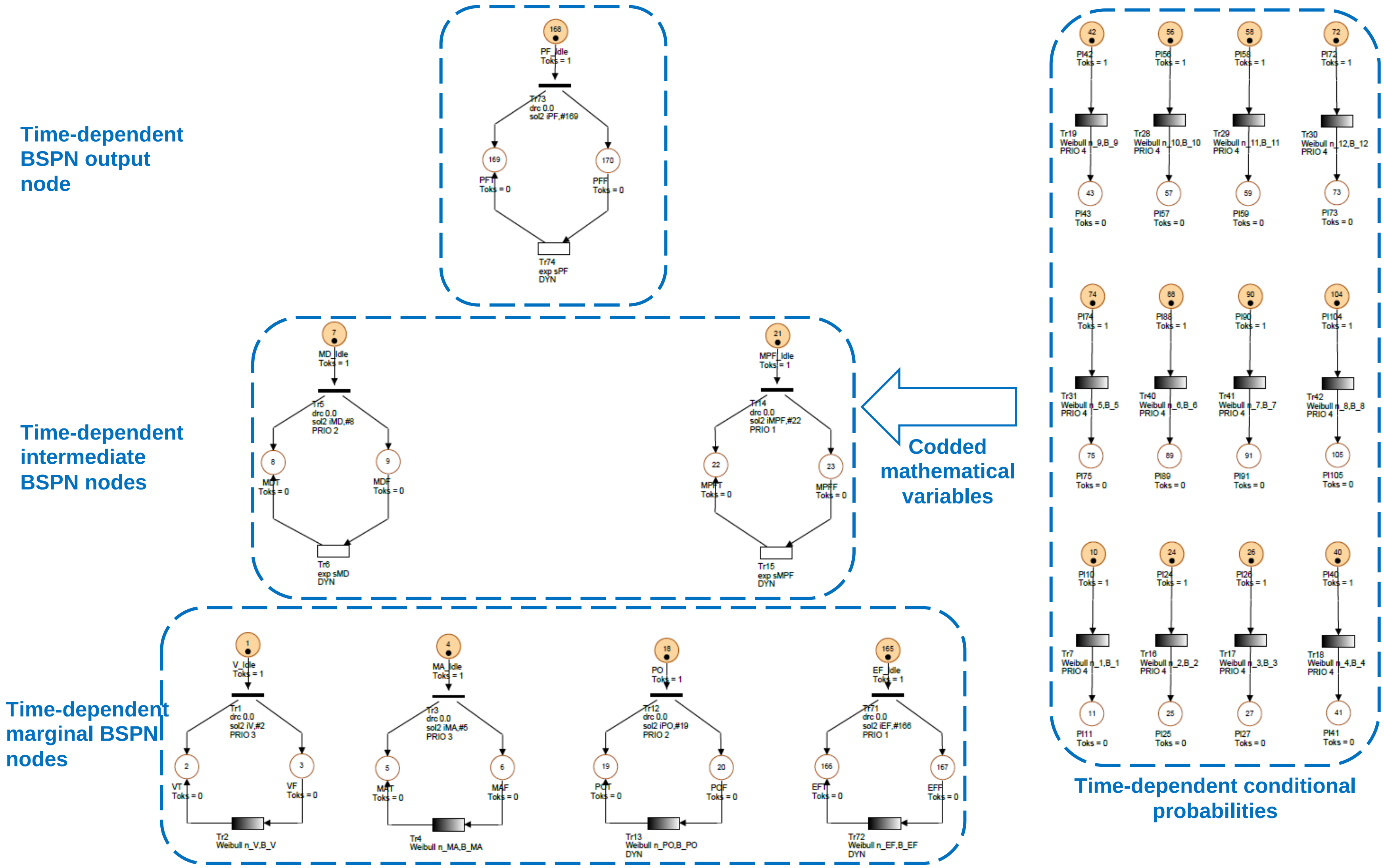


Figure 3. 9 BSPN model for the pump failure scenario

Figure 3.9 presents the BSPN model for the pump failure scenario. This model is generated following the imitation process demonstrated in Figure 3.7 and Figure 3.8 From the graphical point of view, distinct structural forms are adopted to differentiate between the initiator events or basic events (house or pentagon shape) and the intermediate and top event (hexagonal shape). The conditional probabilities are presented as a separate part of the model. Additionally, the nodes are presented in layers consisting of initiator events, intermediate events, and the top event with decreasing transition firing priority to allow proper execution of the model.

From the modelling point of view, every event is presented in a node or a block form. The nodes are physically separated to avoid a congested structure. The mathematical variables capture the dynamic changes in places and transitions. This monitoring capability allows information transfer or communication among the different nodes. The Bayesian model, discussed in step 4, is embedded in the computational part of the model. After the accomplishment of the graphical and mathematical set-put, the time-varying behaviour of the selected variables should be observed by using the statistical computation parameters. The statistical parameter "TR 3" is preferably used in most cases. It observes the probability of having a token in a specific place at each moment. The output analysis and discussion are provided in steps 7 and 8 of the BSPN modelling framework.

- Steps 7 & 8: BSPN model analysis and dynamic risk/failure probability profiles

After fitting of the real-time input data into probability distributions, the parameters of each distribution should be embedded in the BSPN model. Table 3.5 summarizes the input data for the model.

Table 3. 5 Summary of the input probability distributions used in the BSPN model

	Variables	Descriptions	Probability distribution	Scale Par. (n) (hours)	Shape Par. (B)
Marginal probabilities (MP)	EV	Excessive vibration	Weibull	$8x10^5$	0.7
	SM	Shaft misalignment	Weibull	$1x10^5$	2.5
	FF	Fluid fluctuation	Weibull	$9x10^5$	0.3
	ES	Electrical surge	Weibull	$12x10^5$	1
Dynamic conditional probabilities (DCP)	MUT|EVT, SMT	Mechanical unbalance (true) given excessive vibration (true) and shaft misalignment (true)	Weibull	$1x10^3$	0.4
	MUT|EVT, SMF	Mechanical unbalance given excessive vibration and no shaft misalignment	Weibull	$5x10^5$	0.2
	MUT|EVF, SMT	Mechanical unbalance given shaft misalignment and no excessive vibration	Weibull	$2x10^4$	0.3
	MUT|EVF, SMF	Mechanical unbalance given no excessive vibration and no shaft misalignment	Weibull	$2x10^5$	2.5
	HST|MUT, FFT	Hydraulic surge given mechanical unbalance and fluid fluctuaction	Weibull	$5x10^2$	0.3
	HST|MUT, FFF	Hydraulic surge given mechanical unbalance and no fluid fluctuation	Weibull	$1x10^3$	1.5
	HST|MUF, FFT	Hydraulic surge given no mechanical unbalance and true fluid fluctuation	Weibull	$6.5x10^4$	2.5
	HST|MUF, FFF	Hydraulic surge given no mechanical unbalance and no fluid fluctuation	Weibull	$2x10^5$	3
	PFT|HST, EST	Pump failure given hydraulic surge and electrical surge	Weibull	$1.2x10^3$	0.6
	PFT|HST, ESF	Pump failure given hydraulic surge and no electrical surge	Weibull	$1.2x10^4$	0.3
	PFT|HSF, EST	Pump failure given no hydraulic surge failure and true electrical surge	Weibull	$1.2x10^6$	0.4
	PFT|HSF, ESF	Pump failure given no hydraulic surge and no electrical surge	Weibull	$1x10^6$	1

T: true, F: false.

Table 3.5 provides a summary of the probability distribution functions used in the BSPN model to analyze the pump failure scenario. Based on the nature of variation of the initiator events (e.g. increasing failure rate), the Weibull distribution was selected to model the behaviour of those variables. Once the BSPN model is entirely built, the MCS can be set with a large number of histories. In the current work, the simulation runs on 100.000 histories. The BSPN model runs using SPN computational software coupled with MCS, and the obtained results are outlined in Figure 3.10.

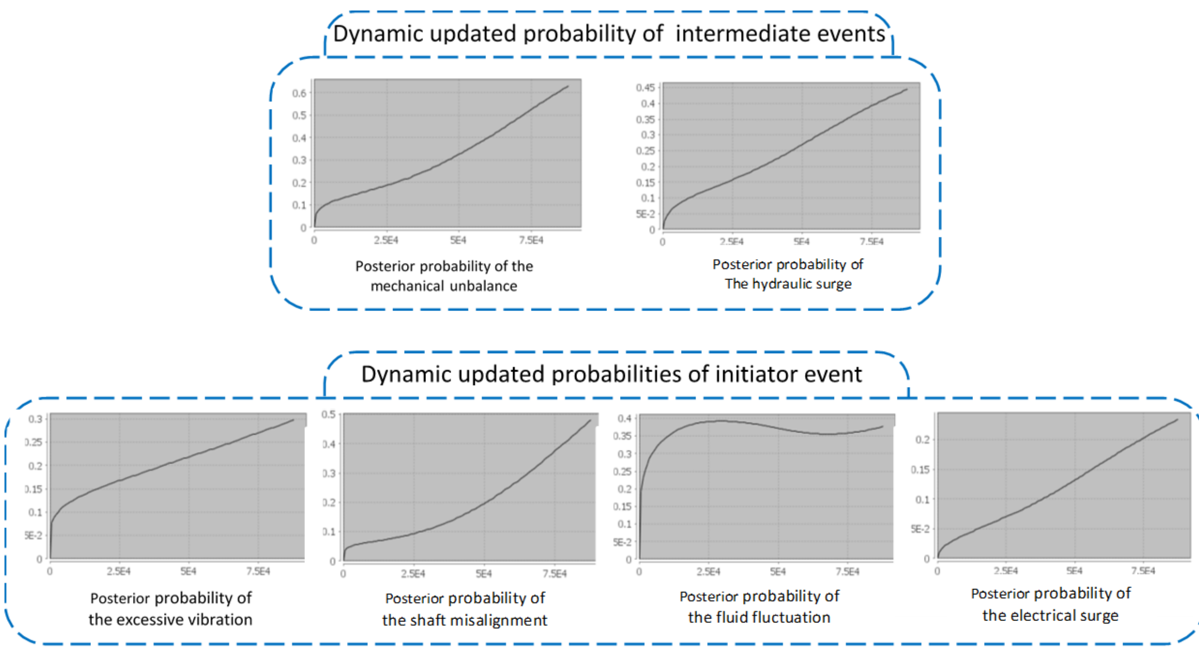


Figure 3. 10 BSPN output data for the pump failure scenario

The posterior failure probability profiles explain the dynamicity of the system failure. It also provides an updated cause-effect relationship between variables that may be changing with time. For example, at an early age (e.g., less than six years of operation), the mechanical unbalance is more likely to be caused by excessive vibration than by a misalignment of the pump's shaft. After around seven years of operation, the mechanical unbalance would be most likely caused by misalignment of the pump shaft as shown in Figure 3.11.

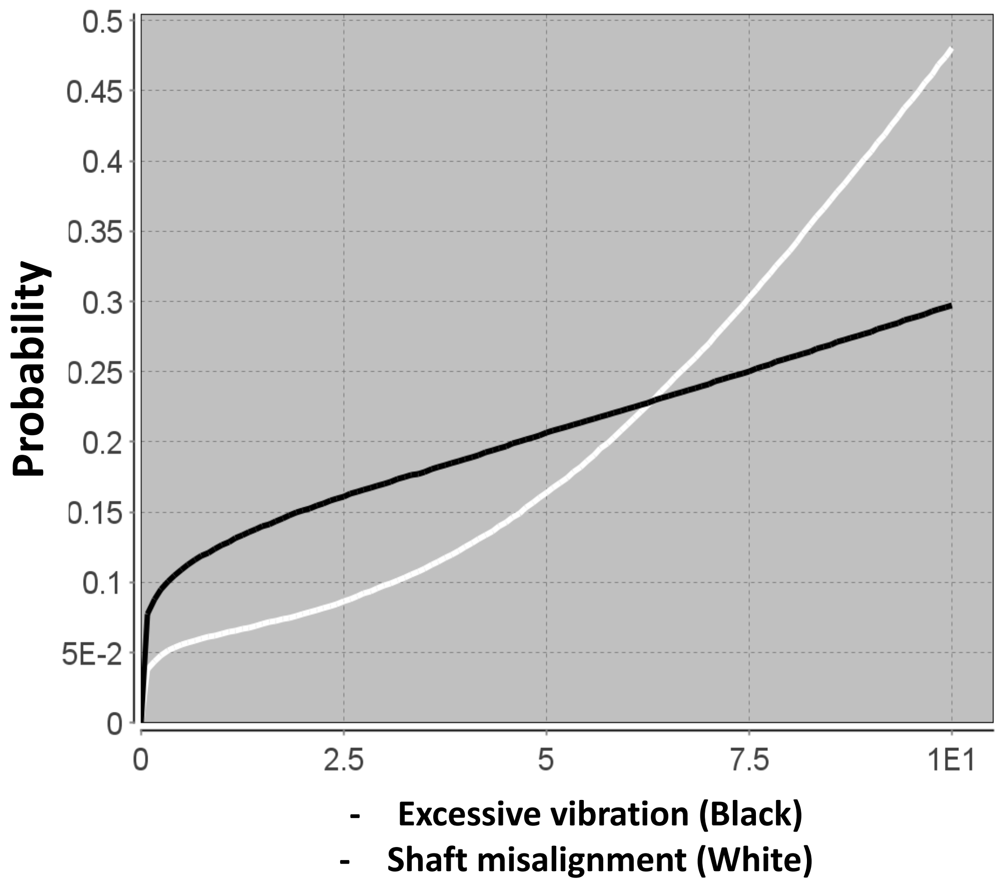


Figure 3. 11 Trends of posterior probabilities of excessive vibrations versus shaft misalignment

Another observation from Figure 3.10, is the slight oscillation of the updated probability of the fluid fluctuation over time. This slight variation can be interpreted as the actual fluid fluctuation level is not contributing in the performance deterioration of the pump, thereby not increasing the failure probability of the pump.

The updated probability of electrical surge increases with time; however, its impact is still lower compared to the hydraulic surge in terms of causing the failure of the pump in ten years of operation.

In summary, the benefit of being able to generate a time-dependent function to represent the conditional probability is to capture the effect of duration of the evidence on the conditional probability trend. In other words, using the proposed BSPN modelling tool the effect of disruptive event (e.g. excessive vibration) is captured in terms of the continuous trend and the continuous trend of the conditional probability capturing the evidence.

3.4 Comparison of the Modelling Capabilities of BSPN with Other Techniques

3.4.1 Fault tree analysis

To compare the modelling capabilities of BSPN, the same scenario of pump failure was analyzed using FTA and BN techniques. The FTA diagram was provided earlier in Figure 3.2 and the results of the fault three analysis were summarized in Table 3.2 The most probable sequence (MPS) is the probability of the highest minimal cut set. Subsequently, the MPS is identified to be excessive vibration along with pump overloading. Based on equations 11 and 12, the MPS has a probability of 0.04, which is responsible for 39% of the cases of pump failure.

$$\mathrm{P\ (MPS)} = \mathrm{P\ (V)} \times P\ (PO) \tag{11}$$

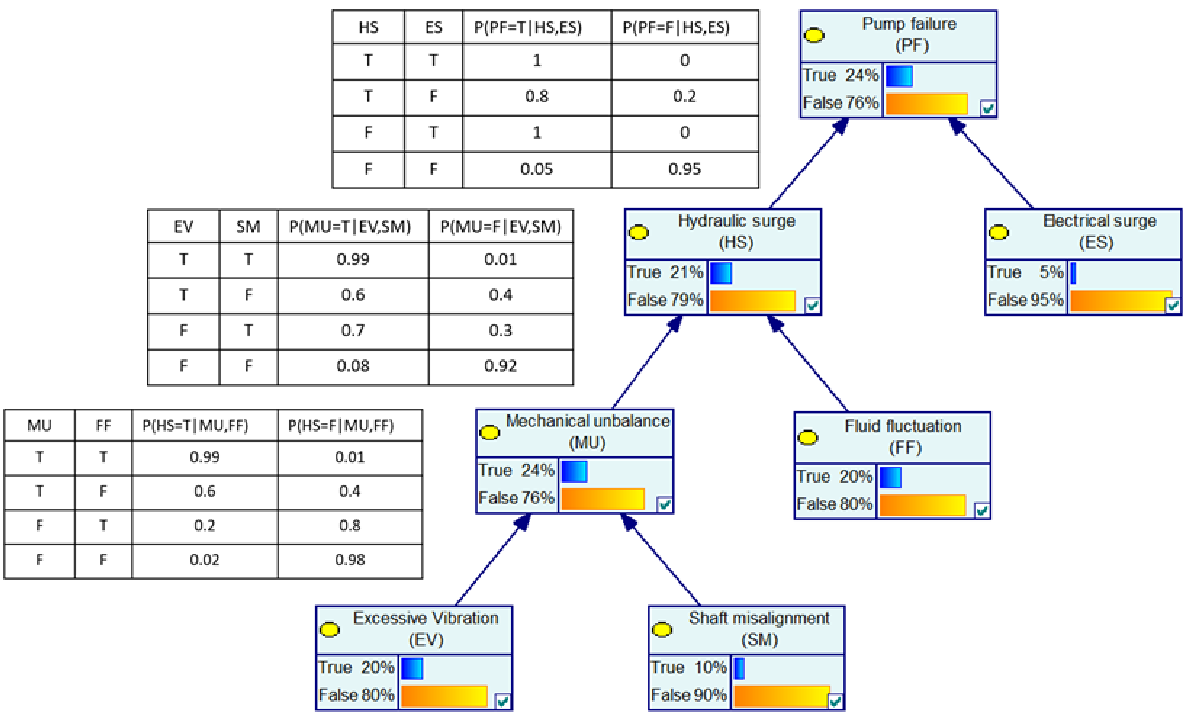
$$\mathrm{Ratio\ (MPS)} = \frac{\mathrm{P\ (MPS)}}{\mathrm{P\ (PF)}} \tag{12}$$

The fault tree analysis has provided useful insight into the scenario of pump failure; however, the analysis is static, and does not incorporate any dynamic behaviour of the variables.

3.4.2 Bayesian network

(a) Static Bayesian network

Static Bayesian network [96], [98] is the conventional form of discrete-time Bayesian network (DTBN) where the computation, based on step 4 in section 3, is founded on the Bayes theorem in a time-independent manner.



HS	ES	P(PF=T|HS,ES)	P(PF=F|HS,ES)
T	T	1	0
T	F	0.8	0.2
F	T	1	0
F	F	0.05	0.95

EV	SM	P(MU=T|EV,SM)	P(MU=F|EV,SM)
T	T	0.99	0.01
T	F	0.6	0.4
F	T	0.7	0.3
F	F	0.08	0.92

MU	FF	P(HS=T|MU,FF)	P(HS=F|MU,FF)
T	T	0.99	0.01
T	F	0.6	0.4
F	T	0.2	0.8
F	F	0.02	0.98

Figure 3. 12 Bayesian network for pump failure scenario.

In section 2, Figure 3.2 shows that a pump can fail by a combination of mechanical unbalance and overloading operations. The mechanical unbalance can be due to excessive vibration or misalignment of the pump shaft. However, other factors may cause a mechanical unbalance or pump failure. The FTA is not able to capture the presence of those other factors. Using the leaky noisy-OR gate, BN can capture those other factors. Figure 3.12 depicts the same pump failure scenario based on BN modelling. The conditional probability tables are attached to Figure 3.12.

Table 3. 6 Summary of the BN modelling results

	Events	Symbol	Probability of failure	Posterior probability
Inputs	Excessive Vibration	EV	0.20	0.34
	Shaft misalignment	SM	0.10	0.19
	Fluid fluctuation	FF	0.20	0.31
	Electrical surge	ES	0.05	0.20
Outputs	Mechanical unbalance	MU	0.24	0.57
	Hydraulic surge	HS	0.21	0.68
	Pump failure	PF	0.24	1

The results presented in Table 3.6 illustrate the BN performances to capture the uncertainty and data updating capability. From the posterior probabilities, we can determine the contributing factors to the pump failure. The results reveal that mechanical and process failure is a significant contributor to failure of the pump compared to electrical failure. As well, excessive vibration has a major role in causing mechanical unbalance of the pump; coupled with pump overloading, these two root causes constitute the highest contribution to the pump failure scenario.

(b) Dynamic Bayesian network

Dynamic Bayesian networks (DBN) are extended DTBN [96], [99], [100] that supports the modelling of the temporal evolution of random variables over a discretized timeline (i.e. time slices). The temporal evolution is presented by the dependency between the node in time (t) and its copy in time (t+△t). The joint probability at time (t+△t) is P ($U^{t+\triangle t}$) as follows:

$$P(U^{t+\triangle t}) = P(X_1^{t+\triangle t}, X_2^{t+\triangle t}, \dots, X_n^{t+\triangle t})$$

$$= \prod_{i=1}^{n} P\left(X_i^{t+\triangle t} \middle| X_i^t, pa\,(X_i^t), pa\,(X_i^{t+\triangle t})\right) \tag{13}$$

Where $X_i^{t+\triangle t}$ and X_i^t are the consecutive time slices of X_i with a time interval of △t, and $pa\,(X_i^{t+\triangle t})$ and $pa\,(X_i^t)$ are the parents sets of X_i at the time slices (t + △t) and (t), respectively.

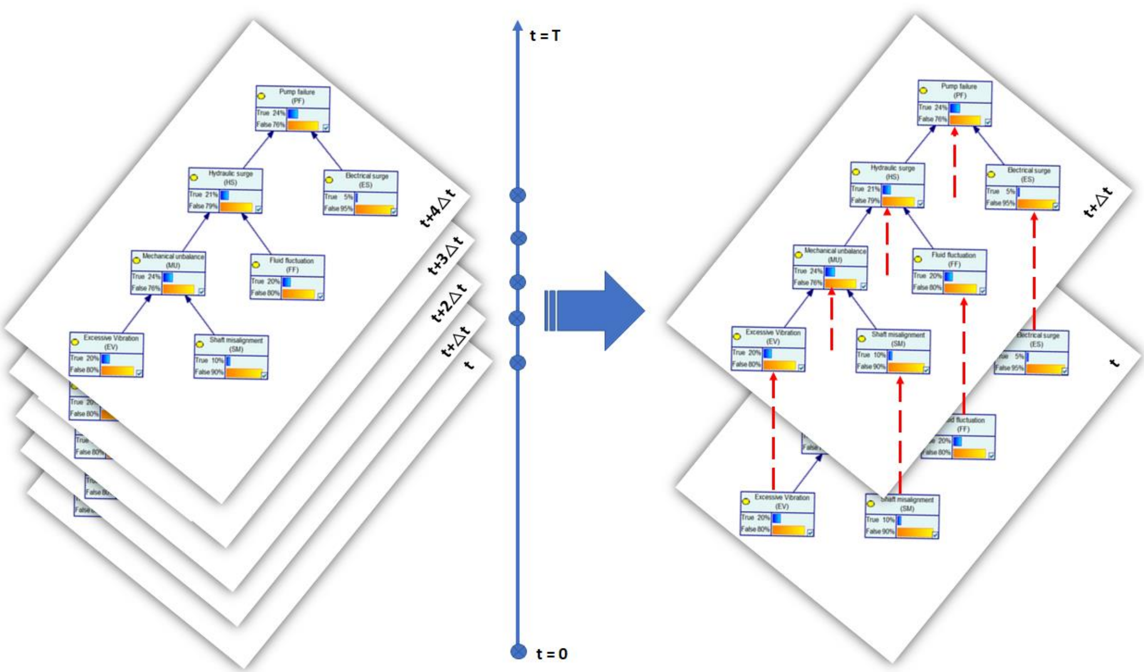


Figure 3. 13 Dynamic Bayesian network for pump failure scenario

Figure 3.13 depicts a DBN as multiple layers of replica of the static BN in Figure 3.12 The temporal arcs, represented in red colour, connect the copies of a same node in consecutive time slices. In this case study, the DBN was built based on discretisation of conditional probability distributions as illustrated in Table 3.7 The discretisation allows to extract a new value of the conditional probability at each time slice.

3.4.3 Stochastic Petri nets

The SPN in Figure 3.14 models the scenario of pump failure considering the occurrence of root causes following exponential distributions. The time-dependent variation of the intermediate and top events are collected at each moment.

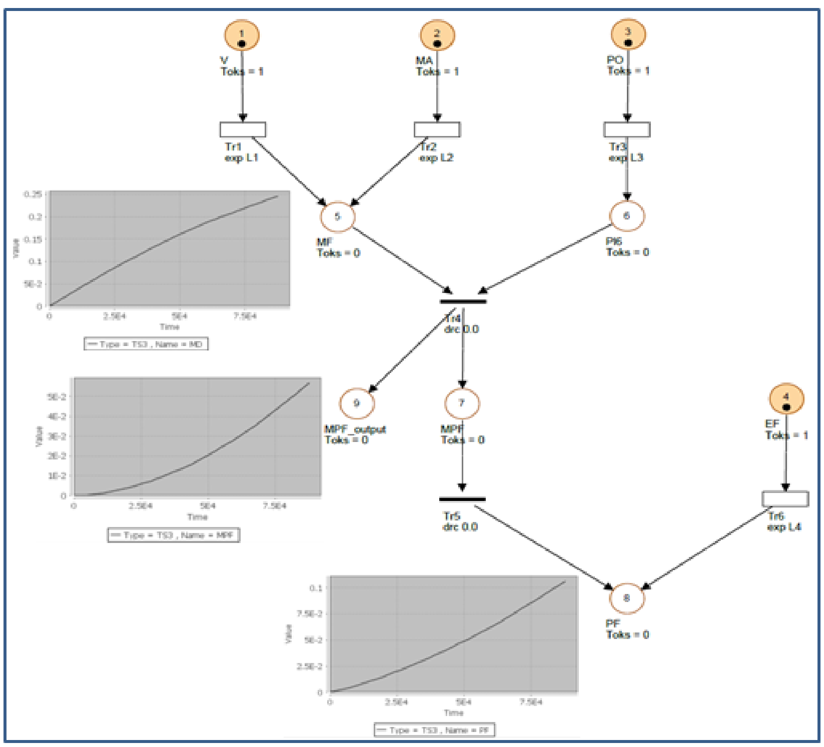


Figure 3. 13 SPN model for the pump failure scenario

Compared to other techniques, the SPN, in Figure 3.14, captures the continuous function of the variables instead of connecting discrete points to draw the continuous variables. This capability gives the model accuracy in capturing the input data and generating the output data. However, the SPN tracks back the effect of evidence in the output on the probabilistic variables, which is commonly known as data updating.

3.4.4 Comparative analysis of the generated models

Initially, it is worth noting that the static models such as FT and static BN can perform time-dependent analysis by choosing some time steps. Each time step has to be small enough to nearly fit the continuous function representing the real trend of the variable. Unfortunately, this is not feasible when monitoring systems during a medium to large periods. In this case study, the system is monitored for a period of ten years of operation. Thereby, technically the static models on multiple time slices cannot provide good performances in dealing with such data variation on a large period. For the presented case study, which is a small-sized model, the CPTs for the DBN model are generated on each time-slice based on the analogy presented in Table 3.7, where the variables (λ_1,λ_2, β_1,β_2, μ_1,μ_2,Ω_1) are generated by data fitting. In certain cases, the variation of the conditional probabilities may follow complex distributions and mapping this behaviour in a set of discretized clones with small time steps for each variable would be a challenging and time-consuming task. Although the BSPN present some uncertainties due to the use of Monte Carlo simulation, it is clear that it explicitly captures the time dependency of the conditional probabilities, which reflects the real complexity of dynamic systems much better than the discretization based methods.

Table 3. 7 Discretized time dependant conditional probabilities table for DBN, example: P($MU_{at\ t+\Delta t}$)

$EV_{at\ t+\Delta t}$		EVT				EVF			
$SM_{at\ t+\Delta t}$		SMT		SMF		SMT		SMF	
$MU_{at\ t}$		T	F	T	F	T	F	T	F
$MU_{at\ t+\Delta t}$	T	$exp(-\lambda_1 x\Delta t)$	$exp(-\lambda_2 x\Delta t)$	$exp(-\beta_1 x\Delta t)$	$exp(-\beta_2 x\Delta t)$	$exp(-\mu_1 x\Delta t)$	$exp(-\mu_2 x\Delta t)$	$exp(-\Omega_1 x\Delta t)$	0
	F	$1- exp(-\lambda_1 x\Delta t)$	$1- exp(-\lambda_2 x\Delta t)$	$1- exp(-\beta_1 x\Delta t)$	$1- exp(-\beta_2 x\Delta t)$	$1- exp(-\mu_1 x\Delta t)$	$1- exp(-\mu_2 x\Delta t)$	$1- exp(-\Omega_1 x\Delta t)$	1

Table 3. 8 Summary of selected results from BSPN and other modelling techniques

			Available/used data type		Pump operating duration (years)									
			Time step	Continuous	1	2	3	4	5	6	7	8	9	10
Prior probabilities	**Initiator events**	Excessive Vibration		√	0.234	0.253	0.269	0.284	0.298	0.31	0.322	0.333	0.343	0.353
		Shaft misalignment		√	0.102	0.111	0.131	0.163	0.207	0.262	0.329	0.402	0.481	0.561
		Fluid fluctuation		√	0.375	0.41	0.432	0.449	0.464	0.476	0.486	0.495	0.503	0.511
		Electrical surge		√	0.057	0.064	0.07	0.077	0.084	0.09	0.097	0.104	0.11	0.116
Intermediate nodes	**Mechanical unbalance**	FTA (time step)	√		0.312	0.336	0.365	0.401	0.443	0.491	0.545	0.601	0.659	0.716
		DBN	√		0.260	0.270	0.290	0.320	0.350	0.380	0.430	0.470	0.520	0.570
		SPN		√	0.030	0.061	0.090	0.117	0.144	0.167	0.189	0.208	0.228	0.245
		BSPN		√	0.169	0.204	0.238	0.277	0.323	0.374	0.433	0.493	0.557	0.619
	Hydraulic surge	FTA (time step)	√		0.117	0.138	0.158	0.180	0.206	0.234	0.265	0.298	0.331	0.366
		DBN	√		0.260	0.270	0.290	0.320	0.340	0.360	0.400	0.430	0.470	0.500
		SPN		√	0.001	0.003	0.006	0.011	0.016	0.023	0.030	0.038	0.047	0.057
		BSPN		√	0.357	0.396	0.44	0.494	0.558	0.626	0.694	0.754	0.807	0.85
End state node	**Pump failure**	FTA (time step)	√		0.167	0.193	0.217	0.243	0.272	0.303	0.336	0.371	0.405	0.439
		DBN	√		0.290	0.300	0.320	0.340	0.360	0.380	0.410	0.440	0.470	0.490
		SPN		√	0.006	0.013	0.021	0.031	0.041	0.053	0.064	0.078	0.092	0.106
		BSPN		√	0.246	0.307	0.36	0.418	0.481	0.545	0.608	0.664	0.714	0.754

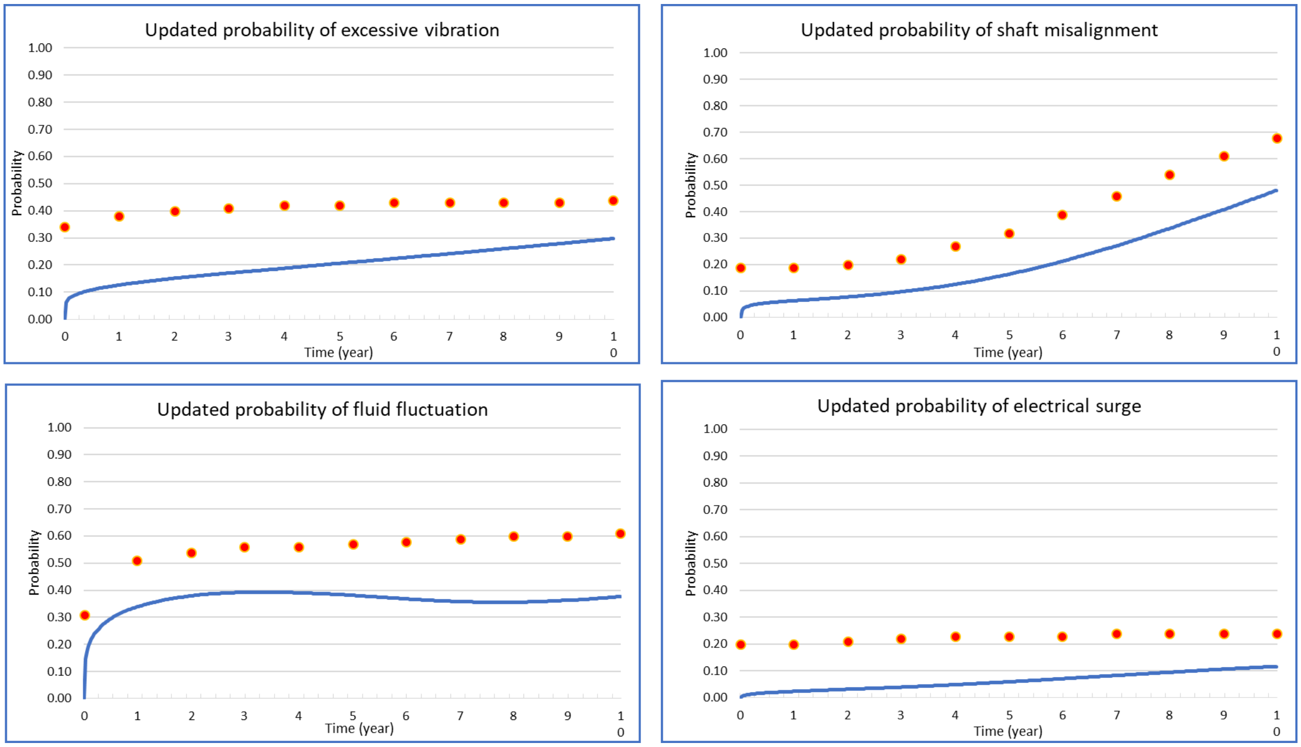


Figure 3. 14 Temporal evolution of updated probabilities using DBN (red dots) and BSPN (blue line)

Table 3. 9 Comparison of the modelling capabilities of BSPN against FTA, BN, and SPN

	Variable	**FTA**	**DBN**	**SPN**	**BSPN**
Basic events	Excessive Vibration	Constant or time-sliced	time-slices	Continuous function	Continuous function
	Shaft misalignment	Constant or time-sliced	time-slices	Continuous function	Continuous function
	Fluid fluctuation	Constant or time-sliced	time-slices	Continuous function	Continuous function
	Electrical surge	Constant or time-sliced	time-slices	Continuous function	Continuous function

Intermediate and top event	Mechanical unbalance	OR gate	Leaky noisy-OR gate	Continuous function	Continuous function
	Hydraulic surge	OR gate	Leaky noisy-OR gate	Continuous function	Continuous function
	Pump failure	AND gate	Leaky noisy-OR gate	Continuous function	Continuous function
Model capabilities	Conditional probabilities	-	Discretized time dependant	-	Continuous function
	Updated probabilities	-	Discretized time dependant	-	Continuous function
	Dynamicity	Low	Low	High	High
	Graphical structure	Explicit	Explicit only if there is limited number of connections	Non-explicit at medium and large model sizes	Explicit with no physical connection between nodes

Table 3.8 and Table 3.9 provide a comprehensive comparison between the modelling capabilities of BSPN formalism against FTA, DBN and SPN techniques. Figure 3.15 depicts the time varying behaviour of the updated probabilities. It can be seen that the BSPN has captured more variation in the trend of the probabilities compared to the DBN. The results are be captured in continuous time-dependent form instead of discrete points assumed to be linearly connected. As with the inputs, the output data are continuous and dynamic in nature. Additionally, the BSPN is endorsed with the capacity to handle dynamic processes, time-dependent data updating along with the explicit (i.e. non congested) graphical structure.

In other words, the basic conditional probability, in BSPN, is considered time-dependent because of the cumulative effect of the failure scenario for example fatigue is a cumulative function, thereby the dependency itself is a varying function. The dependency changes when the time changes. Similarly, an argument can be made toward the vibration effect and the process disturbance events such as high fluctuations of fluid flow.

Furthermore, a discrete model can run multiple times in time slices fashion; however, this remains to be discrete time form. Where continuous model, by defining the conditional dependencies, which is the focus of the work, the model can run in any interval of time, it does not have to be discrete. Furthermore, if the system is running for a period of medium to large period of time, the discrete model has to run at the same frequency as you wish to see the outcome. Additionally, the relationship between the discrete values are considered to be independent. In other words, the dependency remains the same moving forward except the time dependency. Where in BSPN, the variables and the dependencies both are running in a time-dependent form.

3.5 Conclusions and Further Work

This chapter introduced the BSPN as an innovative modelling tool that combines the concepts of BN and SPN in an interactive way. Compared to conventionally used techniques, BSPN offers higher features for modelling complex and dynamic systems with time-varying behaviour. As demonstrated, BSPN relies on, and adopts to, the dynamic data updating as a new concept. Additionally, BSPN can be used as an advanced formalism with ample potential for application in availability and safety analysis. The BSPN has hybridized SPN and BN in one formalism by integrating Bayes theorem into the transition variables. This was established by codding the Bayes rules equations (see equations 1 to 10) in form of mathematical variables that will be concurrently executed while running the SPN simulation. The objective is to strengthen the modelling capabilities of SPN with continuous data updating. This modelling tool, or formalism, takes into account multiple interactions that cannot be considered in either conventional SPN or DBN. The three most commonly used techniques, FTA, DBN and SPN are used to estimate the failure probability of a scenario. The estimated probability is dependent on a constant logic (i.e. dependency) and changes in the prior probability. Where in BSPN, it is accounting for changes in the prior probability but also in continuous changes of the conditional probabilities. This capability has significant importance for failure diagnosis. This formalism has shown a relevant capability to meet the requirements for efficient safety analysis, such as:

a. Ability to handle failure behaviour of complex systems,
b. Dynamic in nature to capture changes in safety and risk-related parameters,
c. Large-scale applicability, and
d. Explicit graphical structure.

Further work needs to be done to test, verify, and optimize the BSPN formalism. For example, the equations and the computational complexity increases with the number of parents' nodes (e.g. over four parent nodes), and the levels of ascendency. This area is subject of further improvement. It is worth noting that no attempt has been made here to perform uncertainty analysis; this will be incorporated in an upcoming paper.

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4. CORROSION RISK ASSESSMENT MODEL WITH APPLICATION

Preface

A version of this manuscript has been submitted and considered for peer review in the Journal of Corrosion Engineering, Science and Technology. I am the primary author of this paper. Along with the co-authors, Faisal Khan and Kelly Hawboldt, I developed the conceptual model and subsequently translated this to a numerical risk assessment model using enhanced Bow-Tie model. I carried out most of the literature review, data collection and analysis. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' feedback. The co-author Faisal Khan helped in developing the concepts/models and their testing, reviewed and corrected the models and results, and contributed in preparing, reviewing and revising the manuscript. The co-author Kelly Hawboldt contributed through support in improving the work. Kelly Hawboldt also assisted in reviewing and revising the manuscript.

Abstract

Corrosion is one of the main threats to asset integrity in the oil and gas production and processing facilities. This chapter presents a practical quantitative corrosion risk assessment methodology with a specific focus on microbiologically influenced corrosion. This includes details of Bow-Tie (BT) corrosion risk model development. The proposed Bow-Tie model is statistically verified against an existing corrosion database, including cases of corrosion occurrences and corrosion-induced failures. The methodology also

provides opportunity to run root-cause contribution analysis, estimation of the probability of corrosion, corrosion-induced failures, and highly probable sequences leading to failure. The methodology is demonstrated using an oil transportation pipeline system. The study identifies and quantifies parameters that help to prioritize the actions needed to prevent and control corrosion and avoid failures. Once implemented, the proposed methodology would serve an important mechanism to identify, assess, and manage corrosion threat to an asset.

Keywords: Corrosion risk assessment, Bow-Tie, Risk, Corrosion, Biocorrosion, microbial influenced corrosion.

4.1 Introduction to Corrosion Risk Assessment (CRA)

Corrosion is a major cause of deterioration and failure of process equipment in the oil and gas industry. Pipelines are particularly susceptible to localized corrosion [4]. In pipeline systems, external corrosion is due to contact with the environment through; (i) acidic atmosphere in above ground pipelines, (ii) corrosive soils in buried pipelines, and (iii) marine life and seawater temperature in submerged pipelines. Internal corrosion takes place when a corrosive fluid comes in contact with a vulnerable metal surface. This process occurs under specific operating conditions and within a pH range favourable to corrosion (e.g. microbiologically influenced corrosion (MIC)). The vulnerability of the metal surface (i.e. wettability, roughness and micro-cracks) is an important factor when it comes to localized corrosion. The rate of localized corrosion can grow faster and cause premature corrosion-induced failure (CIF) of the asset. CIF is typically a leak, which leads to contamination by a hazardous materials spill, vapour cloud explosion (VCE), or toxic releases, depending on the geolocation and nature of the carried fluid inside the pipeline.

Sadiq et al. [6] assessed the risk of corrosion associated failure in a probabilistic form using Monte Carlo simulation. The work focused on the failure prediction when the factor of safety is smaller than 1. This study focused on the probability of failure and did not consider consequences. Several other studies [7]–[9] attempted to assess the risk of corrosion by considering the component of corrosion occurrence without any consideration to the consequences analysis part. A study by Pursell et al. [10], examined both the likelihood and consequences of corrosion. The likelihood of corrosion was estimated based on De Waard & Milliams Method [11] with a correction factor. Where the consequences were assessed in terms of number of persons harmed by a failure, based on the population exposed and likelihood of harm from the failure. Assessing the risk of corrosion in a conventional way requires case-specific consideration with limited flexibility. The proposed methodology overcomes this practicality issue by providing a generic method largely applicable to different process systems and corrosion mechanisms.

Among different corrosion mechanisms, MIC is the most challenging to identify and assess due to high dependency on operating conditions and highly localized nature [12], [13]. Risk assessment of corrosion in general, and MIC specifically, has proven to be a complicated task [14]. This chapter, in its application part, focuses on assessing the risk of MIC; however, the proposed methodology can be applied to different corrosion modes. Table 4.1 summarizes the main contributions to MIC risk assessment in the literature.

Table 4. 1 Review existing of MIC risk models

Model	Output				Factors considered				Ref
	Qualitative	**Quantitativ**	**Measure**	**Modelling approach**	**Chemical**	**Physical/process**	**Biological**	**Molecular**	
Maxwell and Campbell model		✓	MIC rate -Risk of MIC occurrence (Biofilm initiation)	Analytical approach	✓	✓	✓	✓	[32]
Sooknah Model	✓		Internal MIC Risk Factor (RF)	Ranking based approach	✓	✓			[18]
MIC Management Model		✓	Integrated MIC Risk Factor (IMRF), Potential Pit Generation Rate (PPGR).	Analytical approach			✓	✓	[21], [25]
Kaduková Model	✓		Risk of External MIC in transmission pipelines	Risk Matrix (Ranking approach)	✓	✓			[101]
Skovhus Model	✓		Ranking of PoF for RBI	Logical modelling approach	✓	✓	✓		[14]
Neuro-Fuzzy Model		✓	Biofouling probability and directly link it to the MIC probability	A combination of Fuzzy logic with Neural Networks	✓	✓	✓		[102]

The work by Maxwell and Campbell [32] was the first attempt to quantitatively assess the risk of MIC. However, the term "risk" was defined and used as the probability of corrosion occurrence leading to failure with known impact. The proposed model assessed the MIC rate by improving a previous study done by Pots et al.[31]. Maxwell and Campbell considered biological parameters such as number of bacteria per area and bacteria kinetics in assessing the MIC rate; however, no attempt was done to assess the consequences and combine the two measures to properly analyze the risk of MIC in a given system. The work by Skovhus et al. [14] was the only study on MIC that acknowledged the need for consequence analysis and its probabilistic nature to draw the risk profile for MIC in a given system. The study did mention the importance of the consequence analysis, but provided qualitative risk based on known MIC damage information and cannot be used for predicting the MIC risk based on collected data. In addition, the study ignored the probabilistic nature and dependencies of input parameters. Introduction and further discussions on the proposed methodology to overcome the limitations stated above will be discussed in the following sections.

4.2 MIC Induced Failure (MICIF) Database

Studies have shown that MIC is most likely to occur in specific parts of the process circuit due to favourable conditions for microbiological settlement [17]. As stated in the scientific literature: "*the lack of a public database of MIC related incidents and accidents limits the understanding of its full impact*" [103]. A comprehensive database, named "MIC Induced Failure (MICIF) database" is currently under development. It serves as a tool to gather field data on MIC occurrences and the resulting failures. This database is a living document that will gather as much data as possible from investigation reports, scientific literatures and data from operators and servicing companies. For the purpose of the current study, only MIC cases in pipeline systems are shown and statistically analyzed in Table 4.2.

4.3 The Proposed Methodology

A proper CRA study should target a specific corrosion mode, and combine the assessment of likelihood of the corrosion mode (i.e. root-causes analysis) with the analysis of subsequent outputs (i.e. consequence analysis) in terms of CIF. Figure 4.1 depicts the proposed generic diagram to assess the MIC risk in a process system, where PoC is the block assessing the probability of corrosion, and CoC is the block assessing the consequences.

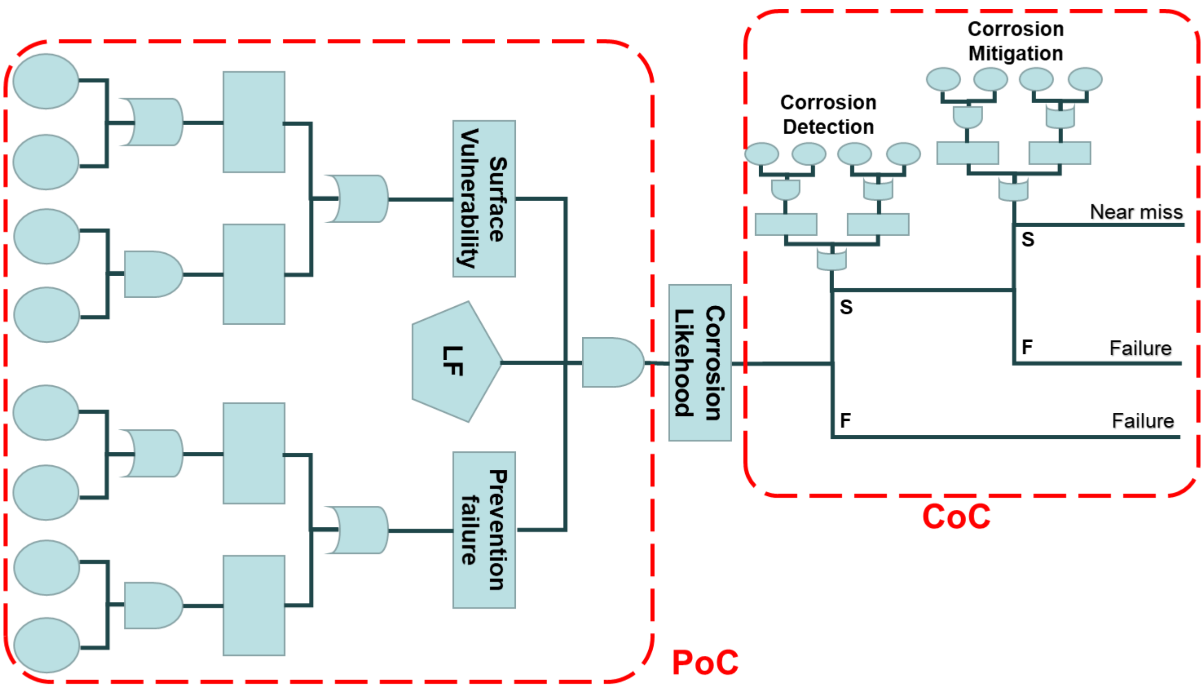

Figure 4. 1 Schematic presentation of the proposed analysis

The logical structure presented in Figure 4.1 is known as the Bow-Tie (BT) diagram [118]. In the present work, the BT diagram is enhanced with the following features:

- Employs auxiliary FTs to assess the probability of consequence barriers (i.e. successful corrosion detection and mitigation). These auxiliary FTs capture the logical relationship between the detection techniques and corrosion mitigation strategies to allow for more accurate assessment.
- Uses a deterministic gate to model the effect of limiting factors. The gate *LF* works as an inhibitor gate and eliminates the false positive corrosion likelihood when one of the limiting factors is not permitting any ignition of the corrosive process (e.g. microbiological growth in case of MIC).
- Employs the voting gate *KooN*, where the output event occurs if at least *K* inputs out of *N* inputs occur. This gate is introduced to allow more flexibility. The output probability of a *2oo3* voting gate can be calculated as follows:

$$P(O_{2oo3}) = P(I_1) \times P(I_2) + P(I_1) \times P(I_3) + P(I_2) \times P(I_3) - 2\,P(I_1) \times P(I_2) \times P(I_3) \quad (1)$$

Table 4. 2 Pipeline cases from MICIF Database

Reported Cases	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16	X17	Ref.
Case 1: offshore pipeline Nigeria						✓	✓				✓				✓			[104]
Case 2: Pipeline in Halfdan field						✓					✓							[105]
Case 3: Subsea water injection pipeline offshore Denmark			✓					✓										[25]
Case 4: pipe in Halfdan production platform						✓	✓											[106]
Case 5: Carbon steel Alaskan pipeline							✓								✓			[107]
Case 6: Pipeline in Otter Production System		✓			✓													[108]
Case 7: Subsea pipeline in offshore Denmark						✓		✓										[109]
Case 8: Crude oil pipelines				✓					✓									[26]
Case 9: Eider Alpha pipelines							✓			✓								[13]
Case 10: Pipes in Alaskan North Slope										✓						✓		[110]
Case 11: pipeline from the Halfdan HBA platform						✓						✓						[111]
Case 12: synthetic produced water						✓			✓						✓			[112]

Case 13: water distribution system in Wisconsin USA	✓			✓			✓		✓				✓	✓			✓	[113]
Case 14: oil pipelines in Iran			✓		✓	✓		✓										[114]
Case 15: pipes in Lost Hills Oilfield, California	✓				✓	✓								✓				[115]
Case 16: Pipeline in offshore India								✓	✓									[116]
Case 17: oil dispatch pipeline						✓	✓			✓								[117]
Contribution ratio	4.3%	2.1%	4.3%	4.3%	6.4%	19.1%	12.8%	8.5%	8.5%	6.4%	4.3%	2.1%	2.1%	4.3%	6.4%	2.1%	2.1%	

The proposed methodology is an extension of a conventional BT analysis method. Adaption was required due to the complex nature of the corrosion phenomena. The adaptation was performed by adding a verification step against the historical incident of corrosion in similar assets and under similar conditions. The verification allows a reduction in the model-based uncertainty, which is one of the main drawbacks of the conventional BT analysis. The verification step was made possible by separating the probability of root-cause events, which is case-specific, and its contribution as a component of the failure sequences. The newly proposed root-cause contribution (RCC) analysis allowed the consideration of the single contribution of each root-cause in the occurrence of the top event. This analysis uses the minimal cut sets (MCSs) analysis to link the root-cause as an element, independently of its probability, to the top event based on equation (2) given that the MCSs occur independently.

$$P(TE) = \sum_{j=1}^{m} P(MCS_j) \tag{2}$$

Where P(TE) represents the probability of the top event, in this case, the targeted corrosion mode; P(MCS_j) is the probability of the Jth MCS, and *m* is the number of MCSs in the analysis. Figure 4.2 depicts, step-by-step, the proposed methodology. It is a three-step process, where each step contains several operations. Details on each step are provided as follows:

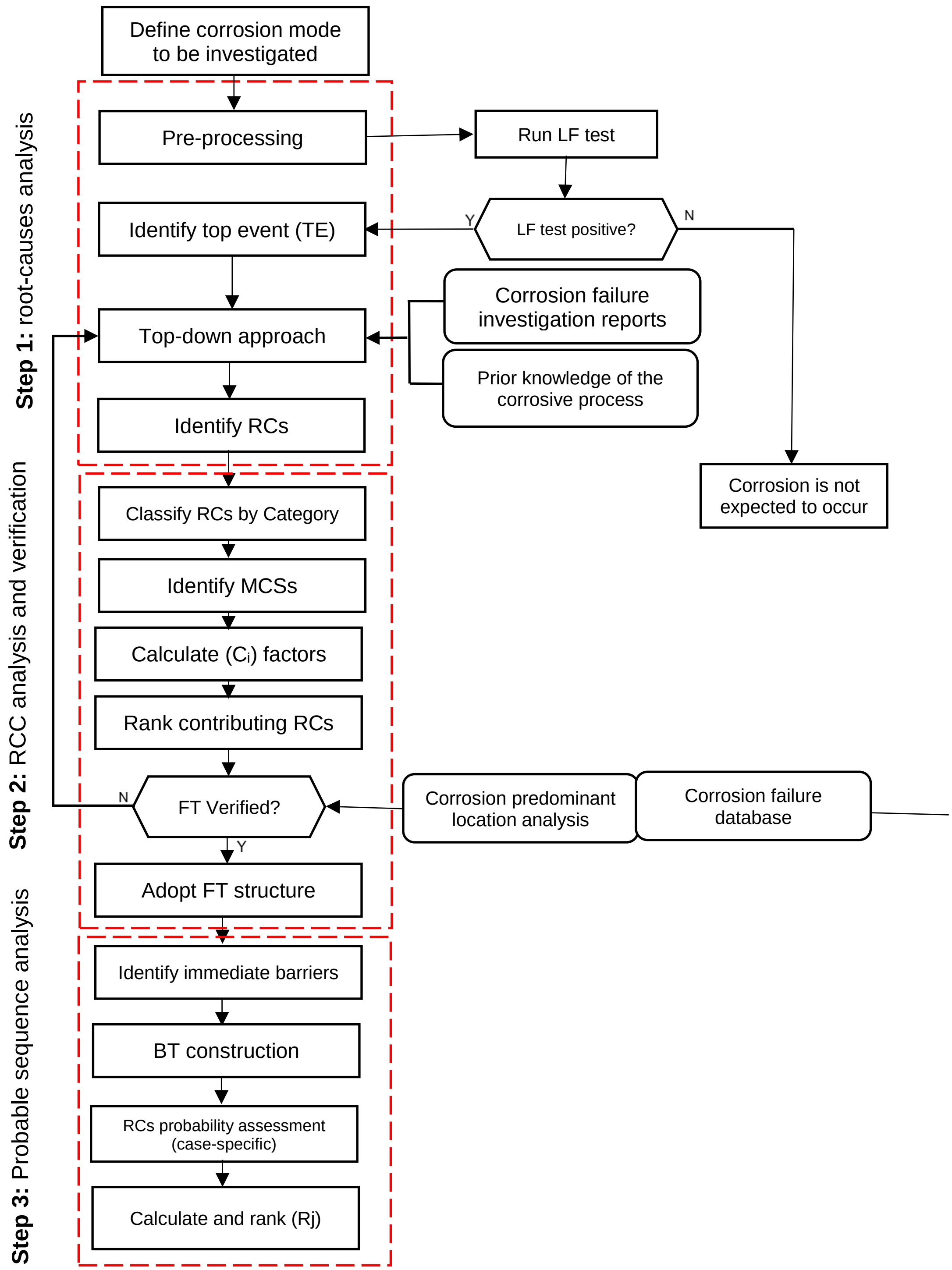

Figure 4. 2 Corrosion risk assessment flowchart

4.3.1 Step 1: Root-causes analysis

Root-causes analysis is the first step in the corrosion risk assessment process. The simplest and most common way to link the root-causes to the occurrence of the unwanted event is to build a fault tree (FT) [59], [119], [120]. FT is a deductive top-down method to calculate the occurrence probability of an unwanted event, called the top event, as a function of the causal events or root-causes leading to it [75], [78], [121], [122]. In this study, the unwanted event is the “targeted corrosion mode”. The corrosion modes are different in terms of their mechanisms, root-causes and operating conditions that allow for their development. Therefore, assessing the risk of corrosion without first specifying its mode is technically incorrect. The proper FT structure should be based on a deep understanding of the corrosion mechanism and failure processes. This understanding should be supported by field data extracted from corrosion failure investigation reports by established institutions. In addition, corrosion-induced failure database should be constructed, as shown in section 4.2.

In the proposed methodology, assessing the risk of corrosion is based on two sets of causal events: (i) causal events that increase the vulnerability of the metal surface to the corrosive process, and (ii) operational and design related specifications that fail to prevent the corrosive process from taking place. This type of classification channels the top-down thinking process while constructing the FT structure and also when performing the BT analysis.

- Microbiological Growth Allowance (MGA) Test:

MIC is a complex process and the limiting parameter for its development is microbiological growth, which in this study is evaluated in terms of microbiological growth allowance (MGA) test. The limiting factors are grouped in a deterministic gate directly communicating with the top event. MGA can take either value 1 (i.e. open gate), which means that a microbiological growth is expected in the system. If there is no clearance from the limiting factors, the deterministic gate remains closed (i.e. MGA = 0), and the MIC is not expected to occur in the system. This MGA test is run as a pre-processing step of the corrosion threat assessment. Figure 4.3 depicts the MGA and its five components.

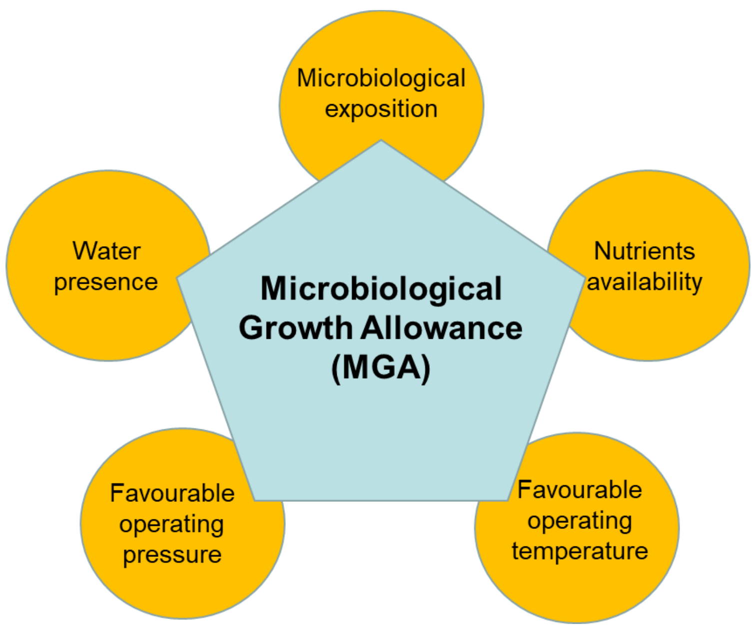

Figure 4. 3 Microbiological Growth Allowance (MGA) Test and its components

Table 4. 3 Microbiological Growth Allowance for each limiting factor

Limiting factor	**MGA_i**
Water presence	> 5 ppm

Operating pressure	< 5 MPa
Microbiological exposition	> 10 CFU/ml
Nutrients sources	> 5 ppm
Operating temperature	< 150 °C

Table 4.3 presents threshold-based MGA for each limiting factor. The operating temperature has a significant impact on microbiological growth. In the literature, studies (e.g. [49], [53]) have assessed the effect of variation of temperature on the likelihood of microbiological growth. A temperature of 150°C was selected as the extreme value for MIC related microorganisms growth. Similar methods, along with SME opinion were used to assess the value of the remaining limiting factors. Figure 4.4 is the FT structure generated by applying Step 1 of the proposed methodology on MIC risk assessment.

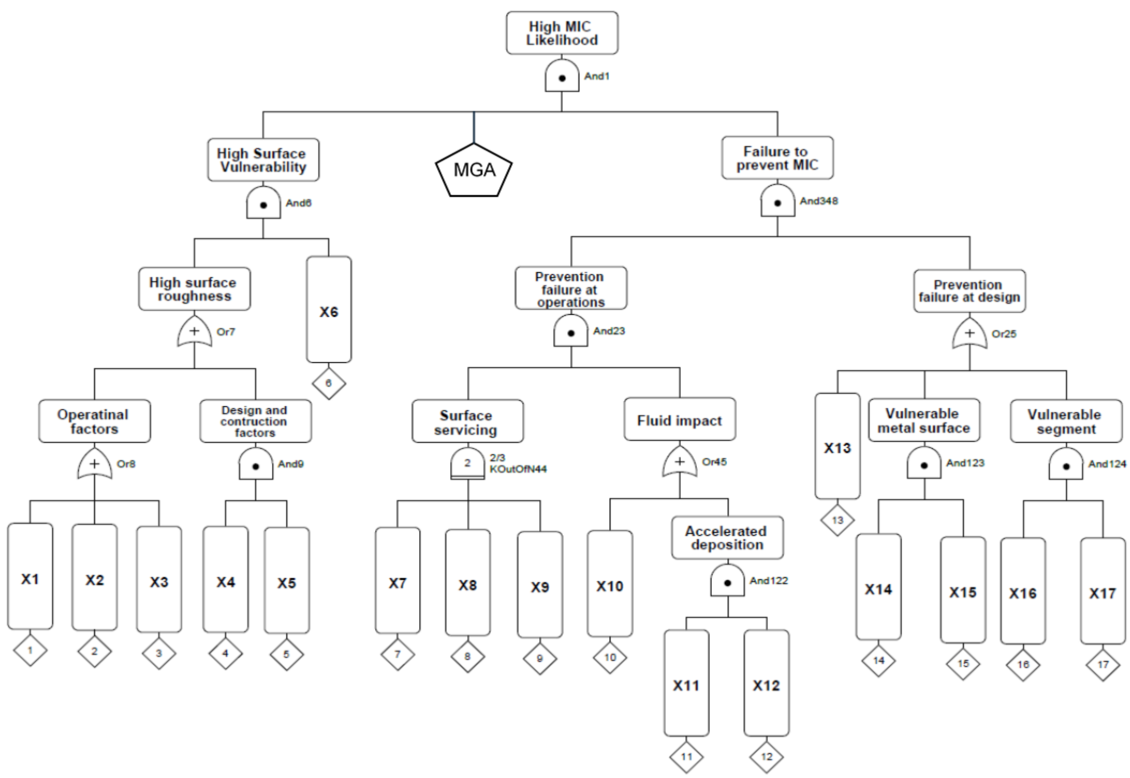

Figure 4. 4 FT model for MIC likelihood

In total, 17 root-causes are identified. Table 4.4 provides the description, category and method to be employed to assess the probability of each root-cause when applied to a given pipeline system.

Table 4. 4 Summary of root-causes, their categories and assessment methods

Root-cause	Description	Design shortcoming	Operational Anomaly	Poor servicing	Other	Assessment method
X1	Welding defects			✓		Revealed by inspection
X2	Rust bubbles presence				✓	Revealed by inspection
X3	Excessive residual stress		✓			Monitored operations and asset integrity data
X4	Frequency of bends and discontinuities	✓				Asset specification
X5	buckling and micro-cracks		✓			Monitored/assessed from asset integrity data
X6	High surface wettability	✓				Asset specification
X7	Poor pigging operations			✓		Assessed from operations and asset integrity data
X8	Damage of internal coating		✓			Assessed/revealed by inspection
X9	Low flow velocity		✓			Assessed from operations data
X10	Poor electrochemical protection			✓		Assessed from operations and asset integrity data
X11	poor equipment draining		✓			Assessed from operations data
X12	Intermittent flow regime		✓			Assessed from operations data
X13	Inaccessibility for pigging	✓				Asset specification
X14	Poor anti-corrosion coating	✓				Assessed from operations and asset integrity data
X15	Low metal PREN value	✓				Asset specification
X16	Dead flow zones	✓				Asset specification
X17	Inaccessibility for inspection	✓				Asset specification

The classification of the root-causes by category will allow generating results for each root-cause and for each category. For example, the contribution of operational anomalies in the development of the corrosive process in a given system is calculated based on the sum of the contributions of the root-causes that are part of this category.

In the top part of the FT, the MIC occurrence is seen as the result of a combination of two main elements (i.e. *AND* gate) within the limiting factors (i.e. *MGA* gate). The first element is the vulnerability of metal surface characterized by its wettability and roughness. The second element is the MIC prevention measures during both operations and design phases. In Table 4.5, this logic is demonstrated in a qualitative form for the sake of simplicity. Root-causes such as welding defects and rust bubbles create spots for microbiological attachment and therefore contribute to biofilm initiation. Additionally, a low flow velocity and an intermittent flow regime contribute to the microbiological deposition on the metal surface and the nutrient diffusion to the biofilm.

Table 4. 5 Illustration of MIC likelihood assessment at the top of the FT

Surface vulnerability	Failure to prevent MIC	MGA	MIC Likelihood
Low	Low	1	Very Low
Low	High	1	Low
High	Low	1	Low
High	High	1	High
Low/High	Low/High	0	Null

The logic breaks down the root-causes into the metal surface susceptibility to a specific corrosion mode and the prevention measures against it, which captures most of the factors affecting MIC presence. In addition, the logic illustrated in Table 4.5 is an efficient way to eliminate the false positive corrosion likelihood when one of the limiting factors is negative. An example of a false positive assessment is when MIC likelihood is assessed to be "*high*" when the extreme operating pressure does not allow for any microbiological existence in the system.

4.3.2 Step 2: RCC analysis and verification

In modelling-based analysis, verification against field data is a highly valued element. The methodology, presented in this work, reduces the model-based uncertainty by proposing a simple statistical verification process. RCC analysis is based on the interference that root-causes form MCSs, and that the MCSs lead to the top event occurrence. Therefore, quantification of the number of times each root-cause is present in a MCS, regardless of its probability, can determine the contribution of the root-cause in the top event occurrence. The contribution of each root-cause or causal event is then checked with the corrosion failure database for verification purpose. If the results of RCC analysis match the data on the CIF database.

- Root-causes contribution (RCC) analysis

After generation of the MCSs, the contribution of each root-cause is calculated based on equation (2). See appendix A for the full list of MCSs along with the generated contributions for each root-cause.

$$C_i = \frac{\sum_{i \text{ in } j} MCS_j}{T} \tag{2}$$

Ci is the root-cause contribution factor, MCSj is the minimal cut set containing the root-cause "i", T is the total number of all occurrences (for this application there are 747 occurrences). Depending on the size of the FT, the count of MCSs containing each root-cause can be calculated manually or it can be automatically generated on MS Excel using the following command:

$$\sum_{i \text{ in } j} MCSj = COUNTIF(RANGE, Xi) \tag{3}$$

Table 4.6 presents the results of contribution of each root-cause using RCC analysis and the contribution ratio from the MICIF database. Table 4.8 presents the contributions by category based on RCC analysis.

Table 4. 6 Statistical verification of root-causes contribution based RCC analysis

Root-cause	Description	C_i from RCC analysis	Contribution ratio from MICIF database
X1	Welding defects	3.61%	4.3%
X2	Rust bubbles presence	3.61%	2.1%
X3	Excessive residual stress	3.61%	4.3%
X4	Frequency of bends and discontinuities	3.61%	4.3%
X5	buckling and micro-cracks	3.61%	6.4%
X6	High surface wettability	14.46%	19.1%
X7	Poor pigging operations	9.64%	12.8%
X8	Damage of internal coating	9.64%	8.5%
X9	Low flow velocity	9.64%	8.5%
X10	Poor electrochemical protection	4.82%	6.4%
X11	poor equipment draining	4.82%	4.3%
X12	Intermittent flow regime	4.82%	2.1%
X13	Inaccessibility for pigging	4.82%	2.1%
X14	Poor anti-corrosion coating	4.82%	4.3%
X15	Low metal PREN value	4.82%	6.4%
X16	Dead flow zones	4.82%	2.1%
X17	Inaccessibility for inspection	4.82%	2.1%

Table 4. 7 Contribution to the TE by category of root-causes

Category	Root-causes	Contribution
Design shortcoming	X4,X6,X13,X14,X15,X16,X17	42.17%
Operational Anomaly	X3,X5,X8,X10,X11,X12	31.33%

Poor servicing	X1,X7,X9	22.89%
Other	X2	3.61%

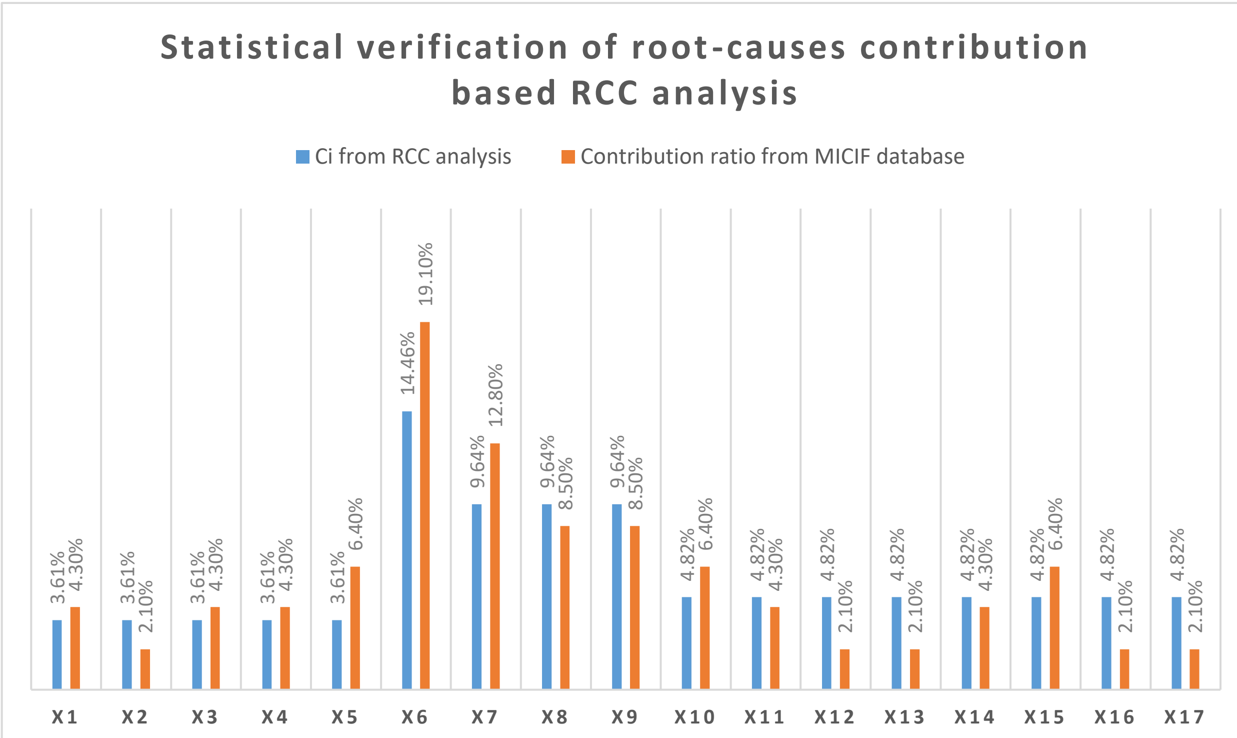

Figure 4. 5 Statistical verification of root-causes contribution based RCC analysis

If the two sets of contributing factors (i.e. from the model and the MICIF database) are statistically close enough, the FT structure is verified and can be applied to assess the MIC risk on a process system. If the verification is not satisfactory, the revision of the FT structure should be performed as shown in Figure 4.2. The results from RCC analysis presented in Table 4.6 reveal that the high surface wettability is the most significant factor contributing to MIC occurrence. In the second rank, the effects of flow velocity, pigging and internal coating were also highlighted as significant causal factors. Based on the results depicted in Figure 4.5, the FT structure is verified by comparing the RCC results with investigations of MIC cases reported on the database. As the database is a living document, the contribution ratios should be updated and compared again to the RCC results. This updating process will allow for dynamic process of risk assessment based on progresses and findings on MIC occurrences and its resulting failures.

4.3.3 Step 3: Probable sequence analysis

After verification of the FT structure, the barriers between the corrosion occurrence and the CIF should be investigation using the same methodology described above. Tables 4.8 and 4.9 are generated using Step 2 of the proposed methodology. For the corrosive process, corrosion detection and mitigation constitute the barriers between the corrosion and its damaging consequences in terms of CIF.

Table 4. 8 Ranking of root-causes based on their contribution to the detection barrier

Contribution Rank	Root-causes	Individual C_i
1	Y4, Y5, Y6	16.67%
2	Y1, Y2, Y3	11.11%
3	Y6, Y7	8.33%

Table 4. 9 Ranking of root-causes based on their contribution to the mitigation barrier

Contribution Rank	Root-causes	Individual C_i
1	Z1, Z2	25%
2	Z3, Z4,Z5	16.67%

4.4 Application of the Methodology to a pipeline system

The verified FT structure is now applied to a case study of a pipeline system carrying oil products. The probabilities in Table 4.10 are generated based on an interview with SMEs from the Canadian company operating the pipeline system.

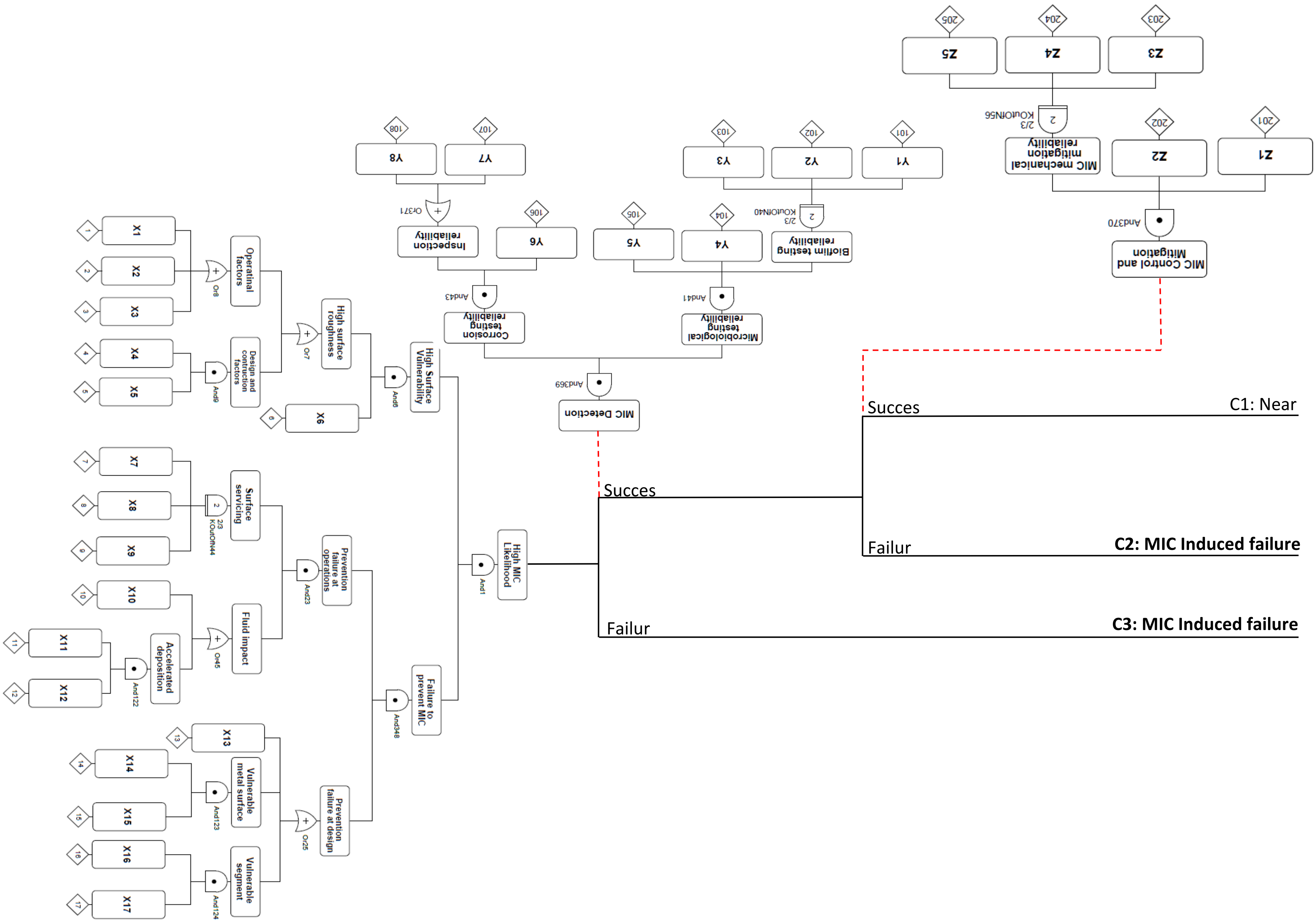

Figure 4. 6 BT of MIC risk assessment

Table 4. 10 The probabilities assigned for the basic causes to a pipeline

Sub-model	Symbol	Description	Probability of occurrence
MIC Likelihood	X1	Welding defects	1.00E-01
	X2	Rust bubbles presence	3.00E-01
	X3	Excessive residual stress	7.00E-01
	X4	Frequency of bends and discontinuities	1.00E-01
	X5	buckling and micro-cracks	5.00E-02
	X6	High surface wettability	3.00E-01
	X7	Poor pigging operations	2.00E-01
	X8	Damage of internal coating	3.00E-01
	X9	Low flow velocity	2.50E-01
	X10	Poor electrochemical protection	2.00E-01
	X11	poor equipment draining	1.00E-01
	X12	Intermittent flow regime	1.00E-01
	X13	Inaccessibility for pigging	4.00E-01
	X14	Poor anti-corrosion coating	3.00E-01
	X15	Low metal PREN value	7.00E-01
	X16	Dead flow zones	4.00E-01
	X17	Inaccessibility for inspection	2.00E-01
MIC Detection	Y1	Reliability of sessile population identification	6.00E-01
	Y2	Capability to monitor biofilm growth	2.00E-01
	Y3	Biofilm composition identification	3.00E-01
	Y4	Capability to detect MIC products	6.00E-01
	Y5	MIC mechanism identification	6.00E-01
	Y6	Corrosion Coupons reliability	7.00E-01
	Y7	Smart pigging reliability (ILI)	7.50E-01
	Y8	Radiographic inspection reliability	1.00E-01
MIC Control and Mitigation	Z1	Biocides injection and monitoring	3.00E-01
	Z2	pH stabilizer injection and monitoring	2.50E-01
	Z3	Mitigative pigging reliability	5.00E-01
	Z4	Equipment draining reliability	4.00E-01
	Z5	Water treatment reliability	3.00E-01

The probability of the most probable sequence (MPS) was calculated as 5.19E-02. The expression of the MPS is given as in equation (4).

$$MPS = \{X3, X6, X7, X9, X10, X14, X15\} \tag{4}$$

$$R_j = \frac{P(MCS_j)}{P(MPS)} \tag{5}$$

The conventional risk assessment methods considers the MPS only. The proposed methodology considers the remaining sequences as highly probable sequences (HPS) based on their MCS ranking factor (R_j). Table 4.11 summarizes the top five probable sequences leading to MIC occurrence along with the lowest probable sequence (LPS).

Table 4. 11 Summary of relevant probable sequences leading to the corrosive process

Title	MCS_j Rank	Root-causes in the MCS_j	$P(MCS_j)$	R_j
MPS	1	X3, X6, X7, X9, X10, X14, X15	5.19E-02	1
HPS_2	2	X3, X6, X7, X9, X10, X13	4.94E-02	95%
HPS_3	3	X3, X6, X7, X8, X10, X14, X15	3.46E-02	67%
HPS_4	4	X3, X6, X8, X9, X10, X14, X15	3.46E-02	67%
HPS_5	5	X3, X6, X7, X8, X10, X13	3.29E-02	63%
LPS	108	X4, X5, X6, X8, X9, X12, X16,X17	6.72E-06	0.013%

The obtained results from the case study application (i.e. input data in Table 4.10 and BT structure in Figure 4.6) are provided in Table 4.12.

Table 4. 12 Summary of the BT modelling results

Parameters	Probability
MIC likelihood (occurrence)	2.10E-01
MIC detection	1.30E-01
MIC control and mitigation	3.70E-01
Near miss (C1)	1.00E-02
CIF probability (C2+C3)	2.00E-01

Near miss, or corrosion without failure, means that MIC occurred in the system, but it was successfully eradicated (i.e. there was successful detection and mitigation). The probability of having a near miss is estimated to be 1.00E-02, which represents 5% of the expected MIC probability. The remaining 95% of the expected MIC probability is estimated to be MIC leading to failure of the pipeline system. This MIC induced failure will mostly manifest in the form of a pinhole in the pipeline wall leading to leakage. In the case of communicating MIC pits, which is a more complex form of MIC, the failure may lead to pipeline burst when the total stress exceeds the residual ultimate strength of the pipe.

The MCS ranking factor (R_j) reveals that: P(MPS) ≈ P(HPS_1). Therefore, it has to be taken into consideration as the same as the MPS. The probability of each remaining sequence from the top five (HPS_3, HPS_4 and HPS_5) constitute two-third of the probability of the MPS. The analysis also revealed that the likelihood of MIC presence in the system in not high. However, if MIC did occur, there is a 95% chance of it leading to pipeline failure. This requires a revaluation of MIC detection techniques and mitigation strategies with more focus on the detection component (failure probability estimated as 87%).

4.4 Conclusions

This chapter presents a detailed methodology and model for corrosion risk assessment. The methodology has adopted the Bow-tie analysis approach. The corrosion risk model is developed using an improved logic-based causation approach (improved fault tree). The proposed model is verified using the collected field data on corrosion and its related failures. Where previous studies had relied on analytical approaches to predict the corrosion rate or its occurrence, the present study has built on the probabilistic approach. The methodology, along with the model, is applied for MIC. The novelties of the current work include:

- A new Bow-tie model for corrosion risk assessment in the probabilistic framework that minimizes the model-based uncertainties.
- RCC analysis allows the assessment of the probability of root-causes and their contribution to the minimum cut sets and the top event occurrence.
- Conventional FT analysis solely considers the MPS as a unique qualitative and quantitative parameter extracted from the MCS analysis. The proposed approach considers the set of highly probable sequences and compares them with the MPS using the proposed Rj factor.
- Assessing the risk of corrosion based on two sets of causal events: (i) causal events increasing the vulnerability of the metal surface to the corrosive process, and (ii) operational and design-related specifications that fail to prevent the corrosive process from taking place. This classification channels top-down thinking processes while performing the BT analysis.
- A pre-processing step is also implemented in this analysis to increase its efficiency and eliminate some of the false-positive assessments.

It is worth noting that even though this methodology reduces uncertainties while assessing the corrosion risk, uncertainty handling is still a factor that requires further improvement. Also, other aspects, such as sensitivity analysis could be further investigated. The proposed methodology and model can be used to assess and monitor corrosion threats.

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5. CORROSION RESILIENCE MODELLING

5.1 Dynamic RAMS Analysis Using Advanced Probabilistic Approach

Preface 1

A version of this manuscript has been accepted and will be published in volume 77 of the Journal of Chemical Engineering Transactions. I am the primary author of this paper. Along with the co-authors Faisal Khan and Zaid Kamil. I developed the conceptual model and subsequently translated this to a reliability-availability-maintainability and safety model using generalized stochastic Petri nets (GSPN). I carried out most of the literature review, data collection and analysis. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' feedback. The co-author Faisal Khan helped in developing the concepts/models and their testing, reviewed and corrected the models and results, and contributed in preparing, reviewing and revising the manuscript. The co-author Zaid Kamil contributed through support in data collection. Zaid Kamil also assisted in reviewing the manuscript.

Abstract 1

The increasing complexity of modern socio-technical systems has raised new challenges to analyze the reliability, availability, maintainability, and safety (RAMS) of oil and gas processing facilities. This chapter presents a new approach to perform RAMS analysis using stochastic Petri nets modelling blocks. Those blocks are small-sized Petri nets (PN)

that independently represent every component of the system. Depending on the component nature, such as repairable component periodically tested, non-repairable/replaced component, or standby component with the probability of failure to start, the PN block models the behaviour and the life cycle changes of the component and subsequently of the entire system. The PN blocks communicate through Boolean variables without being physically connected; this provides a less congested and easily trackable structure. It is observed that the proposed approach provides a robust and reliable mechanism of RAMS analysis. This work constitutes a significant step toward an integrated dynamic model for RAMS analysis. The proposed RAMS model is composed of three strong characteristics: time dependency, robustness, and explicit graphical structure.

5.1.1 Introduction

Reliability, availability, maintainability and safety (RAMS) analysis was first developed for determining the integrity of engineering design. Later on, it came to be used for performance evaluation of the installation and operations. The process facilities always considered to be complex systems due to the involvement of hazardous chemicals, pipeline clusters, assemblies, sub-systems and components, all of which are subject to failure. Therefore, it requires regular maintenance to maintain its integrity and performance [123]. Due to technological and cost limitation, it is not feasible to design a maintenance free installation or equipment. Installation or equipment deteriorate with time due to usage, wear and tear (Eti et al., 2007).

In recent decades, RAMS analysis influenced various industries and facilities, and served as an integral part of the systems' design. It constitutes a useful tool for reliability analysis [125] and availability of systems (Komal et al., 2010). As far as availability is concerned, it is one of the most important performance measures, especially for those industries or facilities where equipment repair is possible (Komal et al., 2010). However, each facility or plant is subject to failures due to the lack of strategic maintenance procedures or the inability to predict the potential hazard, thus resulting in an accident. To avoid the potential hazards, periodic maintenance strategies must be applied. Therefore, maintenance is also considered to be a key factor in enhancing system performance [127]. Any activity that ensures the performance of equipment to perform its intended work is termed as maintenance (Komal et al., 2010). Failure rate and repair time are the key elements that may result in improving both reliability and maintainability of the system. Further, improving both may result in the improvement of system availability too (Nepal and Monplaisir, 2007).

The oil and gas industries have highly complex technological systems that require a strategic approach from the provider for the availability of equipment to meet the increasing demand criteria. Therefore, to implement a strategic approach to RAMS, they require deep knowledge about the system to implement probabilistic tools and methods for identifying the system performance (Corvaro et al., 2017). To evaluate the performances of a system, various methods are available, among them RAMS analysis can be used to measure key performance metrics of the system that may include MTTF (mean time to failure), MTTR (mean time to repair), MTBF (mean time between failure), EDT (equipment down time) and system availability which provides the need of the maintenance to meet the desired objectives (Sharma and Kumar, 2008).

Unlike any other probabilistic technique available, PN blocks can easily represent a large variety of component types, whether it's periodic testing, standby system with failure to start condition, or repaired component. PN is proved to be a robust technique to study safety instrument systems (SIS) (Wu et al., 2018). In the present study, the PN blocks provide the life cycle behaviour of components and subsequently the entire system.

The novelty of the work is to illustrate how PN blocks can represent each component and its behavioural changes in continuous and time-dependent form. Moreover, the new information obtained from the system can be used to update the model and subsequently, resulting in updated failure profile of the system. The updated system profile can be used for decision making in maintenance strategies.

5.1.2 Stochastic Petri Nets with Predicates: Definition and Basic Concept

Stochastic Petri nets (SPN) are bipartite graphs which can provide intuitive illustrations of each component state in a system. It was first introduced in Carl Adam Petri's dissertation (David and Alla, 2010). PN is a promising tool to study and model the relationships between asynchronous, co-current, distributed, parallel, non-deterministic, and/or stochastic systems [133]. The glossary notation of SPN is shown in Figure 5.1.1. As can be seen the places are drawn as circles, and transitions as rectangular bars. Arcs, connecting the former to later, are known as input directed arcs while those connecting the latter to former are known as output directed arcs.

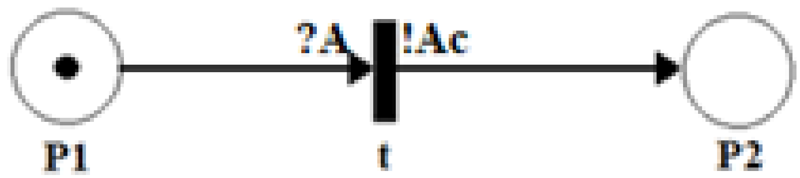

Figure 5.1. 1 Simple example of SPN with predicates and assertions

The primitives of the above notations are as follow;

- The places represent the state or conditions of a component.
- The transitions represent the change in the state/condition of a component from initial, intermediate, to final place. It is capable of modelling the dependencies between the components.
- Transition firing only occur when the multiplicity of tokens is at least equal to multiplicity of the associated input arc.
- Tokens create the dynamicity and trackability of the model
- Directed arcs decide the token from place to transition or transition to place.
- Predicates are the variables represented by "?" (e.g ?A), resulting in validation of the transition.
- Assertions (e.g.!A) are variables which update as a result of transition firing.

5.1.3 Dynamic Modelling Capability of SPN with Predicates and Assertions

To model the complex system behaviour for RAMS analysis, GRIF's Petri nets module [84] has been used in the present study. The PN blocks are capable enough to show both working and dysfunctional states of equipment. Depending on the component nature, such as, repairable systems periodically tested, non-repairable/replaced systems, or standby systems with the probability of failure to start, the PN block models the behaviour and the life cycle changes of the component and subsequently of the entire system. Further, each transition in SPN is capable for reflecting the dependencies among the equipment using stochastic or deterministic variables [131]. The SPN with predicates and assertations suggested in IEC 61508 [93]. It has pre-programmed continuous distributions available to specify the transition configuration, such as Weibull distribution, which is useful to provide installation/equipment time-dependent life cycle.

A transition can be enabled when the input place has at least equal or greater number of tokens than the multiplicities of the input arc associated with the transition. Once transition is enabled, the token moves from the input place and resides in the output place. It is worth noting that the token only resides at places, and transition defines the firing time of them. The firing time is based on the transition specifications and the token migration from input to output place depends upon the input and output functions (Zhou et al., 1990). If there are two or more output arcs from transition to places, then the token migration depends on the priority given for each arc. It is a useful feature which can be used for assigning priorities for working, repairing or testing of equipment. This simple notation is to provide better understanding for the reader about the capability of the PN blocks driven by SPN with predicates and assertion. However, in the next section, its application using a comprehensive case study will be shown.

5.1.4 Petri Nets Modelling Blocks

A PN is constituted of places, transitions, arcs and tokens. Modelling large and complex accident scenarios or reliability assessment models based on these elementary constituents can be a tremendous task for the risk or reliability analyst. This explains why the PN models are less popular, and they require an expert in modelling to build, adjust and track the models.

Table 5.1. 1 Main modelling features of SPN block-based model compared to the conventional techniques

Element of the model	FT	BN	Conventional SPN	SPN block-based model
Root cause element	Basic event (binary state)	Marginal node (multistate)	Embedded in the overall model (not specified)	A physically separated sub-network
The logic	Logic gates (AND, OR, KooN)	Conditional probability table (CPT)	One or more stochastic transitions	Mathematical variable or Boolean function
Connection	Directed arcs (acyclic)	Directed arcs (acyclic)	Directed arcs (cyclic)	Directed arcs or Boolean variables

Table 5.1.1 summarizes the main modelling features of the proposed model and compares it with the conventional techniques such as fault tree [59], Bayesian networks [12], [75]

and the conventional SPN [132]. In total, six PN blocks are capable to model most of the risk and/or reliability process components.

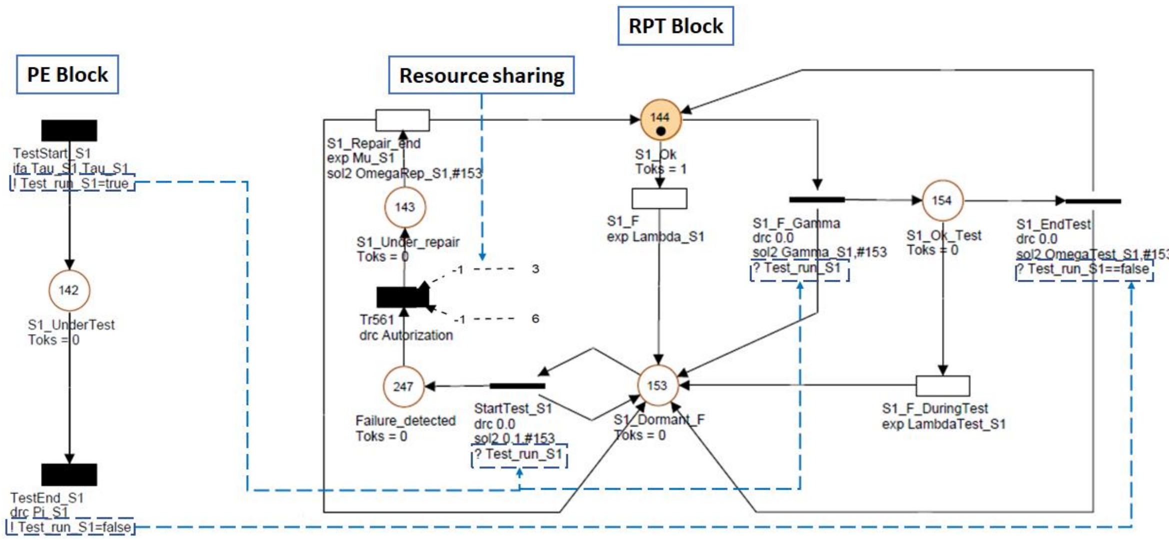

Figure 5.1. 2 RPT and PE bocks and their virtual connections through the Boolean functions

Figure 5.1.2 depicts RPT and PE blocks and highlights some of the virtual connections established through the use of Boolean functions such as “Test_run_S1”. This function communicates the time when the period test (i.e. planned event) will start and when it will end. The transition firing law “ifa”, which means “in advance appointed time” is used to generate a token at the appointed time. The two variables of the law are delay between two fires and delay of first fire respectively. The rest of the Boolean variables and parameters are summarized in Table 5.12 and Table 5.1.3 respectively.

Table 5.1. 2 Summary of the mathematical variables and Boolean functions used in the PN blocks

Variable	Type	Function	Involved in blocks
Test_run_S1	Boolean function	Captures the starting time and ending time of the test (i.e. periodic maintenance)	PE and RPT
Reliability_C_i	Mathematical variable	Observes the probability of having a token in the dormant failure state (e.g. places #2, #5 and #153). See equations 1 and 5.	RPT and RFS
Availability_C_i	Mathematical variable	Observes the probability of having a token in states where the component is available (e.g. running and standby)	RPT and RFS
Maintaina-bility_C_i	Mathematical variable	Observes the probability of having a token in states where the component waiting for repair or under-repair.	RPT and RFS
High_level	Boolean function	This function triggers some transition to fire following the occurrence of a high level in a specific drum. This can be replaced with the appropriate function depending on the process system.	RPT and RFS
UE	Mathematical variable	This variable calculates the probability of TE at each moment based on the variation of the root cause elements.	TE

Table 5.1. 3 Summary of the parameters in the PN blocks mostly taken from OREDA database [134]

Parameter	Meaning	Value/rate (h^{-1})	Appears in	Parameter
Lambda_C_i	Failure rate of component i	5.70E-07	Figures 5.1.2 and 5.1.4	Lambda_C_i
Mu_C_i	Repair rate of component i	0.1667	Figures 5.1.2 and 5.1.4	Mu_C_i
Lambda_test_C_i	Failure rate during test of component i	5.70E-07	Figure 5.1.2	Lambda_test_C_i
Gamma_C_i	Probability of failure to start	0.001	Figure 5.1.4	Gamma_C_i
Gamma_test_C_i	Probability of failure due to starting the test	0.001	Figure 5.1.2	Gamma_test_C_i

Sigma_test_C_i	Probability of detection failure	0.8	Figure 5.1.2	Sigma_test_C_i
Omega_test_C_i	Probability of maintenance failure	0.001	Figure 5.1.2	Omega_test_C_i

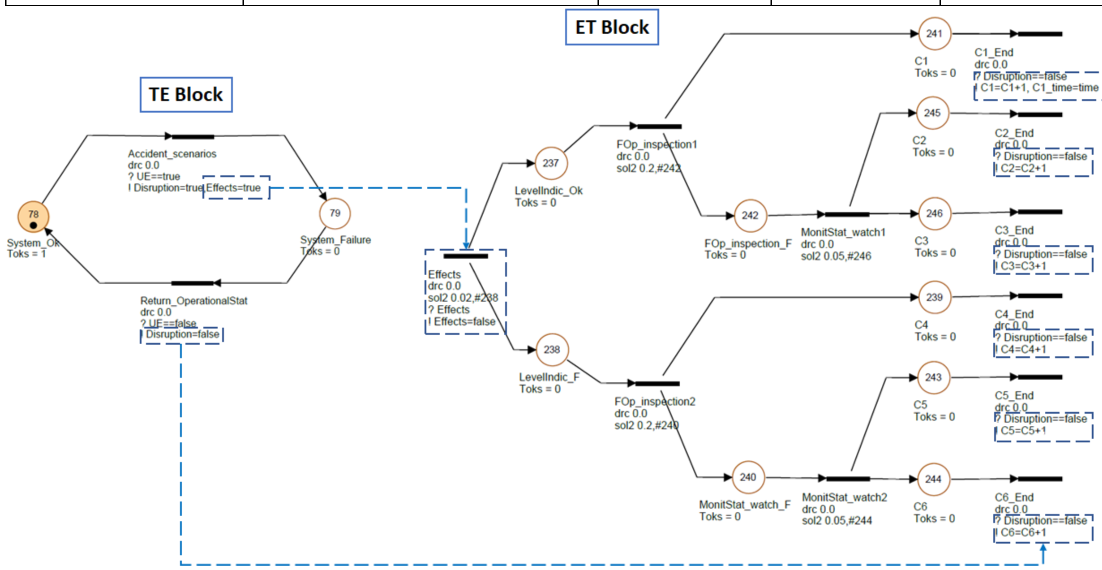

Figure 5.1. 3 TE and ET bocks and their virtual connections through the Boolean functions

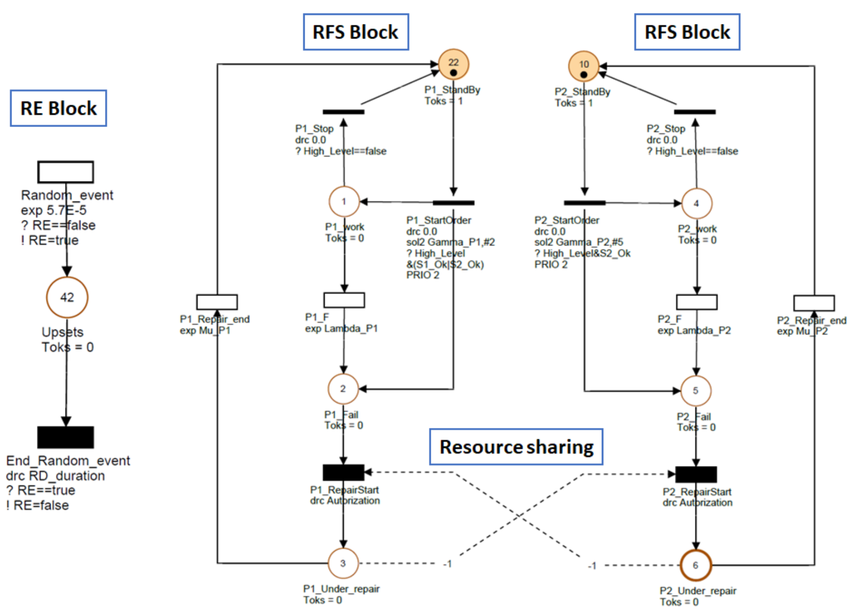

Figure 5.1. 4 RE and RFS bocks and the resource sharing between two RFS blocks (redundant system)

Figures 5.1.3, 5.1.4 and 5.1.5 depict the various types of PN blocks. These figures are adapted and modified from our previous work. The reader interested in learning more about the case study can refer to the work of Taleb-berrouane et al. (2016). The resource sharing shown on Figure 5.1.2 and Figure 5.1.4 model the availability of the maintenance team (i.e. resource) to repair the failing component. Based on the PN block-based model, RAMS parameters for each component can be calculated in the form of mathematical variables as follows:

- RPT block (one component only) in Figure 5.1.2:

Reliability: $R(t) = 1 - P_c\ (\#2)$ (1)

Operational availability: $A = \frac{\text{Time (\#1) + Time (\#22)}}{\text{Overall observed time}}$ (2)

Maintainability: M = Time (Authorization) + Time (#3) (3)

Safety index: $S = P_c\ (\#2) \times$ Criticality index (4)

Where "P_c" is the cumulative probability of having a token in a specific place. In the example "#153" means "place number 153". Time (#143) means the cumulative average time, calculated based on Monte Carlo simulation, of a token in place number 143. The criticality index is a parameter, not included in this model, that assesses the level of criticality subsequent to the failure (i.e. failure consequences). In Figure 5.1.3, the consequences C3 and C6 are considered to be the hazardous situations that alter the plant safety and/or integrity.

- RFS block in Figure 5.1.4:

Reliability: $R(t) = 1 - P_c$ (#153) (5)

$$\text{Operational availability: } A = \frac{\text{Time (\#144)} + \text{Time (\#154)}}{\text{Overall observed time}} \quad (6)$$

Maintainability: M = Time (#247) + Time (#143) (7)

Safety index: $S = P_c$ (#153) × Criticality index (8)

RAMS parameters for the overall system can be extracted from the TE block in Figure 5.1.3:

$$\text{Reliability: } R(t) = 1 - P_c \text{ (\#79)} \quad (9)$$

$$\text{Operational availability: } A = \frac{1 - \text{Time (\#78)}}{\text{Overall observed time}} \quad (10)$$

$$\text{Maintainability: } M = \sum_{C=1}^{n} \text{Time (C1\_Authorization)} + \text{Time (C1\_under\_repair)} \quad (11)$$

$$\text{Safety index: } S = [P_c \text{ (\#246)} + P_c \text{ (\#244)}] \times \text{Criticality index} \quad (12)$$

Some specific details may need to be adjusted to suit some process systems; but the conceptual design of the PN blocks have a large applicability for process systems.

5.1.5 Conclusions and Future Directions

In this chapter, a new approach for RAMS analysis using a PN block-based model was proposed. In total, six block types were developed to model repairable component periodically tested, random and planned events' occurrence, standby component with the probability of failure to start, end-state event or top event and the event tree structure. The PN blocks communicate through Boolean variables without being connected by any arcs and transitions. This arrangement results in a less congested and easily trackable model. In addition, it was demonstrated how an extended form of stochastic PN can be used to overcome the structural complexity and state explosion limiting the use of PN for risk and reliability modelling. In upcoming work, the proposed modelling approach will be applied for a complex process system for extended testing and verification.

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5.2 Dynamic Resilience Modelling of Process Systems

Preface 2

A version of this manuscript has been accepted and will be published in volume 77 of the Journal of Chemical Engineering Transactions. I am the primary author of this paper. Along with the co-author Faisal Khan. I developed the conceptual model and subsequently translated this to a dynamic resilience assessment model using generalized stochastic Petri nets (GSPN). I carried out most of the literature review, data collection and analysis. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-author' feedback. The co-author Faisal Khan helped in developing the concepts/models and their testing, reviewed and corrected the models and results, and contributed in preparing, reviewing and revising the manuscript.

Abstract 2

The hazards in complex process systems evolve at an accelerated rate. It is extremely difficult if not impossible to identify and assess all potential hazards and develop strategies to manage them. This demands next generation of process system that is, intelligent to learn faults and prevent them from further propagating, adaptive to evolving conditions, and quick to recover in case failures take place in a component of part of the system. Resilience engineering is a comprehensive term that captures these three (absorptive, adaptive, and recovery) important characteristics of a system. There are limited tools to qualify or

quantify the resilience of a system. There have been hardly any studies conducted on dynamic resilience assessment. This chapter proposes a dynamic approach to quantify resilience under varying conditions. The approach uses Stochastic Petri-nets (SPN) coupled with Monte Carlo simulation to model and analyze resilience metrics. The proposed approach is tested on a crude oil pipeline system. The test results demonstrate a clear understanding of the resilience characteristics of the system and its evolving nature. This work puts forward a clear pathway for an integrated dynamic model for resilience engineering.

5.2.1 Introduction

Resilience engineering is a comprehensive term that captures the system's characteristics beyond the fundamental concept of reliability. The resilience of a process system is its capability to handle a disruptive event and avoid failure. This can be satisfied by lessening the impact of the disruption on the system performance and/or reducing the disruption duration. According to Bruneau and Reinhorn (2007), a resilient engineering system should operate with reduced failure probability, reduced potential consequences subsequent to failures and reduced restoration time. The U.S National Institute of Standards and Technology [136] defines resilience in term of economic saving by minimizing the cost of a disaster and the ability to return to a state as good as or better than the initial level of performance. Resilience has been largely studied in the field of natural disaster risk reduction by Bruneau and Reinhorn (2006) and (2007) and Ayyub (2014) and (2015).

There is limited work that has attempted to qualify or quantify the resilience of process systems. Sarwar et al. (2018) have assessed resilience as a function of reliability, vulnerability and maintainability. They applied a Bayesian network (BN) approach [12], [47] to analyze the response of a remote offshore vessel in a scenario of a hydrocarbon release during offloading operation. Attoh-okine et al. (2009) define a resilience index as follows:

$$\text{Resilience}=\frac{\int_{t_1}^{t_2} Q(t)\,dt}{100\,(t_1-t_2)} \tag{1}$$

Where Q is the performance or quality of a system, t_1 is the disruption initiation or the time of incident that causes the decrease in the performance of the system, and t_2 is the disruption termination or the time after recovery. The resilience index or resilience measurement as shown in equation (1) is not sufficient to assess the resilience capacity of an engineering system. Other metrics are developed by researchers in the field of natural disaster management. The main resilience metrics are:

(i) The absorptive capacity or robustness which is defined by Bruneau and Reinhorn in [135] as the strength, or the ability to withstand a given level of stress or demand without suffering degradation or loss of function. This concept has been further developed to cover the capability to absorb the impact of the disruptive event through inherent and/or adaptive mechanisms.

(ii) The adaptive capacity is demonstrated in term of the effect of the mitigative and control actions that will temporarily stabilize the performance of the system and afterwards allow the restoration to the new stable level.

(iii) The restorative or recovery capacity is demonstrated in term of corrective actions such as equipment replacement or system reset that will bring the system from a temporary stabilized stage to a fully operational stage in as good as new or other stable levels of performance.

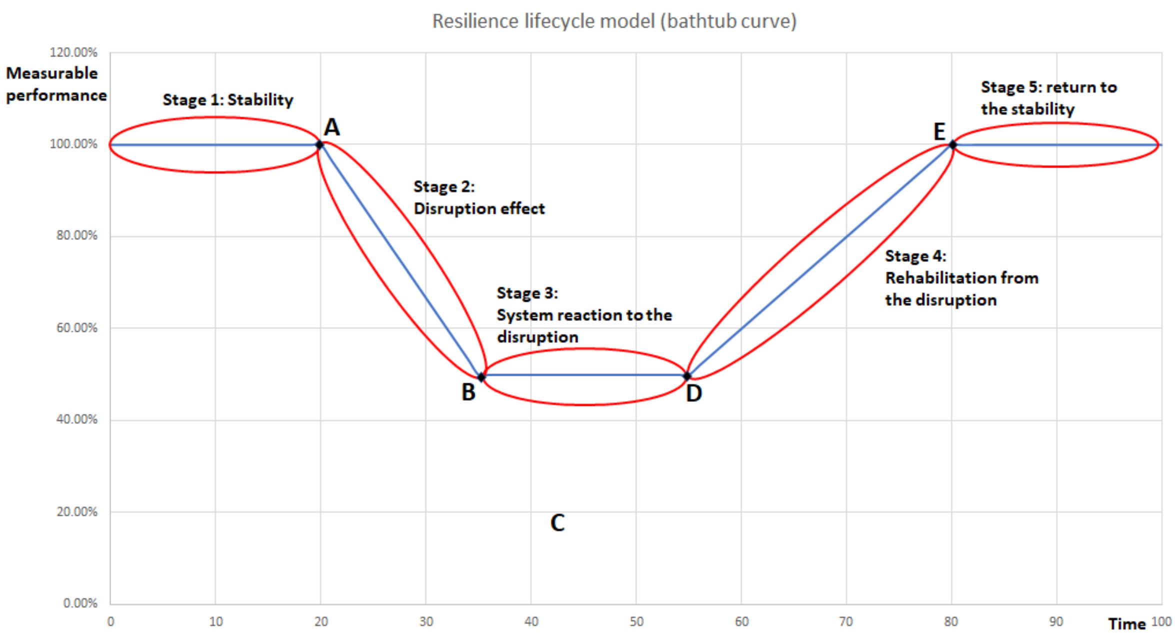

Figure 5.2. 1 The proposed resilience lifecycle model (bathtub curve)

Figure 5.2.1 displays the five stages or bathtub curve of resilience. Stage 1 presents the phase where the system is monitored and stable. Point A is the incident that triggers the disruption, and it can be modeled using a Poisson process. The incident can be a failure of a critical component in the system, an external factor or any event that lowers the performance of the system. Stage 2 expresses the effect of the disruption on the measurable performance. It settles at point B where the control operations react and take effect. Stage 3 shows a temporal stability of the system at a lower performance level. Part BC presents the performance degradation of the system in case no control actions are taken or failure of the control actions. Stage 4 shows the effect of corrective actions that aim to return the performance to the initial stage or a long-term stable level. Stage 5 is the new stable level of performance that can be higher than, equal to or lower than the initial level depending on the adopted maintenance strategy.

The five stages of the bathtub curve are a function of dynamic factors and time-varying processes. This chapter aims to build a dynamic resilience model able to capture those dynamic factors and time-varying processes. The present chapter implements the proposed dynamic model in the field of pipeline corrosion engineering where the pipeline wall thickness is identified to be the practical measurement of system performance.

5.2.2 Background on the modelling technique

Petri networks (PNs) were first proposed in 1962 by Carl Adam Petri, as a new mathematical and graphical model to connect events and conditions [76]. A Petri Net is a weighted bipartite graph (P,T,A,w) [142] with two functional parts, a static and a dynamic.

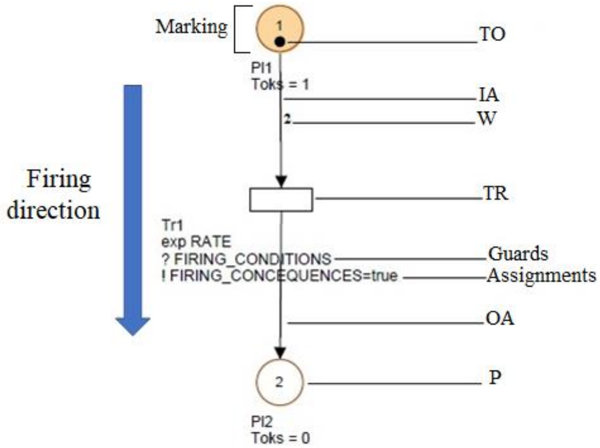

Figure 5.2. 2 Glossary of Petri nets notations adapted from Talebberrouane et al. (2016)

Figure 5.2.2 displays the static part of the PN represented by places (P), transitions (TR) and oriented arcs that connect places to transitions (i.e. input arcs, IA) and transitions to places (i.e. output arcs, OA). (W) represents the weight function on the arcs. For example, an inhibitor arc weights (-1). The dynamic part is expressed by movements of tokens (TO) following firing transitions (i.e. tokens' migration from one or more input places to one or more output places). The marking represents the tokens' number in a place. In addition to the conventional PN, a stochastic Petri Net (SPN) [144] also has non-deterministic firing delays associated with transitions. In a recent extension of SPN, the activation of a transition can be conditioned by one or more mathematical variables through the use of predicates and assertions [92]. The predicates or guards, as defined by IEC 61508-6 [93], are conditions which may be true or false, and control the transition firing. Assertions or assignments are the mathematical variables that receive predefined updates such as incrementation or state switching as consequences of the transition firing. In this chapter, the SPN is coupled with Monte Carlo simulation to enhance its modelling capability. For more details, readers can refer to our previous work,. Taleb-berrouane et al. (2016).

5.2.3 Dynamic resilience model for pipeline corrosion

As pipeline ages, the integrity faces multiple and complex threats. Corrosion is the main threat to the pipeline systems [12], [145]. In this chapter, an SPN model is used to assess the dynamic resilience of crude oil pipeline (e.g. illustrative case). Figures 5.2.3 depicts the proposed SPN model that captures the main dynamic processes that influence the corrosion occurrence, control and mitigation.

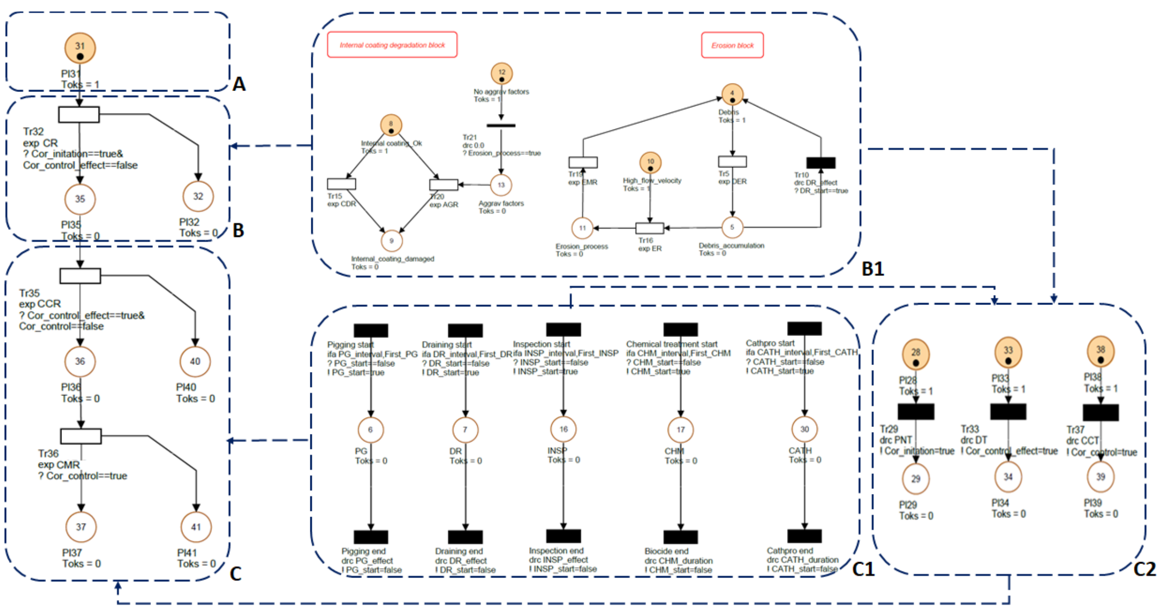

Figure 5.2. 3 SPN overall network for the pipeline resilience modelling

Figure 5.2.3 displays the overall SPN model. The model is built on the interactions between six SPN blocks or sub-networks. The first three blocks (A, B, C) are the model's interface for stage 1, stage 2 and stage 3 (according to Figure 5.2.1 definitions), respectively. Block

“B1” models the erosion process and its impact on the internal coating degradation which accelerates the corrosive process. Block “C1” is assigned to the corrosion control and mitigation actions. It captures the scheduling of pipeline servicing such as pigging and draining, as well as corrosion mitigation such as the cathodic protection and chemical treatment. The variation of the interval between operations and their first-time commencements will cause changes in the model variables. Subsequently, rates such as corrosion rate (CR) and corrosion control rate (CCR) will change accordingly. These changes make the model dynamic to the variations of the coating damage level, erosion process and pipeline servicing and inspection. Table 5.2.1 summarizes the dependencies between the PN main evolutive rates.

Table 5.2. 1 Summary of the main evolutive rates and their details

Main Evolutive rates	Meaning	Estimated value	Variables affecting the rates	Relevant sources
CDR	Coating degradation rate	1×10^{-5}	CDR = f (residual stress, flow, fluid viscosity and composition, surface roughness, penetration resistance)	(Papavinasam et al. 2004)
EMR	Erosion mitigation rate	1×10^{-4}	EMR = f (fluid turbulence, shear stress)	[147]
AGR	Aggravation rate	6×10^{-5}	AGR = f (residual stress, fluid turbulence, shear stress)	(Islam et al. 2013; Ossai 2012; Papavinasam et al. 2004)
DER	Debris entrance rate	1×10^{-4}	DER = f (debris source, fluid turbulence)	[149]
CR	Corrosion rate	1×10^{-4}	CR = f (metal conductivity, fluid chemistry, coating, temperature)	[150]

CMR	Corrosion mitigation rate	1×10^{-3}	CMR = f (cathodic protection, chemical treatment)	[151]
CCR	Corrosion control rate	1.6×10^{-4}	CCR = f (corrosion rate, process anomalies, servicing, cathodic protection, chemical treatment)	[151]

Figure 5.2.4 provides a schematic presentation of the system performance in term of decrease in pipeline wall thickness. The latter is a measurable performance, and it provides a clear understanding of the level of corrosion. The generated data from the SPN model, illustrated in Figure 5.2.4, allows the calculation of dynamic resilience metrics. The control mitigation point (CMP) corresponds to the moment when the corrosion control actions successfully reduce the corrosion rate, thereby decelerating the loss in wall thickness. The CMP and the following trend capture the positive effect of the corrosion control strategy in term of pipeline life extension as demonstrated in Figure 52..4.

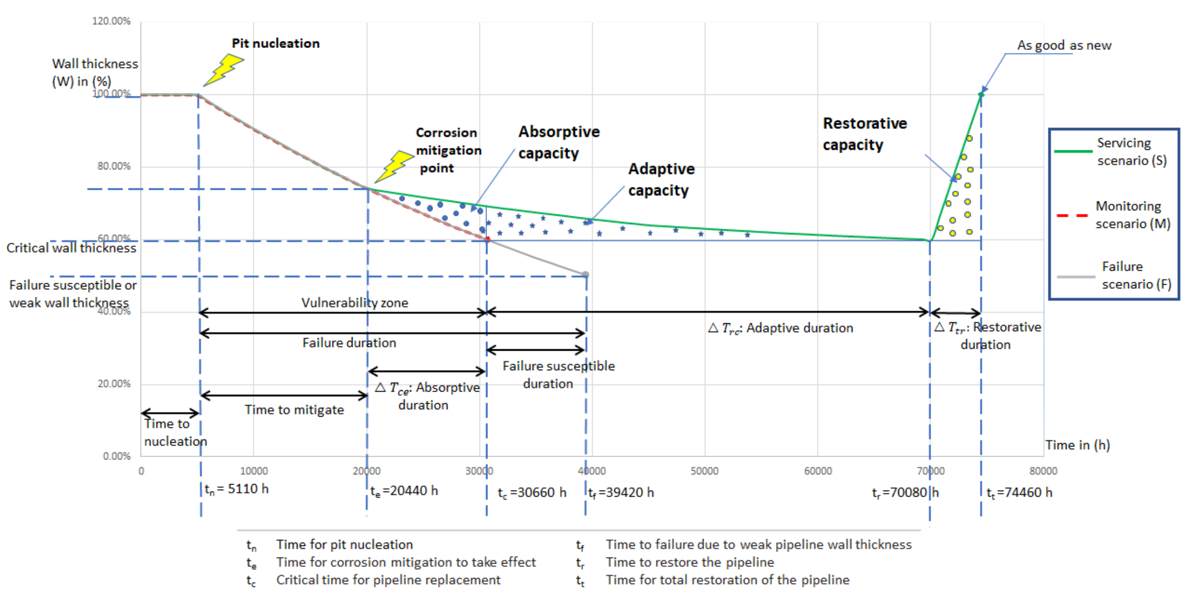

Figure 5.2. 4 Resilience curve for pipeline corrosion control

The absorptive capacity (AB) depicts the ability of the system to absorb the disruption and decelerate the corrosive process. It is expressed in Figure 5.2.4 by the area limited between the "S" and "M" scenarios following equation (2). The developed formulas are inspired from the work of Ayyub (2015).

$$\text{Absorptive capacity} = \frac{\int_{t_e}^{t_c} S(t)\,dt - \int_{t_e}^{t_c} M(t)\,dt}{\int_{t_e}^{t_c} W(t)\,dt} \tag{2}$$

$$\text{Dynamic adaptive capacity} = \frac{\int_{t_c}^{t_r} S(t)\,dt - \int_{t_c}^{t_r} M(t)\,dt}{\int_{t_c}^{t_r} W(t)\,dt} \tag{3}$$

$$\text{Restorative capacity} = \frac{\int_{t_r}^{t_t} S(t)\,dt}{\int_{t_r}^{t_t} W(t)\,dt} \tag{4}$$

$$\text{Dynamic Resilience} = \frac{T_n + DAB \bigtriangleup T_{ce} + DAD \bigtriangleup T_{rc} + DRS \bigtriangleup T_{tr}}{T_n + \bigtriangleup T_{ce} + \bigtriangleup T_{rc} + \bigtriangleup T_{tr}} \tag{5}$$

The adaptive capacity (AD) is the gain in pipeline lifetime due to the adoption of proper corrosion control actions. At this stage, the pipeline survives while operating on low performance. The restorative capacity in the case of pipeline corrosion is mainly represented in terms of pipeline replacement.

Table 5.2. 2 Generated results in term of Resilience metrics

Resilience metrics	**Calculated value**
Absorptive capacity	13.3%
Adaptive capacity	8.7%
Restorative capacity	83.3%
Resilience	22.9%

The obtained resilience metrics, in Table 5.2.2, reveal good performances of the system. Those metrics should be analyzed and compared in terms of cost of investment and return or savings in potential direct and indirect losses such as pipeline replacement at an early age (e.g. M scenario) or pipeline failure (e.g. F scenario). This part is discussed in.[139]. For more details, the reader is directed to aforementioned paper.

5.2.4 Conclusion and Further Work

This chapter introduced the concept of dynamic resilience modelling as a dynamic approach to quantify resilience and resilience metrics under varying conditions while handling the stochastic processes that interact with the system and can impact its performances. The application of the proposed approach to the pipeline corrosion control problem demonstrated its applicability and efficiency. The approach would help prioritize action to prevent and control corrosion prior to the failure stage or the equipment replacement at an early age. Further work needs to be done to optimize this SPN based approach. It is worth noting that the uncertainty analysis and the economical aspect of resilience engineering were not discussed in this work. This will be incorporated in an upcoming paper.

5.2.5 References

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6. CONCLUSION

6.1 Overall Conclusion

Overall, it has been shown in this thesis that the evolving, complex and uncertain microbiological corrosion mechanisms requires advanced risk-based decision-making tools to capture the diverse factors contributing to MIC development in a process system. This thesis has made a significant step toward development of such tool by providing new methods, insights and guidance to:

- Improve the understanding on how to correlate diverse chemical, physical, biological and molecular factors to assess the potential of MIC occurrence in a process system;
- Develop an advanced tool able to diagnostic timely MIC occurrence under dynamic conditions;
- Help corrosion specialists to perform a systematic MIC risk assessment study on their process facilities;
- Provide metrics to assess the resilience of process equipment against the corrosive process.

6.2 MIC Potential Assessment

As discussed in this thesis, modelling the correlation of diverse influencing factors in the MIC occurrence is the key element in any susceptibility or potential assessment of MIC in process systems. Since not all the factors are deterministic and some of them can only be assessed subjectively by a subject matter expert, it was concluded that the probabilistic approaches are the most suitable techniques to address the uncertainties in input data. In addition, the use of Bayesian analysis allows for adaption to missing data and also able to consider new data as evidence to update an earlier prediction.

6.3 Dynamic Model for MIC Diagnosis

When MIC occur in a system, the trends of condition of operations, microbiological analysis and process data constitute significant pieces to build the history of the system and diagnosis the root-causes leading to each stage. The timeline of occurrences reveal the cause-effect and correlation relationships. Therefore, a powerful modelling tool such as the BSPN is needed to capture the dynamic behaviours with respect to time. Even though, the capabilities of BSPN where demonstrated in this thesis, the step-by-step application of BSPN on a case of MIC that has led to equipment failure and the investigation provided sufficient data on the root-causes leading to the failure.

6.4 Corrosion Risk Assessment

A proper corrosion risk assessment framework should be adaptable enough for other cases or other process equipment (i.e. non case specific). The corrosion risk is a combination of likelihood and consequences of corrosion. The two elements and the combination should be assessed in a clear way. Verification of the model is also a critical step before making decisions based on the model outputs, either qualitative or quantities outputs. Reliable data is still a critical element in these data-driven models. Therefore, considerable effort should be make to build multi-sources database.

6.5 Corrosion Resilience Modelling

As reliability assessment is an important analysis in asset integrity management of process facilities, resilience assessment is of equal or higher importance as it measures the characteristics of the system when facing a disturbance. For instance, absorptive, adaptive and restorative capacities are the resilience metrics to be assessed. The study in this thesis shows that corrosion prevention measures contribute toward higher absorptive capacity, while the detection and mitigation strategies contribute toward higher adaptive capacity. The restorative capacity is not very much affected by any of the conventional corrosion management strategies.

6.6 Recommendations

This research work introduces new concepts and overcomes some of the limitations of existing techniques in the field of corrosion engineering with a focus on MIC. This study can be extended further by addressing the following main limitations:

- *Consideration of time dependency in MIC potential assessment:*

It is worth noting that the proposed model for MIC potential assessment only estimates the potential of having MIC at a single moment. It does not assess the development of the potential of having MIC over time. This can be done by improving the existing model (i.e. OOBN model) into dynamic OOBN model. The latter supports the modelling of the temporal evolution of variables over a discretized timeline (i.e. time slices). The temporal evolution is modeled by the dependency (i.e. dependency arc) between the node in time (t) and its copy in time ($t+\triangle t$).

- *Consideration of competing and synergic processes:*

In some field cases, multiple corrosion modes might be present at the same time. For instance, MIC can occur simultaneously with stress cracking corrosion (SCC). The stress can cause a shift to the electrochemical potential by increasing the internal energy level of the metal. SCC generates micro-cracks that damage the protective layer on the metal surface leading to microbiological settlement to later form the biofilm consortium. Erosion can be seen as a competing process by removing early biofilm consortiums from the metal surface. A framework should be developed for cases where multiple corrosion mechanisms are present to capture the overall effect of active mechanisms on MIC development and equipment failure.

- *Test and validation of the BSPN tool on MIC diagnosis case study:*

This thesis proposed a modelling tool able to capture complex dynamic behaviour for diagnosis purposes. The modelling tool was initially tested and verified using a simple pump failure scenario. This modelling tool should be tested on a case study of MIC that has led to equipment failure and the investigation has revealed the exact root-causes leading to the failure. This work will be conducted when sufficient data from an MIC failure investigation report is available for the study.

- *Development of a dynamic model for corrosion risk assessment:*

This thesis identified the factors and parameters that should be taken into consideration when assessing the risk of MIC. The methodology provided in the MIC risk assessment chapter can be further improved by converting the Bow-Tie model into a dynamic model.

In future work, dynamic Bayesian networks will be introduced to allow for dynamic modelling for corrosion risk assessment.

- *Development of Corrosion failure database:*

As can be seen, the proposed models in this thesis require a high amount of data which are often difficult to obtain. Extracting data from existing experiment and literature can be challenging and is subjected to high uncertainties. To overcome this challenge, the development of corrosion failure database using multi-sourcing data collection is required. In the MIC risk assessment chapter, an attempt was made to initiate such database and also illustrates the usefulness of this kind of database in extracting useful data necessary to conduct corrosion analysis studies.

- *Development of a commercial tool:*

Several modelling software tools were used in this thesis for the development and implementation of the proposed models. These tools are not freely available and requires modelling skills to operate them. Therefore, there is a need to develop an MIC dedicated commercial and user-friendly software tool for implementation of the proposed models for practical application. The developed software tool could be used as a comprehensive tool of an MIC threat assessment study.