Internal Corrosion Hazard Assessment of Oil & Gas Pipelines Using Bayesian Belief Network

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Abstract

A substantial amount of oil & gas products are transported and distributed via pipelines, which can stretch for thousands of kilometers. In British Columbia, Canada, alone there are over 40,000 km of pipelines currently being operated. Because of the adverse environmental impact, public outrage and significant financial losses, the integrity of the pipelines is essential. More than 37 pipe failures per year occur in BC causing liquid spills and gas releases damaging both property and environment. BC oil & gas commission (BCOGS) has indicated metal loss due to internal corrosion as one of the primary causes of these failures. Therefore, it is of a paramount importance to timely identify pipelines subjected to severe internal corrosion in order to improve corrosion mitigation and pipeline maintenance strategies, thus minimizing the likelihood of failure. To facilitate the need, this paper presents a Bayesian belief network (BBN)-based probabilistic internal corrosion hazard assessment tool for oil & gas pipelines. A cause-effect BBN model has been developed by considering various information, such as analytical corrosion models, expert knowledge and published literature. Multiple corrosion models and failure pressure models have been incorporated into a single flexible network to estimate corrosion defects and associated probability of failure (PoF). This paper also explores the influence of fluid composition and operating conditions on corrosion rate and PoF. To demonstrate the application of the BBN model, a case study of the Northeastern BC oil & gas pipeline infrastructure is presented. Based on the pipeline's mechanical characteristics and operating conditions, spatial and probabilistic distributions of corrosion defect and PoF parameters have been obtained and visualized with the aid of the Geographic Information System. The developed BBN model can identify vulnerable pipeline sections and rank them accordingly to enhance the informed decision-making process.

Keywords: Oil & gas pipes, internal corrosion, Bayesian belief network (BBN), corrosion depth, failure pressure.

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1. Introduction

The rapid growth of the Canadian oil & gas industry requires increases in pipeline infrastructure, resulting in greater operational and management complexity. Because of the potentially adverse environmental impact and significant financial consequences, however, maintaining the integrity of this infrastructure is essential (Ossai, 2012; Revie, 2015). At the initial stage of production, one of the major threats to the integrity of oil & gas pipelines is internal corrosion (Papavinasam, 2013). The crude mixture extracted from the geological formation, composed of associated water, organic acids, and various dissolved gases such as carbon dioxide (CO_2) and hydrogen sulfide (H_2S), creates a corrosive environment for steel (Nešić, 2007). Despite the understanding of corrosion mechanisms and improved corrosion detection techniques, the industry reports still show that internal corrosion plays a significant role in pipeline failure. For example, according to an Alberta Energy Regulator report (AER, 2013), from 1990 to 2012, more than 9,000 failures occurred due to internal corrosion (Figure 1), which accounts for 54.8% of all spills. The oil & gas companies in the US spend 1.052 billion dollars yearly to mitigate internal corrosion (Papavinasam, 2013). Given this problem, coupled with companies' limited budgets, there is a need for informed decisions to facilitate an effective corrosion mitigation strategy.

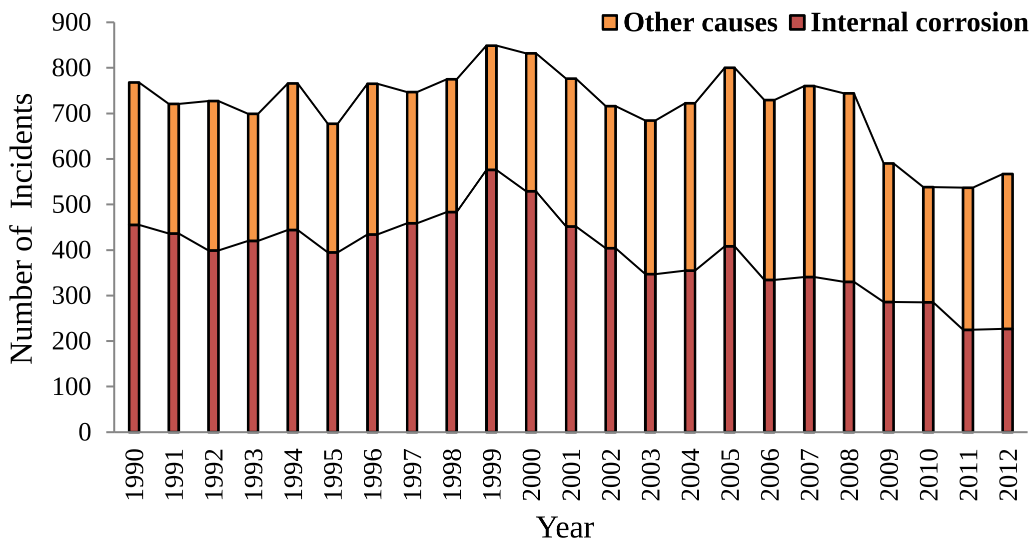

Figure 1 Pipeline failures due to corrosion in Alberta from 1990 to 2012 (AER, 2013)

Quantitative and qualitative methods have been proposed to model corrosion of oil & gas pipelines (El-Abbasy, Senouci, Zayed, & Mosleh, 2015; Lahiri & Ghanta, 2008; Marhavilas, Koulouriotis, & Gemeni, 2011; Nataraj, 2005; Shahriar, Sadiq, & Tesfamariam, 2012; Sinha & Pandey, 2002). Qualitative methods are frequently based on an index system, whereas quantitative methods are usually based on numerical simulations (Z. Han & Weng, 2011). When substantial historical data is available, rigorous statistical or data mining techniques can be used to develop predictive tools (e.g. Artificial Neural Networks). However, in case of sparse, ambiguous or imprecise data, soft computing techniques (e.g. decision tree models, fuzzy rule-based models and Bayesian belief networks (BBN) can be used to quantify cause-effect relationships and handle uncertainties (Ismail, Sadiq, Soleymani, & Tesfamariam, 2011). A detailed comparative analysis of commonly applied soft computing techniques is reported elsewhere (Kabir, Tesfamariam, Francisque, & Sadiq, 2015).

Internal corrosion is a time-dependent random process (Nešić, 2007; Papavinasam, 2013). Any measurement or estimation of the corrosion rate will inevitably contain a degree of uncertainty, as it is influenced by a number of factors subject to aleatory and epistemic uncertainties (Ayello, Alfano, Hill, & Sridhar, 2012). BBN is particularly suitable to deal with such processes because of its ability to establish a cause-effect network through integration of the various types of available information, such as analytical models, expert knowledge, published literature and historical data into a single flexible framework (Chen & Pollino, 2012; Cockburn & Tesfamariam, 2012). This combination is a beneficial when dealing with processes, that analytical modeling alone fails to describe (e.g. microbiologically influenced corrosion). Furthermore, BBN breaks down a complex problem into its components and then graphically represents them, thus facilitating a better understanding of this problem. In BBN, the associated uncertainties (can be a data uncertainty, model uncertainty or both) are explicitly treated by propagating them throughout the network up to the final node (Uusitalo, 2007).

The objective of this paper is to develop a BBN-based internal corrosion hazard estimation tool for oil & gas pipelines. The BBN model has been developed considering two general corrosion mechanisms of mild steel, CO_2 and H_2S corrosion. Expert judgment has been used to create (and then integrate in the framework) knowledge based BBNs for microbiologically influenced corrosion, erosion-corrosion, and pitting corrosion. Figure 2 depicts the proposed conceptual framework, which integrates analytical and knowledge based corrosion models as well as two failure pressure models to quantify the probability of failure (PoF). Sensitivity analysis has been performed to evaluate the effects of different parameters on internal corrosion hazard. To demonstrate the developed BBN model, a case study for the oil & gas pipeline infrastructure located in the Northeast of British Columbia (BC), Canada is presented. Based on the pipeline characteristics and operating conditions, spatial and probabilistic distributions of corrosion defect as well as PoF have been obtained and visualized with the aid of the Geographic Information System (GIS). The developed model can be employed to identify pipeline sections vulnerable to internal corrosion and rank them to improve the corrosion mitigation program as well as the pipeline maintenance strategy.

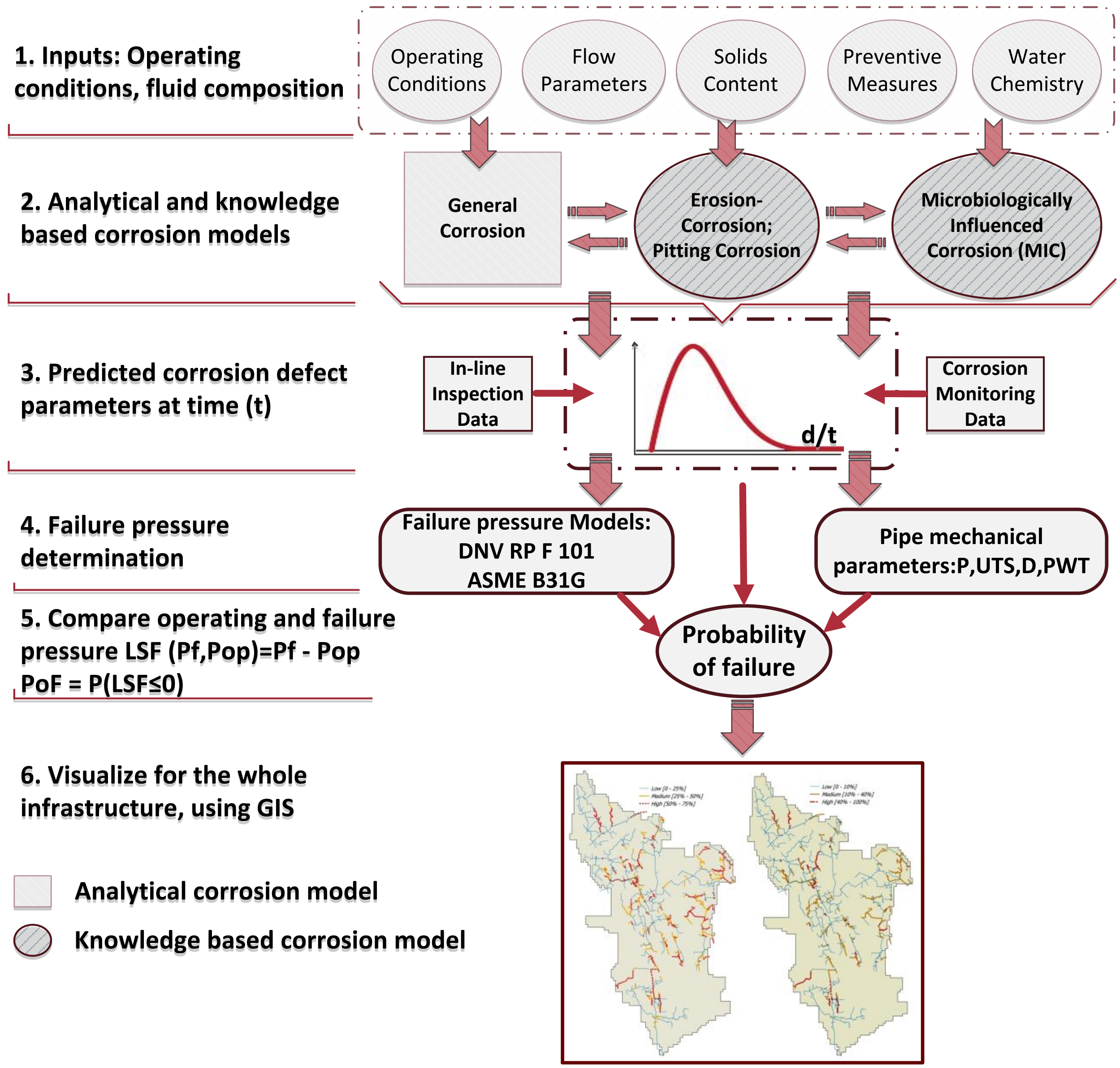

Figure 2 Conceptual BBN for internal corrosion

2. Bayesian belief network

BBN is an analytical framework that permits the visual representation of causal dependencies among given variables in a probabilistic manner (Pearl, 1988). The BBN approach has been applied in the analysis of various complex engineering problems, such as structural reliability analysis, deterioration modelling, and has proven to be particularly effective in the sphere of risk analysis and decision support under uncertainties (Cheng, Bell, & Liu, 1997; Lee, Park, & Shin, 2009; Tesfamariam, Sadiq, & Najjaran, 2010). A BBN model can be efficiently applied to make informed decisions when the available data is imprecise, ambiguous or incomplete (Kabir et al., 2015).

A BBN is based on a Directed Acyclic Graph (DAG), which consist of many stochastic variables and the directed links between them. The links denote probabilistic conditional dependence, whereas nodes represent parameters of interest (Cockburn &

Tesfamariam, 2012). Each unknown parameter is determined, by using Bayes' theorem, which for the n mutually exclusive hypotheses (j=1,...,n) is represented by the relationship:

$$P(H_j|E) = \frac{p(E|H_j) * p(H_j)}{\sum_{i=1}^{n} p(E|H_i) * p(H_i)} \qquad [1]$$

where P (H_j|E) is the posterior probability for the hypothesis H(j=1,...,n) ,based on the obtained evidence (E); p(H_j) denotes the prior probability; p(E|H_j) represents conditional probability, assuming that H_j is true, the denominator represents the total probability which is a constant value (Pearl, 1988). Prior or unconditional probability is the likelihood of an event before any evidence is provided. Posterior probability refers to the likelihood after the observation is made. Equation 1 is used in BBN to perform a probabilistic inference for a subset of parameters as new data or evidence is acquired about any other parameters (Janssens et al., 2006).

In a BBN model, variables are related to each other in a manner of family relationships. This relationship is shown in Figure 3, where variables X1 and X2 are parents and variable Y is a child. A variable X1 is considered to be a parent of Y if the connection link goes from X1 to Y. The variables are defined by a set of mutually exclusive states, whereas their relations are quantified by introducing conditional probabilities for each possible combination of these states. As depicted in Figure 3, the following steps are to be fulfilled to create a BBN model:

1. Variables that have an effect (X1, X2) on the outcome parameter (Y) are identified.
2. Conditional dependence between the parameters is formulated and represented using arrows. It is essential that variables are linked based only on the cause-effect assumption, not on the correlation.
3. Collectively exhaustive and mutually exclusive states are assigned to parent variables by evaluating prior probability of each state (e.g. P1, P2…P4). The unconditional probability of variables which have no parent nodes can be unknown a priori. In this case, the principle of insufficient reasoning can be applied, assigning for each state 1/n probability, where n is the total number of states of the variable (Tesfamariam & Martín-Pérez, 2008)

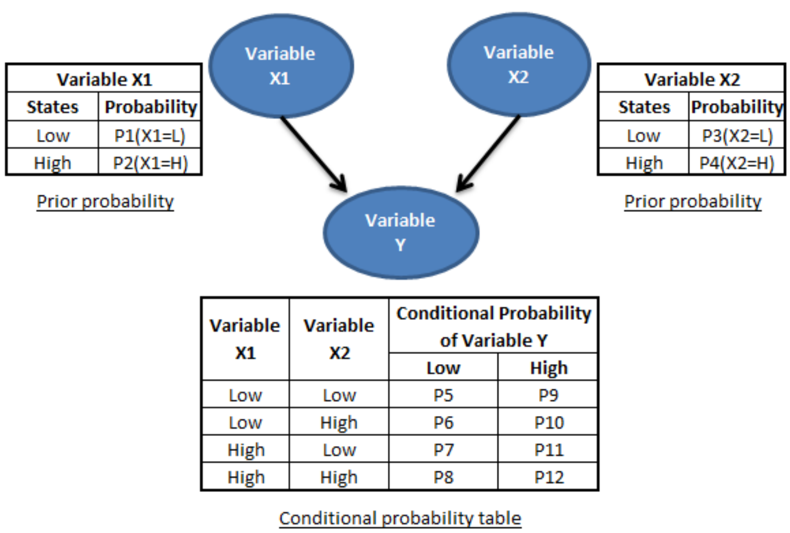

Figure 3 Example of BBN (Tesfamariam and Liu 2013)

The conditional probabilities for each child node are assigned (e.g. P5, P6…P12). This step is the most important, but very time-consuming, since all possible state combinations of parent nodes must be provided to fill in the condition probability table (CPT). The CPT may be completed by assigning subjective probability that is used in BBN to reflect the associated uncertainties (Fan & Yu, 2004; Pearl, 1988). The conditional probabilities can be quantified by using information obtained from the field data, expert opinion, analytical model or a combination of them. However, in a complex process with less understood underlying mechanisms, the application of expert knowledge is preferable (Daly, Shen, & Aitken, 2011; Liu, Lu, Chen, & Shen, 2012). When multiple analytical models or expert opinions are available, credibility factors (weights) may be assigned to reach the final decision, but the higher the complexity of the problem the greater the uncertainty that emerges (Ismail et al., 2011; Ross, 2009; Sadiq, Kleiner, & Rajani, 2008).The fundamental symmetry property of Bayes' theorem permits the probability to be inferred in forward (predictive analysis) and backward (diagnostic analysis) directions. This characteristic allows a cause-effect network to use reverse logic, thus the BBN model can be exploited as a diagnostic model by introducing new information in the effect variable to infer a probable cause (Ismail et al., 2011; Kabir et al., 2015). In this study, Bayesian network development software Netica has been used to develop the proposed model (Norsys Software Corp, 2015).

3. BBN internal corrosion model development

The proposed BBN model is used to quantify the PoF for gathering and production pipelines (i.e. prior to the purification stage) subjected to aqueous corrosion. It includes pipelines transporting crude oil, oil effluent, produced water and others. The BBN model has been developed using extensive review of the corrosion literature, industry reports and current standards of oil & gas pipelines. Forty four different factors (e.g. operating conditions, corrosion mitigation measures, etc.) affecting pipeline corrosion rate and PoF are incorporated in the network. The developed BBN model for corrosion hazard estimation is shown in Figure 4. Details of the model for general corrosion, pitting corrosion, erosion-corrosion and MIC, are discussed in the following subsections.

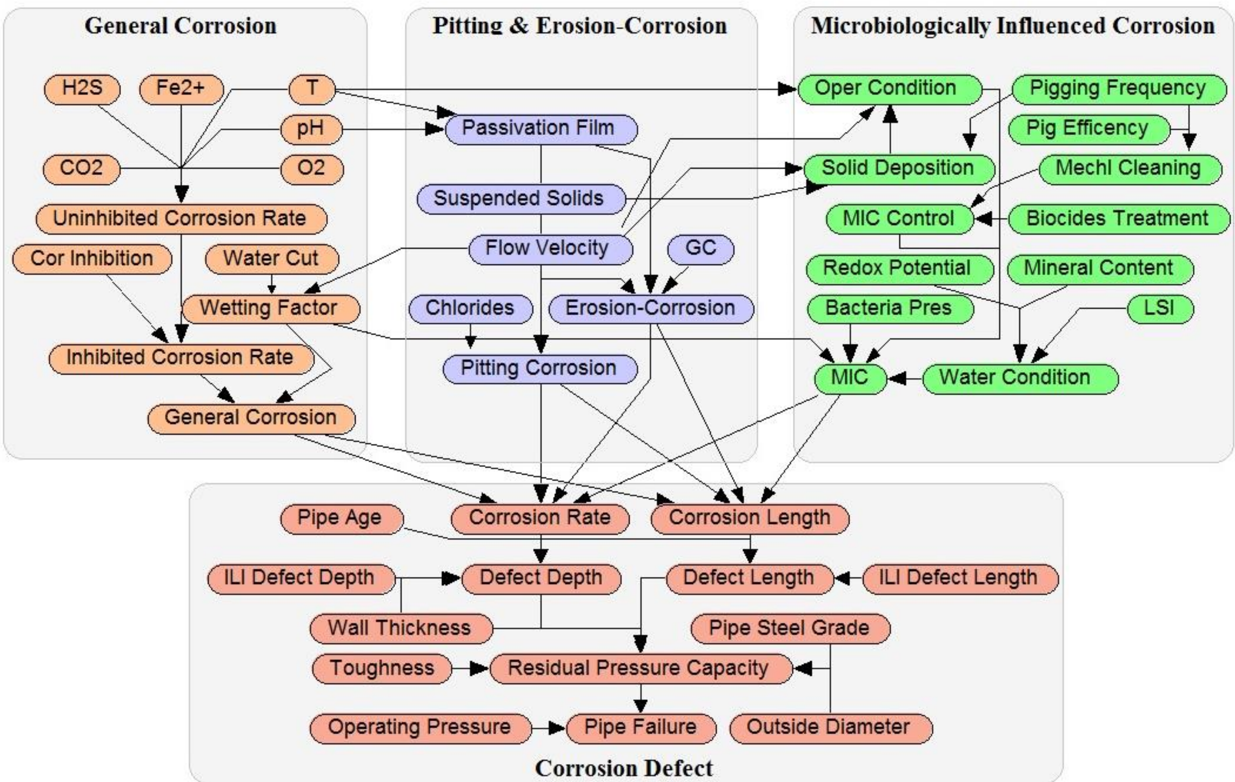

Figure 4 Proposed BBN for internal corrosion assessment

3.1 General corrosion model

Numerous corrosion models have been proposed to estimate corrosion rate. Multiple factors and their interactions are required to be considered in the analysis.Table 1 shows commonly used factors in different analytical corrosion models. Due to different underlying assumptions and random nature of corrosion, analytical corrosion models may give different results even for the same inputs (Koch, Ayello, Khare, Sridhar, & Moosavi, 2015). Therefore, there is a significant modeling uncertainty that needs to be accounted for (Ayello, Jain, Sridhar, & Koch, 2014). In this study, for the *Uninhibited Corrosion Rate (UCR)* prediction, a BBN model developed by Ayello et al. (2014) has been adopted. This models was derived with consideration of different model uncertainties. Table 2 reflects the discretization details of corrosive species concentration, pH, *Temperature (T)*, *Inhibitor Efficiency (IE)* and *Wetting Factor (WF)* which are used in the BBN general corrosion model to quantify *General Corrosion Rate (GCR)*.

Corrosion Inhibitor (CI) node is coupled with *UCR* node to account for the inhibitor application, which can significantly mitigate the corrosion rate. As a result, the *Inhibited Corrosion Rate (ICR)* is computed as (Ayello et al., 2013; Papavinasam, 2013):

$$ICR = UCR \times (1 - IE) \qquad [2]$$

where, *ICR* is the inhibited corrosion rate (mm/year), *UCR* is the uninhibited corrosion rate (mm/year), *IE* is inhibitor efficiency (%).

Table 1 Parameters applied in different corrosion models, modified after (Papavinasam, 2013)

Corrosion models	Considered parameters								
	CO_2 concentration	***H_2S concentration***	***Temperature***	***Effect of flow***	***pH level***	***Bicarbonate***	***Acetic acid***	***Field data***	***Ca^{2+}***
(De Waard, Lotz, & Milliams, 1991)	√	×	√	√	√	√	×	×	×
(Srinivasan & Kane, 1999)	√	√	√	√	√	√	×	×	√
(Nešic & Postlethwaite, 1991)	√	×	√	√	√	√	√	×	×
(Mishra, Al-Hassan, Olson, & Salama, 1997)	√	×	√	×	√	√	×	×	×
(Dayalan, De Moraes, Shadley, Rybicki, & Shirazi, 1998)	√	×	√	√	√	√	×	×	×
(Anderko, McKenzie, & Young, 2001)	√	√	√	×	√	√	×	×	×
(Oddo & Tomson, 1999)	√	×	√	×	√	√	×	√	√
(Pots et al., 2002)	√	×	√	√	√	√	×	√	√
(Papavinasam, Doiron, & Revie, 2010b)	√	√	√	√	√	√	√	√	×
(Adams, Garber, Singh, & Jangama, 1996)	√	×	√	×	√	√	√	√	×
Proposed BBN	√	√	√	√	√	×	×	√	×

Probability of corrosion is minimal when water is not in contact with the steel surface. Thus, *Wetting Factor (WF)* node is introduced to assess either the pipe surface is wetted with the water phase or not. The wettability is a complex phenomenon that is affected by many parameters such as water cut, flow regime, internal diameter, liquid velocity, fluid density and fluid viscosity (Tang, Richter, & Nesic, 2013). However, conservative assumptions can be made by considering water cut and fluid velocity as the only contributors to the wettability (McAllister, 2013). *Water Cut (WC)* and *Flow Velocity (FV)* are introduced in the BBN as parent nodes for the *WF* node. Then, *WF* [0.1, 1.0] is used as an adjustment factor to compute *GCR* as follows:

$$GCR = ICR \times WF \qquad [3]$$

where, *GCR* is general corrosion rate, and *ICR* is inhibited corrosion rate. *WF* values close to 0.1 correspond to water cut below 0.5% and flow rate higher than 1.5 m/s, whereas when the water cut is above 30% *WF* equals unity, regardless of the fluid velocity (Pots et al. 2002, Nyborg 2002a). The discretization details of the nodes, reflecting the aforementioned discussion described in **Table 2**.

Table 2 General corrosion discretization details

Variables and reference for discretization	Sub criteria	Performance measure	
General Corrosion (GCR), mm/year (Ayello et al., 2014; Institute for Energy Technology, 2009)	Inhibited corrosion rate (ICR), mm/year; Wetting factor (WF);	Extremely Low Very Low Low Medium High Very High Extremely High	$0 \leq GCR < 0.01$ $0.01 \leq GCR < 0.1$ $0.1 \leq GCR < 1$ $1 \leq GCR < 2$ $2 \leq GCR < 5$ $5 \leq GCR < 10$ $10 \leq GCR$
Uninhibited Corrosion Rate (UCR), mm/year (Ayello et al., 2014)	CO_2 partial pressure (CO_2),Bar	Very Low Low Medium High	$0 \leq (CO_2) < 0.1$ $0.1 \leq (CO_2) < 1$ $1 \leq (CO_2) < 10$ $10 \leq (CO_2) < 100$
	Temperature (T), ºC	Low Medium High Very High	$20 \leq T < 40$ $40 \leq T < 60$ $60 \leq T < 80$ $80 \leq T < 100$
	Fe^{2+} Concentration (Fe^{2+}), ppm	Low Medium High	$0 \leq (Fe^{2+}) < 10$ $10 \leq (Fe^{2+}) < 50$ $50 \leq (Fe^{2+}) < 100$
	O_2 Concentration (O_2), ppb	Low Medium High Very High	$0 \leq (O_2) < 10$ $10 \leq (O_2) < 100$ $100 \leq (O_2) < 1000$ $1000 \leq (O_2) < 10000$
	H_2S Concentration (H_2S), ppm	Low Medium High Very High	$0 \leq (H_2S) < 10$ $10 \leq (H_2S) < 100$ $100 \leq (H_2S) < 1000$ $1000 \leq (H_2S) < 10000$
	pH level (pH)	Low Medium High Very High	$4 \leq pH < 5$ $5 \leq pH < 6$ $6 \leq pH < 7$ $7 \leq pH < 8$
Inhibited Corrosion Rate (ICR), mm/year (Ayello et al., 2014)	Uninhibited corrosion rate (UCR), mm/year	Extremely Low Very Low Low Medium High Very High Extremely High	$0 \leq UCR < 0.01$ $0.01 \leq UCR < 0.1$ $0.1 \leq UCR < 1$ $1 \leq UCR < 2$ $2 \leq UCR < 5$ $5 \leq UCR < 10$ $10 \leq UCR$
	Inhibitor efficiency (IE), %	Extremely Low Very Low …….. Extremely High	$0 \leq (IE) < 10$ $10 \leq (IE) < 20$ …….. $90 \leq (IE) < 100$
Wetting Factor (WF)	Water cut (WC), %	Very Low Low Medium High Very High	$0 \leq WC < 0.5$ $0.5 \leq WC < 5$ $5 \leq WC < 15$ $15 \leq WC < 30$ $30 \leq WC < 100$
	Flow velocity (FV), m/s	Stagnant Very Low Low Medium High Very High	$0 \leq FV < 0.1$ $0.1 \leq FV < 0.5$ $0.5 \leq FV < 1$ $1 \leq FV < 2$ $2 \leq FV < 3$ $3 \leq FV < 4.5$

3.2 Pitting corrosion and erosion-corrosion models

The pitting corrosion is assumed to be caused only by chemical dissolution of the protective film. This film forms on the metal surface depending on pH and temperature of the fluid. It has been shown that the protective films are more likely to cover a metal surface at a pH level higher than 6, as well as elevated temperatures (higher than 40ºC) (J. Han, Yang, Nesic, & Brown, 2008; Papavinasam, 2013). These assumptions have been followed to create a *Passive Film (PF)* node. Localized chemical removal of this film is substantially affected by chloride presence. Chlorides are widely reported as a dominant contributor to the localized corrosion of steel; therefore, many corrosion models apply chloride concentration as an indicator of localized corrosion severity (Papavinasam, Doiron, & Revie, 2010a; Srinivasan & Kane, 1996). It is assumed that chlorides cause and intensify only pitting corrosion. Then, *Chlorides (Cl)* and *Pitting corrosion (PC)* nodes are introduced, assuming that pitting corrosion is high when a corrosive film covers the pipe's internal surface with high chloride concentration.

At a high flow velocity, if suspended solid particles are present in the fluid, they can mechanically damage the steel surface. In addition, in the presence of protective corrosion films, the localized corrosion rate may accelerate because of the synergetic effect between corrosion and erosion (Malka, Nešić, & Gulino, 2007; Shadley, Shirazi, Dayalan, Ismail, & Rybicki, 1996; Zhou, Stack, & Newman, 1996). The erosion-corrosion manifests itself even more significantly when a pipeline segment has a geometry change (i.e. elbow, tee, etc.) The dominant factors in this process are flow velocity and the presence of solid particles (Malka et al., 2007). Shadley et al. (1996) have identified three velocity intervals affecting erosion-corrosion rates. At the lower velocity threshold, the corrosion protective film is intact; therefore the corrosion rate is low. On the other hand, intermediate velocities cause partial film removal, promoting localized corrosion in these areas. In the case of a higher velocity threshold, solid particles damage the protective film uniformly; hence, the corrosion severity becomes high, but is distributed relatively uniformly (Shadley et al., 1996). This approach is adopted assigning the following velocity values [0 to 1] m/s for the lower threshold, [1 to 3] m/s for intermediate and [3 to 4.5] m/s for the higher threshold respectively. *Erosion-Corrosion (EC)* nodes, as well as the nodes that cause it such as *Flow Velocity (FV)*, *Passive Film (PF)*, *Suspended Solids (SS)* and *Geometry Change (GC)* are integrated and the discretization details are summarized in **Table 3**.

Table 3 Erosion-Corrosion and pitting corrosion discretization details

Variables and reference for discretization	Sub criteria	Performance measure	
Erosion-corrosion discretization details			
Erosion-Corrosion (EC), mm/year	Suspended solids (SS); Flow velocity (FV); Geometry change (GC); Passive film (PF)	Low Medium High	$0 \le EC < 0.01$ $0.01 \le EC < 0.1$ $0.1 \le EC < 1$
Erosion-Corrosion (EC), mm/year (Haile et al., 2013)	Suspended solids (SS)	Absent Low High	No measured parameter is considered
	Flow velocity (FV), m/s	The same as in Table 2	
	Geometry change (GC)	Yes No	No measured parameter is considered
	Passive film (PF)	Yes No	No measured parameter is considered
Pitting corrosion discretization details			
Pitting Corrosion (PC), mm/year	Chlorides (Cl), ppm; Passive film	Low Medium High	$0 \le PC < 0.01$ $0.01 \le PC < 0.1$ $0.1 \le PC < 1$
Pitting Corrosion (PC), mm/year	Chlorides (Cl), ppm	Negligible Low High	$0 \le Cl < 500$ $500 \le Cl < 30{,}000$ $Cl \ge 30{,}000$
	Passive film (PF)	Yes No	No measured parameter is considered

3.3 Microbiologically influenced corrosion (MIC) model

The microbiologically influenced corrosion (MIC) model has been developed considering water chemistry, operating conditions and MIC mitigation parameters. Favourable and unfavorable conditions for MIC, as well as its mitigation measures, have been developed with knowledge garnered from Haile and Sooknah models and published literature (Haile, Papavinasam, & Zintel, 2013; Sooknah, Papavinasam, & Revie, 2008). These models were shown to give a reliable indication of MIC damage because they were validated against field tests and demonstrated a good agreement (Haile et al., 2013; Sooknah et al., 2008). The MIC contributing factors are clustered into three major categories: *Operating Conditions (OC), Water Condition (WC) and MIC Control (MICC)*.

3.3.1 Operating conditions

Operating conditions such as flow rate, temperature, fluid composition and others can significantly affect bacterial activity. It was shown that bacteria could grow under a variety of pressure ranges, even dramatic change of this parameter did not harm a bacterial population (Javaherdashti, Nwaoha, & Tan, 2013). Hence, operating pressure is excluded from consideration. The same applies for fluid pH, because biofilms are active over a broad pH range and have an aptitude to buffer pH. Flow velocity significantly influences biofilm formation. For instance, when the flow rate is higher than 2 m/s, biofilms begin to deteriorate (Pots et al., 2002). Conversely, when the flow velocity is very low or stagnant, it forms suitable conditions for the attachment of corrosive biofilms (Papavinasam, 2013). Furthermore, if suspended particles are presented in these sections with relatively low flow rates, solid deposition may occur, providing bacteria with a breeding ground (Papavinasam, 2013).

Corrosive biofilms can survive under a broad range of temperatures. However, most species involved in corrosion reactions better thrive within a narrower temperature interval (between 15°C and 45°C) (Sooknah et al., 2008). At decreased temperatures, the bacterial activity can be reduced due to the inhibition of the metabolic processes, whereas at high temperatures denaturation may kill bacterial population. To reflect the aforementioned discussion, *Temperature (T), Flow Velocity (FV), Pigging Frequency (PF) and Suspended Solids (SS)* nodes were created and incorporated in the *Operating conditions (OC)* factor. The discretization details of the nodes, constituting this factor are summarazied in **Table 5**.

3.3.2 Water condition

Recent studies suggest that if free water is not presented in a pipeline, then the likelihood of MIC is negligible (Revie, 2015). However, if even a small amount of water wets a pipe interior surface (e.g. due to flow abnormalities or changes in operating conditions), biofilm formation can be initiated (Nyborg, 2002; Sooknah, Papavinasa, & Revie, 2007). Thus, water contact with a metal surface affects MIC propagation. To account for that impact, *WF* has been coupled with *MIC* node applying the following formula (Revie, 2015):

$$MIC = MIC_w \times WF \qquad [4]$$

MIC_w is microbial corrosion rate in the presence of water.

Besides presence of water, its chemistry also plays an important role in the MIC propagation. The following water parameters affect biofilm growth: *Mineral Content (MC)*, *Redox Potential (RP)* and *Langelier Saturation Index (LSI)* (Javaherdashti et al., 2013). These parameters have been combined in the *Water Condition (WC)* factor to describe a suitable environment for bacterial populations to thrive.

The node *MC* indicates the total dissolved solids concentration in water. It can be presented by sulfates, chlorides, bicarbonates, etc. It has been reported that the MIC damage is correlated with the concentration of dissolved minerals (especially chlorides and sulfates) in the transported fluid (Papavinasam, 2013). The *LSI* parameter indicates if the water has the corrosive or scaling tendency. MIC is more likely to happen when scales are formed, which provide shelter and a breeding ground for bacterial population (Papavinasam, 2013). *LSI* higher than 0.5 shows a scaling formation tendency, whereas *LSI* being in the range close to [-0.5; 0.5] indicates that water is balanced; hence it does not affect the MIC. *RP* shows the oxidative-reductive nature of the mixture. It can be used to indicate oxygen concentration in the environment, thus differentiate anaerobic and aerobic conditions. Negative values of *RP* correspond to anaerobic bacteria activity, whereas positive *RP* reflects aerobic bacteria activity. MIC occurrence correlates with *RP*; it was reported that corrosive bacteria species are predominantly active when redox potential falls in the range of [-50; +150] mV (Sooknah et al., 2008). The discretization details of *LSI*, *RP* and *MC* nodes are provided in the **Table 5**.

3.3.3 MIC Control

MIC can be mitigated by mechanically removing biofilms (brush pigging) from the pipeline's interior surface or adding in the flow chemical reagents (biocides), which control biofilms growth. An efficient MIC mitigation strategy includes both means. A pig cleaning frequency significantly affects bacterial populations, the higher the pigging frequency the less time a bacterial would have to proliferate. It has been shown that once every two weeks is the sufficient cleaning frequency to inhibit bacterial growth (Pots et al., 2002; Sooknah et al., 2007). There is an enormous variation of cleaning pig types and each has a specific efficiency with respect to MIC mitigation (King, 2007). Table 4 shows pig efficiency levels to mitigate MIC depending on the pig type and its configuration.

Table 4 Bacteria removal efficacy depending on the pig type, modified after (Papavinasam, 2013)

Pig type	Sphere	Foam Swab	Foam Poly	Cast	Mandrel	Brush	Plow blade	Bidirectional	Pin wheel	Multi-diameter	Bypass	Gel
Bacteria cleaning efficacy	Poor	Poor	Fair	Poor	Fair	Excellent	Fair	Good	Fair	Fair	Fair	Fair

Biocide treatment can also substantially reduce bacterial activity. However, if the same biocide is applied continuously, bacterial populations can develop a natural resistance to it, thus decreasing chemical treatment effectiveness. Therefore, to remove corrosion biofilms, biocides should be injected in a systematic manner (Pots et al., 2002; Sooknah et al., 2007).

To reflect the aforementioned, *MICC* node is introduced in the model. It is based on the two defined parameters, namely *Biocides Treatment (BT)* and *Mechanical Cleaning (MCL)*. The latter one is comprised by *Pig Efficiency (PE)* and *Pigging Frequency (PF)* sub criteria. Pigging frequency describes cleaning intervals, as well as the condition when the pipeline is not designed for pigging or has never been pigged. Pig cleaning efficiency levels from Table 4 have been adopted for *PE* node. The *BT* node reflects biocide regime injection and the condition when biocides are not applied. The discretization details of *PF*, *PE*, and *CT* nodes are provided in the Table 5.

Table 5 MIC discretization details

Variables and reference for discretization	Sub criteria	Performance measure	
MIC, mm/year	Operating conditions (OC); Water condition (WC); MIC control (MICC); Bacteria presence (BP);	Low Medium High	$0 \leq$ MIC< 0.01 0.01$\leq$ MIC < 0.1 $0.1 \leq$ MIC < 1
Bacteria Presence (BP)	---	Yes No	No measured parameter is considered
Discretization details of the BBN Node for "Operating conditions"			
Operating conditions (OC)	Flow velocity (FV), m/s; Solid deposition (SD); Temperature (T), ºC ;	Non suitable Low Medium High Suitable	No measured parameter is considered
Flow Velocity		The same as in Table 2	
Solid Deposition (SD) (Pots et al., 2002; Sooknah et al., 2007)	Suspended solids (SS)	The same as in Table 3	
	Flow velocity (FV), m/s	Stagnant Very Low Low Medium High Very High	$0 \leq$ FV< 0.1 $0.1 \leq$ FV < 0.5 $0.5 \leq$ FV < 1 $1 \leq$ FV< 2 $2 \leq$ FV< 3 $3 \leq$ FV< 4.5
	Pigging frequency (PF)	Very High High Medium Low Very Low Not applied	Once 2 weeks Once 4 weeks Once 12 weeks Once 24 weeks Once 48 weeks Never
Temperature (T), ºC	---	The same as in Table 2	
Discretization details of the BBN Node for "Water condition"			
Water condition (WC)	Langelier saturation index (LSI); Mineral content (MC), ppm; Redox potential (RP), mV;	Non suitable Moderately suitable Suitable	No measured parameter is considered
Water condition (WC) (Haile et al., 2013)	Langelier saturation index (LSI)	Low Neutral High	$- 6 \leq$ LSI < - 0.5 $- 0.5 \leq$ LSI < 0.5 $0.5 \leq$ LSI < 6
	Mineral content (MC), ppm	Low Medium High	15,000 > MC 15,000$\leq$MC< 150,000 MC $\geq$ 150,000
	Redox potential (RP), mV	Low Medium High	-50 > RP -50 $\leq$ RP < 150 RP $\geq$ 150
Discretization details of the BBN Node for "MIC Control"			
MIC Control (MICC)	Mechanical cleaning (MCL); Biocides treatment (BT)	Low Medium High	No measured parameter is considered
Mechanical cleaning (MCL) (Pots et al., 2002; Sooknah et al., 2007); (Papavinasam, 2013)	Pigging frequency (PF)	Very High High Medium Low Very Low Not applied	Once 2 weeks Once 4 weeks Once 12 weeks Once 24 weeks Once 48 weeks Never
	Pig efficiency (PE)	Poor Fair Good Excellent	No measured parameter is considered
Biocides Treatment (BT) (Pots et al., 2002; Sooknah et al., 2007)	Biocides treatment (BT)	Systematic Non systematic Never	No measured parameter is considered

3.4 Corrosion defect model

In this study internal corrosion depth and length are modeled as independent variables (Alamilla, Campos, & Sosa, 2012; Ayello et al., 2014). Ultimate *Corrosion Rate (CR)* is obtained as a combined effect of general corrosion, pitting corrosion, erosion-corrosion and MIC (Ayello et al., 2014; Papavinasam et al., 2010a). Linear growth model for the future defects is assumed to be valid for corrosion depth propagation. In the case of corrosion length, there is no analytical method to predict its value. However, some conclusions regarding its magnitude can be made based on the history of the predominant corrosion type in the system (Ayello et al., 2013). For instance, the defect length of corrosion-erosion is far greater than that for pitting corrosion. In many studies this parameter was either assumed to be proportional to pipe dimensions or to follow an assumed distribution type (Maes, Dann, & Salama, 2008; Teixeira, Soares, Netto, & Estefen, 2008). Therefore, expert judgment is applied to fill the CPT for the defect length node and the discretization details are summarized in Table 7.

A number of failure pressure models have been developed to assess corrosion defects in pipelines (e.g. ASME B31G, modified ASME B31G, RSTRENG, Shell-92, DNV-RP-F101, and others (American National Standards Institute, 1991; Cosham, Hopkins, & Macdonald, 2007; Veritas, 2004). These models are built based on the basic mechanics provided in (Kiefner, Maxey, Eiber, & Duffy, 1973):

$$\sigma_\theta = \sigma\left[\frac{1-\left(\frac{A}{A_0}\right)}{1-\left(\frac{A}{A_0}\right)\frac{1}{M}}\right] = \sigma\left[\frac{1-\left(\frac{d}{t}\right)}{1-\left(\frac{d}{t}\right)\frac{1}{M}}\right] \quad [5]$$

where A is projected area of defect on axial plane; A_0 is original cross section area; M bulging factor; sigma – flow stress; σ_θ is predicted hoop stress at failure.

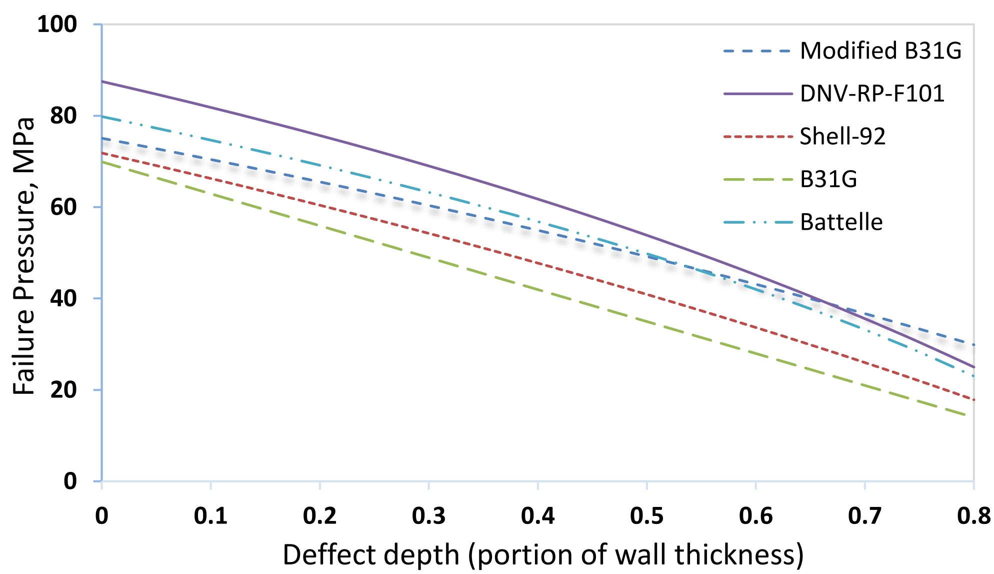

Figure 5 Comparison of different failure pressure model predictions

The enumerated models are mainly concerned with the corroded area geometry and pipe internal pressure. Figure 5 depicts models output, indicating significant discrepancy for the same input parameters. As is shown, ASME B31G gives the most conservative results, followed by Shell-92 (Caleyo, Gonzalez, & Hallen, 2002; Opeyemi, Patelli, Beer, & Timashev, 2015). On the contrary, Modified B31G and DNV-RP-F101 models have been concluded to be the most accurate (Cosham et al., 2007). Consequently, this study considers DNV-RP-F101 and modified ASME B31G models together to estimate residual pressure capacity and PoF. The difference in results between these two models is also quite high, accounting for nearly 20% for the low defect depts. Such discrepancy in outputs is attributed to the difference in defect profile approximations and the difference in reference stress interpretation. The necessity of applying these models together in the analysis is governed by the following reasons:

1. Because mechanical behaviour of old and modern pipeline steels are quite different, biased results can be obtained if DNV-RP-F101 is applied for old line pipe steels or modified ASME B31G for modern steels (Cosham et al., 2007; Hasan, Khan, & Kenny, 2012).
2. In practice, oil & gas pipeline infrastructure may contain both old and recently commissioned segments and there is no commonly accepted criterion regarding the applicability of these models under differing conditions.

The Pipeline Defect Assessment Manual (PDAM) summarizes best methods and practices regarding assessment of the different defect types. It also recommends that DNV-RP-F101 can only be applicable for moderate to high toughness steel, which is defined as follows: (Cosham et al., 2007; Cosham & Hopkins, 2001):

- Line pipe steel, which satisfies axial strain requirements of the API 5L standard
- Line pipe steel, which shows at least 18 J of impact energy in upper shelf Charpy V-notch test
- Line pipe steel, which is known to have no inclusions, second-phase particles, and other contaminants (it is a typical characteristics of old low grade line pipes such as A and B)

These guidelines were followed and node *Toughness (TO)* has been introduced with states *low* and *high* which reflect the aforementioned criteria. For those pipelines, which do not satisfy these criteria ASME B31G model is applied.

The outlined failure pressure models are deterministic, they evaluate a corrosion defect severity applying nominal values for the demand (the pipeline internal pressure loading, P_{OP}) and capacity (the pipeline failure pressure, P_F) (Caleyo et al., 2002). Such deterministic approach makes them impossible to be employed for quantifying the PoF. Therefore, to estimate PoF, a probabilistic approach must be established. A limit state function (LSF) has been formulated as the difference of the remaining capacity (failure pressure, P_F) and demand (operating pressure, P_{OP}):

$$\mathrm{LSF} = \mathrm{P}_F - \mathrm{P}_{OP} \qquad [6]$$

$$\mathrm{PoF} = \mathrm{P}\ (\mathrm{LSF} \leq 0) \qquad [7]$$

To obtain PoF, formulas outlined in Table 6 have been used in BBN. If the defined LSF > 0 (i.e. $P_F > P_{OP}$), then the pipeline is considered to be safe to operate. Conversely, if LSF ≤ 0, then there is likelihood for pipeline to fail. The other failure criterion is assumed to be met when defect depth exceeds 80% of the wall thickness. This criterion is widely applied in defect assessment standards, and no operation is allowed when the defect depth exceeds this value (American National Standards Institute, 1991; Veritas, 2004).

Table 6 Failure pressure models and their application based on steel toughness

Models	Toughness
ASME B31G $PoF = P(LSF \leq 0);\ LSF = \frac{2(\sigma_y + 68.95)t}{D}\left(\frac{1-0.85\frac{d}{t}}{1-0.85\frac{d}{t}M^{-1}}\right) - P_{op}$ $M = \sqrt{1 + 0.6275\frac{L^2}{Dt} - 0.003375\frac{L^4}{D^2t^2}}\ for\ \frac{L^2}{Dt} \leq 50;\ M = 0.032\frac{L^2}{Dt} + 3.3\ for\ \frac{L^2}{Dt} > 50$	Low
DNV-RP-F101 $PoF = P(LSF \leq 0);\ LSF = \frac{2\sigma_u t}{D-t}\left(\frac{1-\frac{d}{t}}{1-\frac{d}{t}M^{-1}}\right) - P_{op};\ M = \sqrt{1 + 0.31\frac{L^2}{Dt}}$	High

Table 7 Corrosion defect discretization details

Variables and reference for discretization	Sub criteria	Performance measure	
Corrosion Rate (CR), mm/year; (Ayello et al., 2014)	General corrosion (GCR), mm/year; Pitting corrosion (PC), mm/year; Erosion-corrosion (EC) mm/year; MIC mm/year;	Extremely Low Very Low Low Medium High Very High Extremely High	0 ≤ CR< 0.01 0.01≤ CR < 0.1 0.1≤ CR < 1 1≤ CR < 2 2≤ CR < 5 5≤ CR < 10 10≤ CR
Corrosion Length (CL), mm/year	General corrosion (GCR), mm/year; Pitting corrosion (PC), mm/year; Erosion-corrosion (EC) mm/year; MIC mm/year;	Low Medium High	0 ≤ CL< 10 10≤ CL < 100 100≤ CL
Defect Depth (DD), d/t	Pipe age (PA), years	Extremely Low Very Low …….. Extremely High	0 ≤PA< 1 1 ≤ PA < 2 …….. 35 ≤ PA < 40
	Corrosion rate (CR), mm/year;	The same as above	
	Wall thickness (WT), mm	Extremely Low Very Low …….. Extremely High	2 3 …….. 20
	ILI defect depth (IDD), mm	No defect Extremely Low Very Low …….. Extremely High	0 0 ≤ IDD < 0.03 0.03 ≤ IDD < 0.06 …….. 0.8 ≤IDD
Defect Length (DL), mm	Pipe age (PA), years	The same as above	
	Corrosion length (CL), mm/year	The same as above	
	ILI defect length (IDL), mm	No defect Low Medium High	0 0 ≤IDL< 10 10 ≤ IDL < 100 100 ≤ IDL < 1000
Failure pressure (FP), MPa	Wall thickness (WT), mm	The same as above	
	Outside diameter (OD), mm	Extremely Low Very Low …….. Extremely High	88.9 114.3 ….. 457.2
	Toughness (TO)	Low High	No measured parameter is considered
	Pipe steel grade (PSG) ,MPa	API 5L X52 API 5L X56 API 5L X60	200 ≤PSG< 300 300 ≤ PSG < 400 500 ≤ PSG < 600
	Defect depth (DD), d/t	Extremely Low Very Low …….. Extremely High	0 ≤ DD < 0.03 0.03 ≤ DD < 0.06 …….. 0.8 ≤ DD
	Defect length (DL), mm	Low Medium High Very High	0 ≤ DL< 10 10 ≤ DL < 100 100 ≤ DL < 1000 1000≤ DL
Pipe Failure (PF)	Failure pressure (FP), MPa	Extremely Low Very Low …….. Extremely High	0 ≤ FP < 5 5 ≤ FP < 10 …….. 90≤ FP < 100
	Operating pressure (OP), MPa	Extremely Low Very Low …….. Extremely High	0 ≤ OP < 5 5 ≤ OP < 10 …….. 90≤ OP< 100

4. Sensitivity analysis

Sensitivity analysis identifies a degree of influence caused by input parent nodes on the child output nodes. It is essential to perform sensitivity analysis because the final output of BBN depends on probabilities assigned a priori. A sensitivity analysis identifies critical input parameters that significantly impact the output results (Tesfamariam & Martín-Pérez, 2008). A sensitivity analysis in BBN can also be applied in order to identify important uncertainties, thus facilitating prioritization of the additional data collection (Ismail et al., 2011). A number of different techniques have been proposed to perform sensitivity analysis, including: entropy reduction, variance reduction and variance of beliefs estimations (Pearl, 1988; Uusitalo, 2007). In this study, the variance reduction method is used to determine the sensitivity of the BBN model's output (nodes *CR* and *PoF*) This method calculates the expected reduction in variance of the expected real value Q given the evidence F as (Norsys Software Corp, 2015; Pearl, 1988; Saltelli et al., 2010):

$$V(q|f) = \sum_{q} p(q|f)\left[X_q - E(Q|f)\right]^2 \qquad [8]$$

where, f is the state of varying node F, q is the state of the query node Q, p(q|f) is the conditional probability of q when node F is given to be in state f, X_q is the numeric value corresponding to state q, and E(Q|f) is the expected real value of Q due to a finding of state f in node F.

Based on the degree of influence, parent nodes are ranked accordingly and sensitivity analysis results are illustrated in Figure 6 and Figure 7.

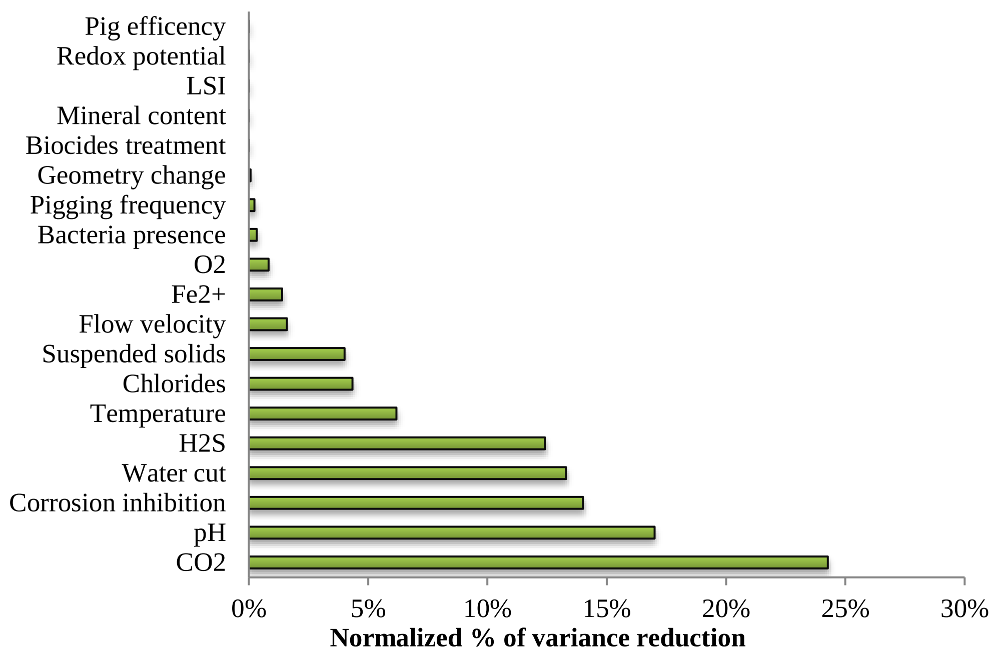

Figure 6 Sensitivity analysis of the *CR* node based on variation in the input nodes

As is shown in these figures, CO_2 concentration and flow velocity nodes have the greatest contribution in the variance reduction for the outcomes, accounting for 24.2% in *CR* node. The high degree of influence of pH can be attributed to the fact that pH is a governing parameter affecting protective films formation. When the pH is low, a pipe surface is unprotected by corrosion films, which causes high general corrosion. Conversely, at high pH levels, a corrosion film protects steel, but has the potential to be locally disrupted, and thus initiating localized corrosion. Because chlorides and suspended solids can be a predominant cause of protective film damage, these nodes have relatively high contribution for corrosion rate, making up 4.5% and 4.1% of the variance reduction. In addition, the sensitivity analysis indicates high effect of corrosion inhibition measures, namely (14.0%) for *CR* node. Parameters that are assumed to govern wettability, such as *FV* and *WC* significantly contribute to the variance reduction for the outcome. These nodes affect multiple corrosion mechanisms, which indicate its great importance for the overall corrosion assessment. The input nodes, which represent the suitability of the environment for bacteria activity (*MC, RP, BT,* and *LSI*) have a minor effect on the outcome.

Sensitivity analysis of the final output node has indicated that *Operating pressure (OP)* and *Defect Depth (DD)* are crucial parameters affecting PoF. These factors are followed by *CR* and *Outside Diameter (OD)* nodes accounting for 11.7% and 7.2% of the variance reduction. As can be noticed form Figure 7 the node *Toughness (TO)* moderately contributes to variance reduction and therefore is of importance in the proposed model.

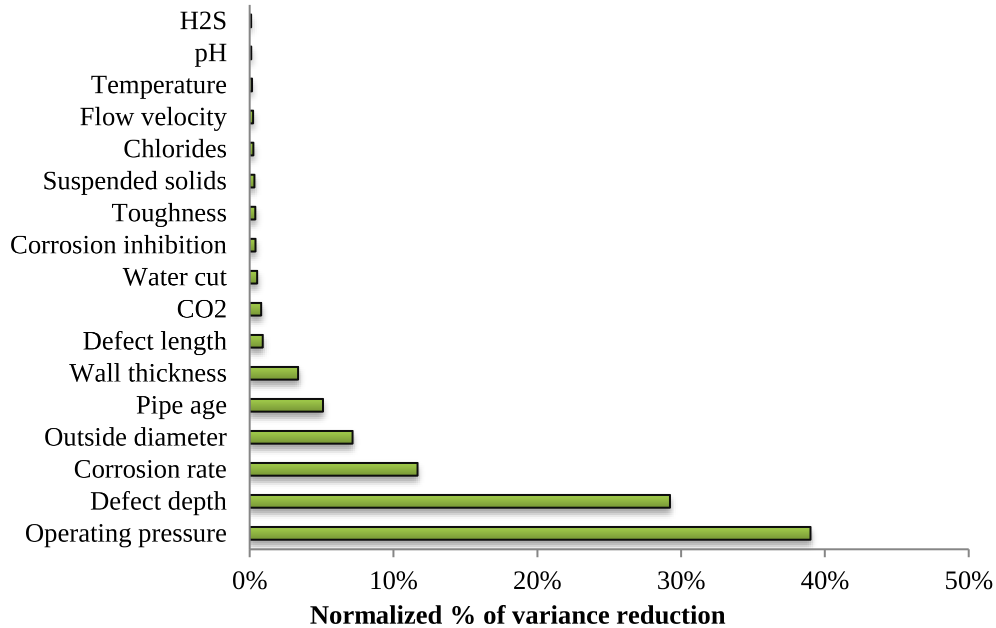

Figure 7 Sensitivity analysis of the *Pipe Failure (PF)* node based on variation in the input nodes

5. Discussion and scenario analysis

In complex probabilistic models, inputs frequently contain a various degree of uncertainty. To deal with this uncertainty, inputs can be described as random variables with defined probability distributions (Sadiq, Rajani, & Kleiner, 2004). These distributions are either subjectively defined (when data is limited or unavailable) or obtained from statistical fitting of the available data. Consequently, the output given by such probabilistic models is also a random variable with predicted distribution and associated uncertainties. In this work, two types of uncertainties are considered. It includes modelling and data uncertainties. The modelling uncertainty arises from simplified assumptions made for a complex natural process. The data uncertainty can either result from natural heterogeneity (variability) or lack of knowledge. The latter one can be reduced by obtaining more data. However, variability is the inherent property of the parameter and cannot be reduced (Oberkampf, Helton, Joslyn, Wojtkiewicz, & Ferson, 2004).

To propagate these uncertainties to the output parameters, Monte Carlo simulation is used. Monte Carlo simulation is a widely applied alternative to analytical methods to determine parameters of the output distribution based on the randomly generated values from known input distributions (Sadiq et al., 2004). To demonstrate the application of the proposed BBN model, a random vector of operation and pipeline parameters has been generated from subjectively defined distributions. Then, this random vector is applied in Monte Carlo simulation for 4000 iterations. Parameters used as well as characteristics of the applied probability distributions are summarized in Table 8.

Table 8 Probabilistic data of input parameters

Parameter		Scenario 1			Scenario 2			Scenario 3		
		PDF	Mean	Stdev	PDF	Mean	Stdev	PDF	Mean	Stdev
1	pH level	LN	6.5	0.65	LN	5.8	0.58	LN	5.3	0.53
2	Temperature (ºC)	N	37	5	N	42	7	N	29	9
3	CO_2 pressure (Bar)	U	[0…7]		LN	1.191	0.596	LN	0.621	0.311
4	H_2S (ppm)	fixed	0		LN	7500	3750	LN	10000	5000
5	O_2 (ppb)	Unknown			Unknown			Unknown		
6	Fe^{2+} (ppm)	Unknown			Unknown			Unknown		
7	Flow Velocity (m/s)	N	1.18	0.2	N	2.18	0.218	N	2.5	0.25
8	Water cut (%)	LN	18	12.6	U	[50…100]		U	[10…60]	
9	Geometry change	Yes			Unknown			Yes		
10	Suspended solids Concentration	No			No			No		
11	Bacteria presence	No			Unknown			Unknown		
12	Chlorides (ppm)	Low			Unknown			Unknown		
13	Mineral content (ppm)	Unknown			Unknown			Unknown		
14	Langelier saturation index	Unknown			Unknown			Unknown		
15	Redox potential (mV)	N	50	20	Unknown			Unknown		
16	Biocides treatment	No			Yes			Yes		
17	Cleaning frequency	U	[12…48]		U	[4…48]		U	[4…48]	
18	Cleaning efficiency	Unknown			Unknown			Unknown		
19	Inhibitor efficiency (%)	Unknown			Unknown			U	[50…80]	
20	Pipe age	fixed	2		fixed	9		fixed	15	
21	Wall thickness (mm)	fixed	3.2		fixed	4.8		fixed	3.2	
22	Outside diameter (mm)	fixed	88.9		fixed	168.3		fixed	88.9	
23	Toughness (Low/High)	High			High			High		
24	SMYS (MPa)	LN	395	27.65	LN	395	27.65	LN	395	27.65
25	OP (MPa)	LN	6.96	0.696	LN	3.97	0.397	LN	2.07	0.207

N – normal distribution; LN – Lognormal distribution; U- uniform distribution

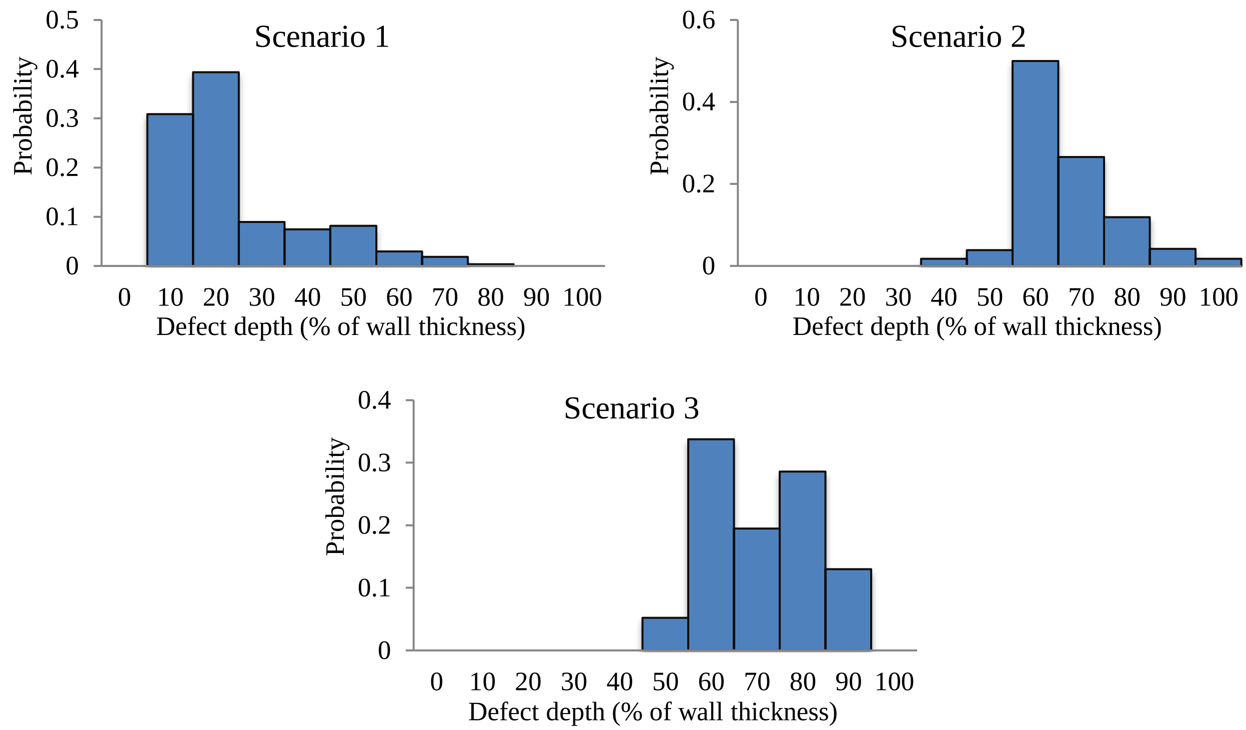

Figure 8 Predicted relative defect depth distribution for scenario analysis

The first scenario reflects recently constructed small diameter pipeline operating under high pressure in sweet environment, carrying fluid with up to 10% mole fraction of CO_2. Scenarios 2 and 3 show pipes operating under moderate and low pressure, conveying oil effluent with 0.75% and 1% H_2S, respectively, (sour conditions). Corrosion inhibition as well as regular pigging are used as major means to combat internal corrosion in the given pipelines. The simulation output reflecting current internal corrosion situation is presented in the Figure 8. The 50th and 90th percentile values represent central tendency estimate (CTE) and reasonable maximum estimate (RME) (Table 9).

Table 9 median and maximum defect depth and PoF

Parameter	Scenario 1	Scenario 2	Scenario 3
Defect depth (CTE)	0.21	0.59	0.63
PoF (CTE)	0.01	0.26	0.29
Defect depth (RME)	0.57	0.75	0.79
PoF (RME)	0.18	0.51	0.69

Figure 8 shows that output results for the scenario 1 has a substantial scatter, which can be explained by significant uncertainties in the input data. More data should be gathered to reduce this epistemic uncertainty in order to clarify if the pipeline has very low or moderate PoF. In scenario 2, median defect depth reaches 0.59 of wall thickness, but due to moderate operating pressure median PoF is 0.26. Scenario 3 has the highest predicted median defect depth, which can be explained by the high corrosivity of the transported fluid and long elapsed time (15 years). Despite the reduced operating pressure, this pipeline has the highest median value of PoF, thus it needs to be inspected first to eliminate uncertainties and reach the decision regarding appropriate maintenance strategy.

Since in scenario 1 pipeline showed corrosion problem shortly after it has been commissioned, it is essential to know corrosion defect and PoF evolution over its lifetime. In order to prevent leak or rupture at the later stage of pipeline operation, it is a common practise in the oil & gas industry to reduce the operating pressure as the pipeline ages. In this paper, it is assumed that the pipeline operator decreases the mean value of the operating pressure linearly up to 50% of its initial value at the end of the service life (20 years). It can be expressed as follows:

$$P(t) = \left(1 - \frac{t}{40}\right) * P_{in} \quad [9]$$

where P(t) is the mean value of the operating pressure at time t (MPa); P_{in} – is the mean value of the initial operating pressure.

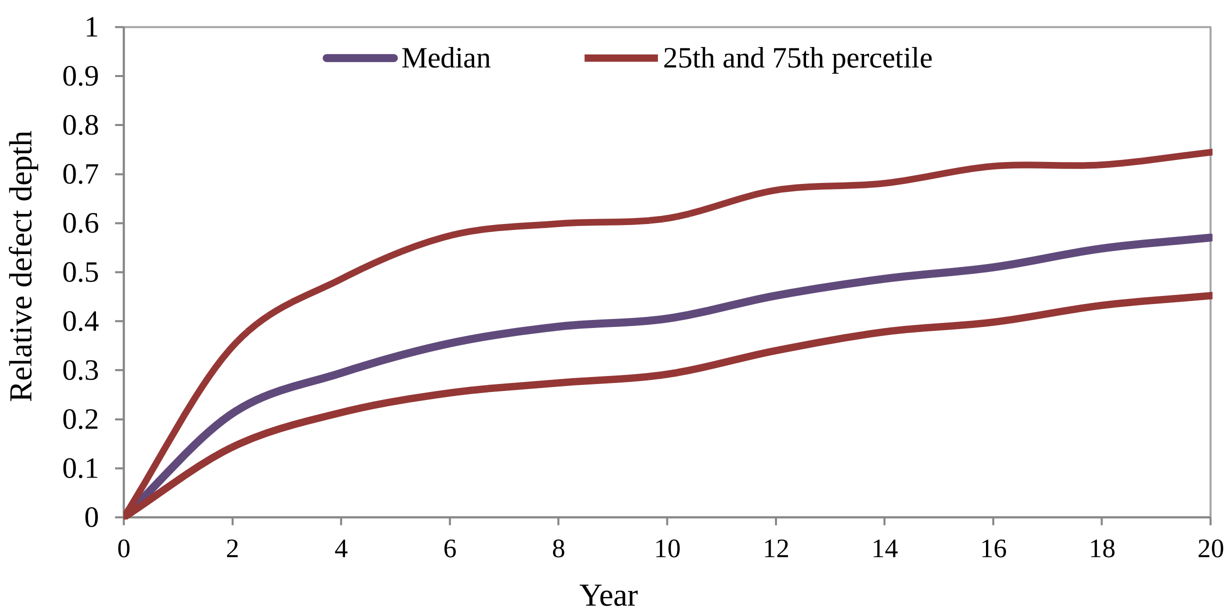

Figure 9 defect depth evolution over 20 years of the pipeline service time

Figure 9 demonstrates a substantial growth of the corrosion defect within 4 years with the following stabilization. The 25th and 75th percentile interval shows the uncertainty range in the simulated data.

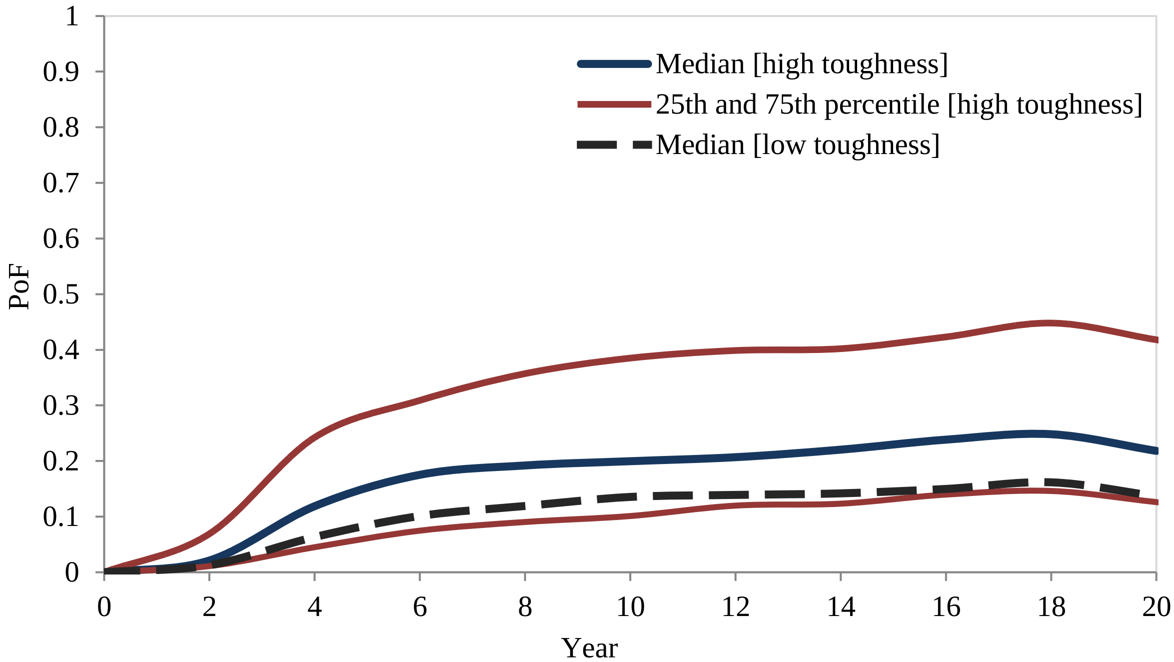

Figure 10 PoF evolution over 20 years of the pipeline service time considering different toughness

Figure 10 depicts the predicted evolution of the PoF as a function of time in service. As is shown, PoF significantly increases within 6 years of the pipeline operation. This is due to a rapid growth of the defect depth and length within this time, which leads to a reduction in pressure resistance capacity. In addition, it is observed that despite the gradual decrease in operating pressure, median PoF grows till 18 years, reaching the value of 0.248. Subsequently, scheduled decline in operating pressure contributes more to PoF than corrosion defect growth, which results in the overall drop of the PoF. As mentioned before it is essential for the PoF prediction to have information regarding toughness of the pipeline steel, which governs the selection of the appropriate failure pressure model. To demonstrate this, the same analysis has been implemented, while considering low steel toughness. Figure 10 shows that the difference in PoF is quite significant, accounting for 73.2% at its maximum (t = 6 years). As was expected, uncertainty in failure probability prediction and corrosion defect depth increases with elapsed time.

6. Case study of Northeastern BC pipeline infrastructure

In this paper, to illustrate the application of the proposed BBN model, internal corrosion hazard has been assessed for oil & gas pipeline network, located in Northeast of British Columbia (BC), Canada. The region under study is the most essential gas production area in BC, and accounts for more than half of the provincial gas production (BCOGS, 2014). As of 2014, 75% of the product was being extracted from unconventional sources, with production levels reaching 2.3 billion cubic feet/day accompanied by substantial generation of condensate and gas liquids. To transport the extracted fluid, over 3000 kilometers of pipeline infrastructure has been constructed. Since the gas production boomed in the mid-2000s the majority of the pipelines are in the early stage of their life cycle (less than 10 years). Figure 11 summarizes important data on the studied region. Around 65% of the infrastructure is operated in sour environment with H_2S concentration ranging from 0.01% to 32% mole fraction.

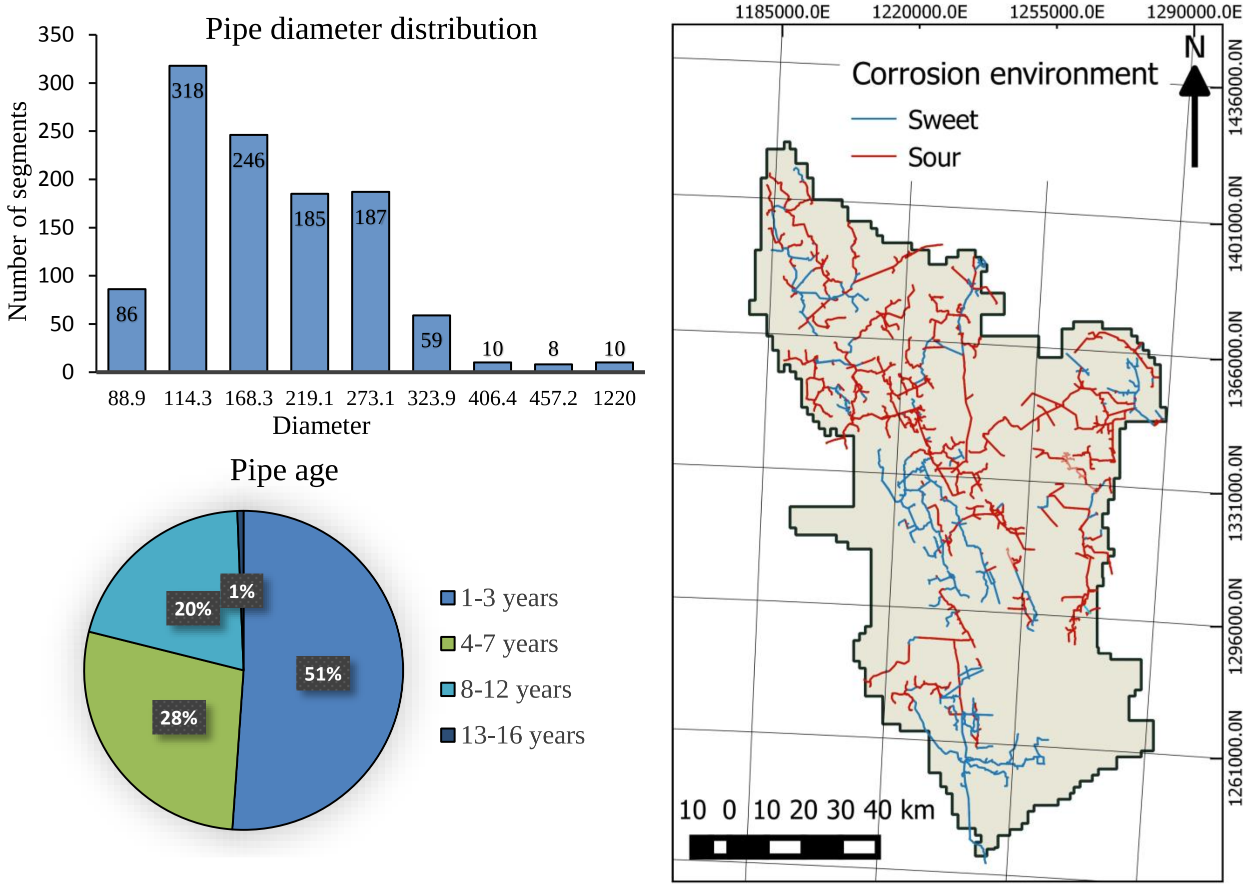

Figure 11 Data summary on studied region

To perform the analysis, spatial, mechanical and fluid composition data has been obtained from publicly available sources (BCOGS, 2015a; BCOGS, 2015b). Although, several parameters were unknown, the most important ones for the model (based on the sensitivity analysis), namely operating pressure, outside diameter, pipe age, wall thickness were available for each segment, making the analysis feasible.

The output of the proposed BBN model is reported as maximum defect depth in the pipeline segment and its PoF due to this defect. For simplicity and representation purposes, the output is grouped in *low, medium* and *high* categories, which corresponds to [0-25%], [25%-50%], [50%-75%] of the wall thickness loss for defect depth parameter and [0-10%], [10%-40%], [40%-100%] for the probability of failure. Though, a decision maker can tune these thresholds, according to experience or pipeline condition and location.

Figure 12 shows the BBN model predictions for various diameters of Northeastern BC oil & gas pipeline infrastructure. This figure indicates that the majority of the pipe segments with small diameter (88.9 mm and 114.3 mm) may contain corrosion defects with medium or high depth. Consequently, pipelines of this type have 71% and 6% of segments being in medium and high risk of failure states. Mostly, it can be explained by the high corrosivity of the transported fluid as well as thin walls of small diameter pipes. To eliminate failure, operators and regulatory authorities should pay a special attention to these pipelines, establishing appropriate monitoring and preventive measures (e.g. gradual pressure reduction, corrosion inhibition.) Segments with high diameter (168.3 and higher) have been predicted to be relatively safe to operate, without being in the high state for probability of failure. However, to minimize failure, timely inline inspections or repair actions are recommended for some segments of pipelines (with diameter of 168.3, 219.1 and 273.1 mm), because they most likely contain corrosion defects with the high relative depth.

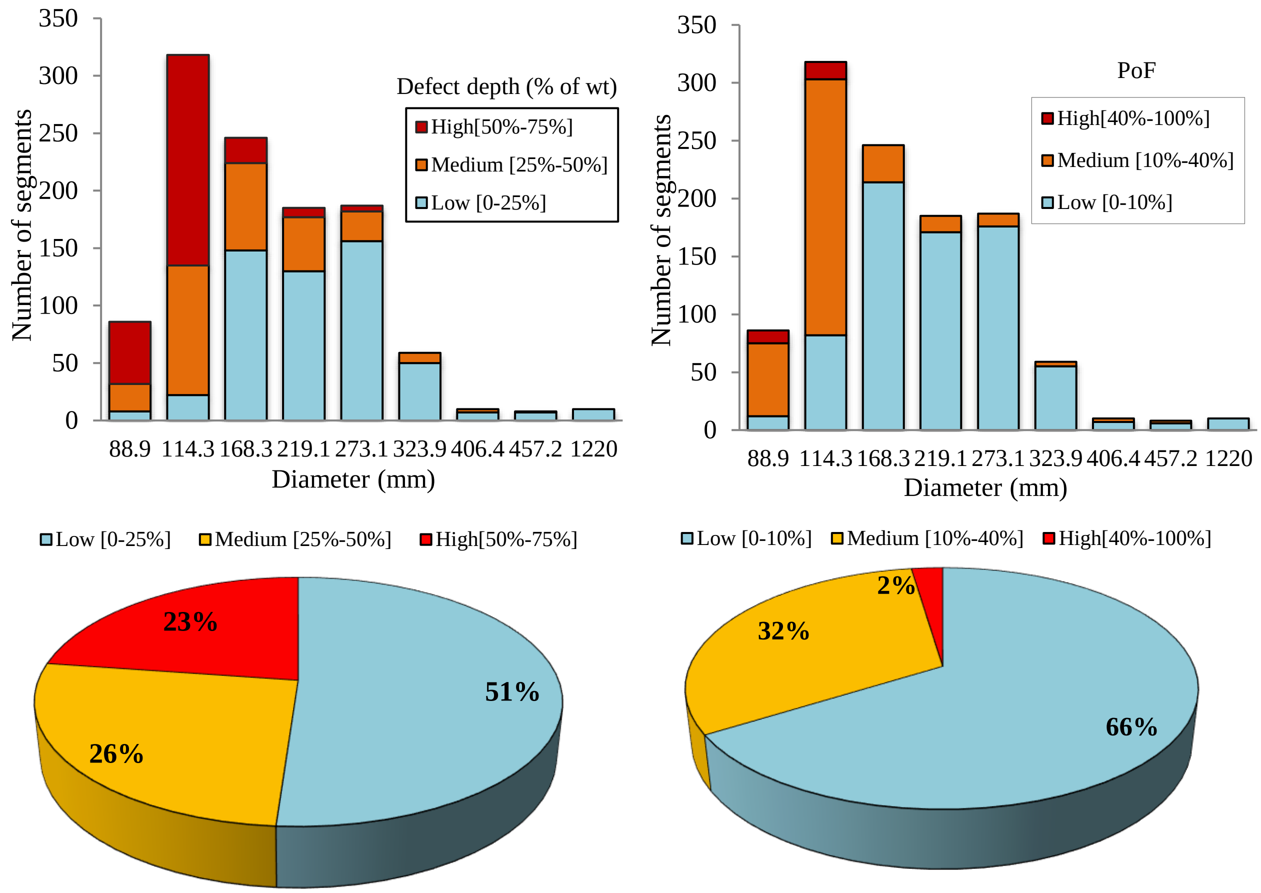

Figure 12 Median defect depth (left) and PoF (right) distributions for the Northeastern BC pipeline infrastructure

Finally, to facilitate failure mitigation programs and to improve resources allocation strategies for Northeastern BC infrastructure, spatial distribution of the predicted parameters have been created with the aid of publically available GIS software QGIS (QGIS, 2015).

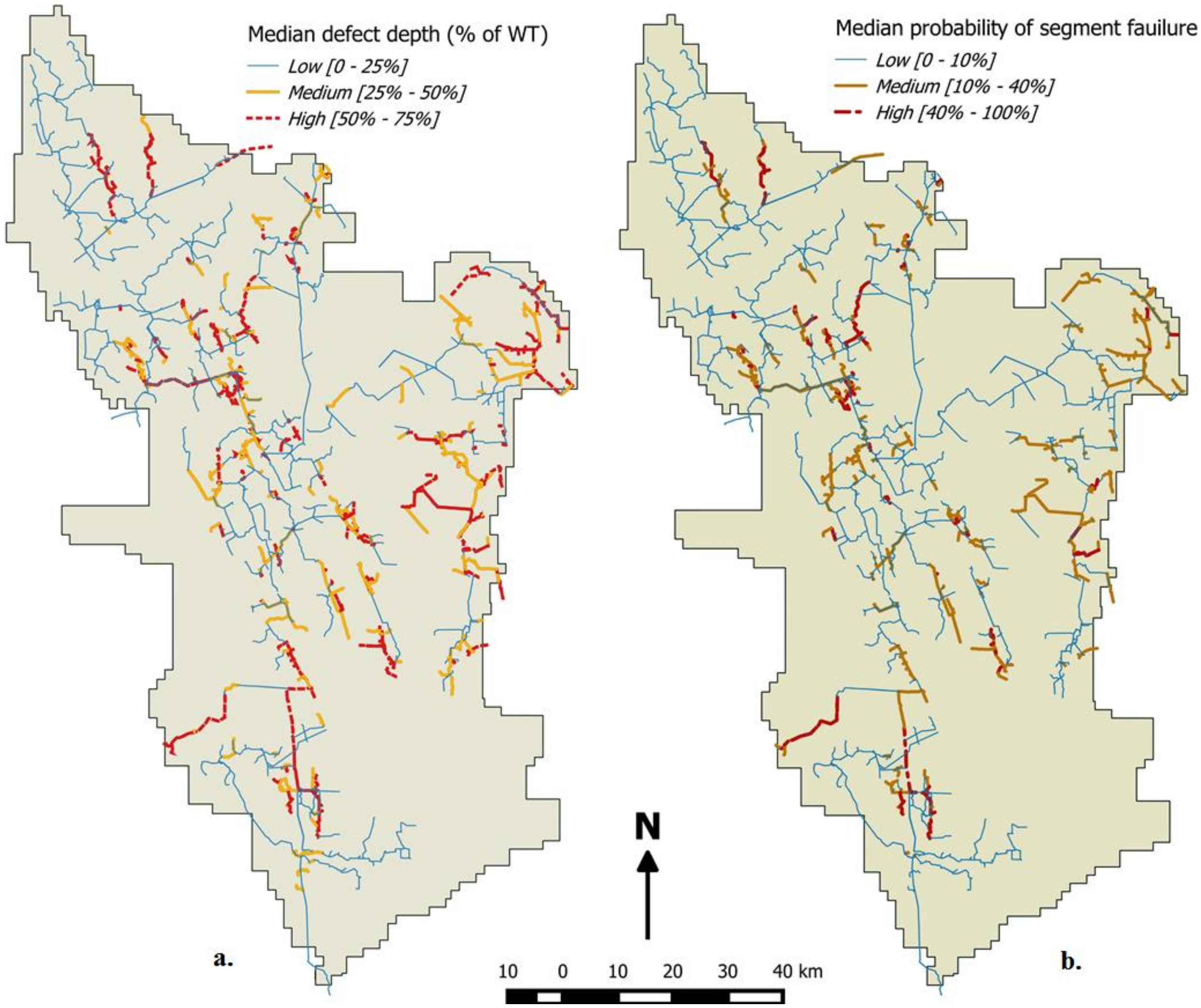

Figure 13 Spatial distribution of the predicted median defect depth (a) and median probability of failure (b)

7. Conclusions

The main objective of this research was to develop a flexible approach that incorporates analytical models (based on physical properties of the system), published literature and expert judgments in order to determine defect depth and PoF in pipeline infrastructure subjected to internal corrosion. This incorporation is particularly useful for the purpose of corrosion assessment because corrosion modeling results, predicted by different models are often inconsistent with each other and with the actual field data. A thorough literature review has been performed to identify forty four different factors and their interdependencies, affecting corrosion severity and PoF. Quantitative probabilistic approach using BBN has been performed to predict the output parameters. The necessity of using this approach was dictated by the high degree of uncertainty in the input data as well as by uncertain nature of the corrosion process. MC simulations have been applied to the BBN model, which is comprised of various corrosion models and failure pressure models. Scenario analysis has been performed to illustrate the proposed model performance. In addition, the BBN model has been used to estimate corrosion propagation and PoF evolution over a pipeline service time. Also, the proposed BBN model is able to distinguish between low and high toughness of the pipe steel, which is rarely considered in reliability analyses, but as was demonstrated, can drastically affect the outcome. Internal corrosion severity as well as probability of failure has been estimated for Northeast BC pipeline infrastructure. Results indicated that small diameter pipelines are the most vulnerable and prone to failure. The flexibility of the proposed BBN approach allows the model to be extended in order to include more corrosion contributing factors as well as new information. Furthermore, the proposed model is able to perform a diagnostic analysis, which can indicate a cause of severe corrosion.

Sensitivity analysis indicated that such inputs as operating pressure, corrosion defect depth, and corrosion rate predominantly influence the model output. It is essential to accurately estimate these parameters in order to precisely predict PoF. Corrosion rate has been shown to be strongly dependent on fluid pH, water cut, CO_2 and H_2S concentrations as well as corrosion inhibitor efficiency. It indicated the importance of developing and applying proper analytical models which lay the foundation for the proposed BBN model. Results obtained from this study can be employed to identify pipeline sections vulnerable to internal corrosion in order to improve the corrosion mitigation program as well as pipeline maintenance strategies. In addition, the model can be used to predict the safe operating pressure at a given time in the future (t). Thus, field operating pressure can be adjusted accordingly to guarantee pipeline integrity over its full service time.

8. Acknowledgement

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