Ocean Engineering 226 (2021) 108852

Contents lists available at ScienceDirect

Ocean Engineering

journal homepage: www.elsevier.com/locate/oceaneng

Microbiologically influenced corrosion (MIC) management using Bayesian inference

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ARTICLE INFO

Keywords:
Safety management
Subsea pipeline
Uncertainty
Pipeline
Markov chain Monte Carlo method
Bayesian analysis

ABSTRACT

Microbiologically influenced corrosion (MIC) is a complex phenomenon that occurs when a microbial community is involved in the degradation of an asset (e.g. pipelines). It is widely recognized as a significant cause of hazardous hydrocarbon release and subsequently, fires, explosions, and economic and environmental impacts. This paper presents a new MIC management methodology. The proposed methodology assists in accurately monitoring MIC activity and accordingly develop strategies to manage it. The MIC monitoring and management activities are achieved using Continuous Bayesian Network (CBN) technique with Hierarchical Bayesian Analysis (HBA). The integration of HBA and CBN helps overcome the Bayesian network's discrete value limitations (BN) and source-to-source uncertainty for each node in the network. The methodology can provide the precise value of parameters, such as failure probability and MIC occurrence rate which are verified using observed data. The application of the methodology is demonstrated on a subsea pipeline. The study provides a better understanding of the influencing factors of MIC rate and failure probability. This assists in developing effective MIC management strategies.

1. Introduction

Microbiologically influenced corrosion (MIC), also known as biocorrosion, is a significant threat to asset integrity in most industries especially in oil and gas industrial sectors (Taleb-Berrouane et al., 2018; Technol and Gu, 2012; Xu et al., 2016). Because of their activities based on metabolites MIC is caused by microbial biofilms, where their activities reflect in reservoir souring and asset deterioration (Gu et al., 2019; Ibrahim et al., 2018). As industrial assets age, MIC becomes a common risk factor leading to an accident (e.g. fluid flooding, leakage, rupture, *etc*). Besides, MIC has been extensively reported as annually causing the loss of billions of dollars in the US (Walsh et al., 1993). MIC has been attributed to approximately 10% of corrosion cases in the UK (Romero et al., 2000), the largest, Prudhoe Bay's oil spill occurred due to MIC in 2006 (Ibrahim et al., 2018), and Alaskan pipeline leakage was caused by microbial activities.

Staying with the aforementioned introduction, performing MIC management is therefore vital, whereby operators can use quantitative, semi-quantitative, and qualitative models to support decision making to manage corrosion. MIC management, underlying the idea of corrosion management approaches, should employ the key factors of recently introduced corrosion management systems (CMS) (Morshed, 2011) to make sure that all required MIC preventives, control and mitigative actions are performed in a sustainable, well-established, and effective manner (Lund et al., 2017; Skovhus et al., 2018). Three main steps need to be considered in any corrosion management approach: (i) understanding the MIC threat mechanism and how it affects the assets, (ii) recognizing and performing an appropriate management practice, and (iii) monitoring the management practices to examine whether the practices are effective or need further modifications (Lund et al., 2017; Skovhus et al., 2016). These steps are taken into account based on CMS procedures on a daily, weekly, monthly, and annual basis. Thus, corrosion management in general, and MIC specifically, can be viewed as a supporting program, in which management practice is presented and facilitated. It should be highlighted that MIC management in an ongoing and continuous process since MIC is known as an asset integrity threat, which further increases the operational risk. Therefore, MIC management has to follow the ISO 31000 ("ISO 31000: Risk Management," 2009) framework on risk management.

There are a considerable number of corrosion management programs

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https://doi.org/10.1016/j.oceaneng.2021.108852
Received 3 September 2020; Received in revised form 2 March 2021; Accepted 3 March 2021
Available online 19 March 2021
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based on the reliability/availability of assets proposed by both the academic and industrial sectors over the past few decades. These management programs are typically categorized into different classes, namely: (i) calculating the failure probability of asset (pipeline) over a period (before and after launching in-line inspection and cleaning tools), (ii) repairing the defect if required, (iii) optimizing the periodic schedule of in-line inspection tools to determine the defects and corresponding sizes of the defects, (iv) manipulating operational parameters, (v) using chemical compounds (e.g. inhibitors and biocides), (vi) applying coating and cathodic protection, and combination of the classes (Gomes et al., 2013; Gomes and Beck, 2014; Javaherdashti and Alasvand, 2019a; Teixeira et al., 2008; Zhang and Zhou, 2014; Zhao et al., 2009; Zhou, 2010, 2011).

The pit depth growth models play an important role in proposing a corrosion management practice, to approximate the failure probability of the pipeline as a function of time, predicting the remaining strength of the pipeline, as well as examining the defect's location and determining the efficiency of each management practice. This is why utilizing the data collected from pipeline history over time is essential for the industry to develop a pit depth growth model in a much more realistic way. In literature, pit depth growth models can be developed by using conservative and non-conservative techniques. The latter may lead to critical defects being overlooked by the management practice and increase the occurrence of serious consequences. On the other hand, the conservative pit depth growth models will increase the uncertainty of management practice (Zhang et al., 2014). Developing a mechanistic model for pit depth growth models is an intrinsically complex process as it may include two types of variables, namely temporal and spatial. The temporal variables are defined as the pit depth growth path of a defect that varies over time, while the spatial variables are defined as the pit depth growth path of more than one defect. However, all variables may be correlated. The probabilistic pit depth growth model is widely used in the literature as random variables and stochastic-based models. It simply means that the pit depth growth is considered to follow a linear or power-law function of time (Ahammed, 1998; Ahammed and Melchers, 1996; Teixeira et al., 2008; Zhang and Zhou, 2014; Zhou, 2010, 2011). As an example, the growth of a corrosion defect is characterized by utilizing the Markov process and a gamma distribution with a shape and scale parameter as time-variant and time-invariant, respectively (Noortwijk, 2009; Noortwijk et al., 2007; Pandey et al., 2009). A gamma process is employed to characterize corrosion growth of the multiple defect (Maes and Dann, 2007). A non-homogenous Markov process is used for pit growth according to the experimental data for Aluminum (Maes and Dann, 2007). A non-homogenous Markov process is also used by (Caleyo et al., 2009; Valor and Caleyo, 2007) to characterize the pitting corrosion, in which Weibull distribution is assumed for corrosion initiation time. A power-law function of time is considered to model the parameters in transition probability. In another study, the time-dependent transition intensities were examined by collecting the pipeline defect information with in-line inspection tools (Hong, 1999). However, there are significant challenges associated with modeling the pit growth by adopting Markov process-based models: (i) selecting a transition probability function and the sufficient numbers of damage state, (ii) using data from in-line inspection tools introduces the uncertainties as well as errors, and (iii) facing the spatial correlation between the defects.

This is why the Bayesian-based methodologies are robust and powerful tools, utilizing data for pit depth growth modeling. As an example, hierarchical Bayesian methodology and dynamic Bayesian networks, by incorporating new data, have been used to analyze the deterioration mechanistic model of corrosion and updating the parameters in the model (Palencia et al., 2019; Teixeira et al., 2019; Xiang and Zhou, 2018; Zhang and Weng, 2020). The hierarchical Bayesian analysis (HBA) is utilized to model the pit growth in the pipeline (Zhang et al., 2014). Researchers used a non-homogenous gamma process to derive the probability distribution for the parameters within multiple defects. In another study, Al-Amin et al. (2014) developed a pit depth growth model for a specific defect using HBA based on the data obtained from the in-line inspection tools. A hierarchical Bayesian framework was developed by Qin et al. (2015) to model defect generation and growth of metal deterioration in oil and gas steel pipelines. Pesinis and Tee (2018) proposed a framework to estimate corrosion-based failure probabilities of underground natural gas pipelines and corrosion growth defects by using a hierarchical Bayesian model. A hierarchical Bayesian model based on a non-homogeneous gamma process is proposed considering the operational conditions of a pipeline over a period of time (Groth, 2019). Zhang and Wang (Zhang and Weng, 2020) used a Bayesian network (BN) to construct a knowledge-based model by analyzing the failure probability and leakage size of corrosion for an underground gas pipeline.

However, in all aforementioned studies, there is a lack of comprehensive pit depth growth modelling considering both model and data uncertainties, which further helps on-site operators to make decisions by proposing a management practice. Therefore, to deal with the lack of previous studies, CBN along with HBA can be used. CBN which can be considered as an extension of typical BN (Song et al., 2017) is a powerful tool and can handle model uncertainty using adaptive models. In addition, CBN, by utilizing continuous nodes, can better reflect those variables that change continuously in nature. CBN and its extensions have been broadly used such as, but not limited to the field of safety, reliability, and risk management (Hossain et al., 2019; Kabir et al, 2018, 2020; Khakzad et al., 2013; Misuri et al., 2018). HBA is also a robust technique to deal with different sources of information known as data uncertainty. In safety, reliability, and risk management domains, the existing data is generally inadequate to conduct analysis, especially modeling the pit depth growth, where improper modeling causes pipeline failure. Thus, to obtain acceptable results to support decision making, HBA utilizes and then aggregates a wide range of information. In addition, in recent years, the availability of Markov Chain Monte Carlo (MCMC) using a sampling application can help decision-makers to fully track performing HBA (Kelly and Smith, 2009; Khakzad et al., 2014b; Siu and Kelly, 1998; Yang et al., 2012).

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

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

1.1. Continuous Bayesian Network

The BN has enough capacity to analyze the behavior of each node over time given new data, making it one of the most powerful and robust tools. Common BN-based approaches have been widely used in different engineering domains such as, but not limited to (Abimbola et al., 2016; Adesina et al., 2020; Arzaghi et al., 2018; Noroozi et al., 2013; Taleb-Berrouane et al., 2020; Yazdi et al., 2020; Zarei et al., 2019; Zinetullina et al., 2019). BN-based approaches can employ different types of input data (objective or subjective) to estimate the probability centered event by reducing the model uncertainty with consideration of interdependency between all the participating nodes. However, the common BN-based models ignore the preciseness and modeling flexibility since the discrete nodes are used in the models. In other words, the common BN-based approaches consider the continuous nature of causal factors in

the network as discrete variables. Therefore, these types of estimations provides uncertainty during the analysis process (Adumene et al, 2020a, 2020b, 2020c; Bhandari et al., 2015; Xia et al., 2018; Yazdi et al., 2019; Zarei et al., 2020). In real-world applications, there are often variables that continuously change over time and therefore cannot be modeled using common BN-based models with discrete variables. Such is the case for MIC.

To deal with the abovementioned drawbacks, the common BN-based approaches can be further developed as a CBN considering the continuous causal factors. In CBN, the nodes of the models can be represented as a combination of discrete and continuous variables. To see how CBN can be constructed from a common BN-based model, Guozheng et al. (Song et al., 2017) proposed a framework to convert BN into the CBN. According to this study, two significant changes are required so that the parental nodes can quantitatively signify the child nodes. First of all, all nodes with a continuous nature in BN-based modes must be defined by employing measurable variables. Next, the child nodes' value in CBN needs to be represented as a function of the parental nodes' value. This simply means that the conditional probability tables (CPTs) in the common BN-based models are transferred into the conditional probability distributions or mathematical functions that represent the relationships between the value of the child and parental nodes.

In CBN, the computation of posterior distribution becomes much more complex and therefore the analytical methods or Monto Carlo simulations cannot compute the posterior distributions. Markov Chain Monto Carlo (MCMC) is a robust tool and has high level capacity to compute the complicated posterior distribution with high dimensions. To elaborate, MCMC has two main parts (i) Monto Carlo, and (ii) Markov Chain. Monto Carlo refers to a method that relies on the generation of random numbers and Markov Chain refers to a sequence of numbers in which each number depends on the previous number in the sequence. However, Monto Carlo simulations fail to sample from the complicated distribution which has different types of dependent variables. To handle this issue, Markov Chain is used to assist Monto Carlo, and therefore MCMC is utilized. To obtain more details about MCMC and its algorithms one can refer to (Gilks, 1996).

1.2. Hierarchical Bayesian Analysis

Simply put, Bayesian analysis is one of the main elements of the Bayesian methods that deal with the unknown parameters of a mechanistic process as random variables instead of using deterministic values. The Bayesian analysis makes use of prior knowledge about the mechanistic process' parameters which may be derived from expert opinion, past experience, and information from previous research studies. Subsequently, the prior knowledge is adjusted based on the newly observed data to update the opinions about the parameters of a mechanistic model. Furthermore, the updated belief can then be considered as the prior distribution for updating in the future as the new data becomes obtainable. Thus, by repeating this process, the data uncertainty about the parameters of the mechanistic model is reduced. Hierarchical Bayesian Analysis (HBA) (Banerjee et al., 2014) is a unique case of the Bayesian methods, in which the prior distribution is disjointed into the conditional distribution sequentially (Robert, 2007). HBA is a powerful tool for making statistical inferences about the parameters of the mechanistic model in which there are complicated interactions between the parameters. In addition, HBA is principally appropriate for population, where the model's parameters described as a sample in the population are measured to be associated with the parameters for another sample from the same population (Al-Amin et al., 2014; Demichelis et al., 2006).

Let it be assumed that there is a population of n random variable, $\mathscr{Y}_i(1=1,2,3,\ldots,n)$ which can describe similar mechanistic processes. Consider that there is a set of unknown parameters where θ_i denotes the probability distribution of a random variable $\mathscr{Y}_i$. The prior distribution $p(\theta_i|\omega)$can be assigned to θ_i, in which $p(\theta_i|\omega)$ signifies the PDF of θ_i and is conditioned on the known parameters ω, and are considered to be common to the population of $\mathscr{Y}_i$. Moreover, let it be us assumed that y_i denotes a set of observed data for $\mathscr{Y}_i$. The updated opinion of θ_i can be obtained using Bayes' theorem (Fenton and Neil, 2013) by combining the prior distribution and the observed data in the following Equation:

$$p(\theta_i|y_i)=\frac{L(y_i|\theta_i)\times p(\theta_i|\omega)}{p(y_i)} \tag{1}$$

$L(y_i|\theta_i)$ is the known likelihood function is based on the information provided by the data, which is conditional on θ_i. Besides, the entity $p(\theta_i|\omega)$ is called the posterior distribution, which reflects the combination information of prior information and obtained new data. The quantity $p(y_i)$ is the normalizing constant which confirms that the left-hand side of Equation (1) is a probability distribution. The $p(\theta_i|y_i)$ integrates to be unity and is known as the marginal likelihood, which can further be determined by integrating the numerator on the right-hand side of Equation (1), regarded as θ_i.Therefore, the following Equation can be derived:

$$p(y_i)=\int L(y_i|\theta_i)\times p(\theta_i|\omega)d\theta_i \tag{2}$$

Keeping the normalization constant in mind, using proportionality symbol ($\propto$), Equation (1) can be rewritten as:

$$p(\theta_i|y_i)\propto L(y_i|\theta_i)\times p(\theta_i|\omega) \tag{3}$$

The abovementioned explanations are based on standard Bayesian formulations, where it is assigned a prior distribution into the parameterθ_i by controlling the distribution $\mathscr{Y}_i$. However, the standard Bayesian formulations can be further developed by considering that the parameter ω which controls the distribution of θ_i is a random variable as well, by assigning the prior distribution, $p(\omega|\psi)$, into the ω. According to this extension, the$p(\omega|\psi)$ is named as hyper-prior and ψ in named as hyper-parameter (Banerjee et al., 2014; Robert, 2007). In addition, the hyper-parameter can be known and can present the prior belief about ψ. In practice, ω can be also be treated as random variables and proceed to the next level of hierarchy. As can be seen from Fig. 1 (modified after (Banerjee et al., 2014)), the simple graphical structure of a common HBN of extended Bayesian model is provided. Therefore, the extended Bayesian model can be summarized as follows:

i. Likelihood of data: $L(y_i|\theta_i)$,
ii. First stage of prior:$p(\theta_i|\omega)$,
iii. Second stage of prior:$p(\omega|\psi)$,
iv. Posterior distribution of θ_i:$p(\theta_i|y_i)\propto L(y_i|\theta_i)p(\theta_i|\omega)$,
v. Posterior distribution of ω:$p(\omega|\theta_i)\propto L(\theta_1,\theta_2,\ldots,\theta_n|\omega)p(\omega|\psi)$.

In such cases, HBA can be defined in four levels, due to the fact that level one is based on inspection data, i.e., the defect depths described by

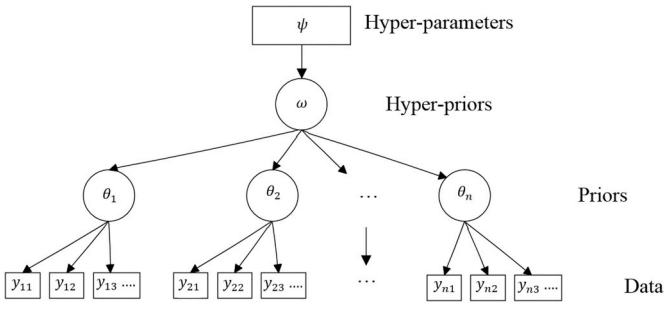


Fig. 1. The simple graphical structure of a common hierarchical Bayesian Network (square and circle nodes represent the deterministic and stochastic component).

inspections which are connected to measurement uncertainties, level two highlights the auxiliary variables, including the actual depths at the times of inspections and increments of the actual depths between two consecutive inspections, level two also makes the likelihood function for the measured depth mathematically tractable and facilitates the Bayesian updating, in level three the parameters for level two are provided (e.g., the parameters in gamma distributions), and finally in level four hyperparameters assist in finding out the parameters in level three. It should be added that based on the type of decision making problem, the level can be increased or shortened. By studying the literature and with the support of decision-makers such as, but not limited to (Al-Amin et al., 2014; El-gheriani et al., 2016; El-Gheriani et al., 2017; Khakzad et al., 2014a, 2014b), and to the best of the authors' understanding, some of the merits of HBA compared to other statistical models can be highlighted as following:

(i) HBA enables one to deal with the source to source uncertainties by utilizing the hierarchical prior assignment. Thus, the feature of HBA makes a robust estimation of the parameters, in which the posterior results are based on the average from different possible prior options (Robert, 2007).
(ii) HBA using the conditional hierarchical priors can better describe the spatiotemporally (space-time) correlated data (Congdon, 2020).
(iii) The computations of the Bayesian model are commonly simplified by the hierarchical structure within posterior distribution simplification. This results from priors' decomposition. Thus, different sampling algorithms can be employed to update the parameters (Banerjee et al., 2014; Congdon, 2020; Robert, 2007).
(iv) In HBA, a specific group or singular parameter can derive information from the equivalent of the parameters(Ntzoufras, 2011). Thus, the level of singular inference can be obtained as precisely as possible and shows its merits when the observed data and sample size are small. To characterize the pit depth for a single MIC defect of a subsea pipeline, HBA using inferences is practically advantageous, since the information that is linked to give defect is commonly limited.

The mean, standard deviation, and other probabilistic characteristics of random variables, which are entered in HBA can be determined by integrating and combining the posterior distribution. However, there is a lack of close form solutions to obtain the posterior distribution when the Bayesian Network has high dimensions and is complex. Therefore, similar to the CBN mentioned in Preliminary 2, the difficulties can be handled using MCMC techniques. In the MCMC methods, a Markov chain is initially constructed to consider the start values of the parameters, and subsequently converges to the posterior distribution which is actual target density. It should be added that the sample is dependent on the start value; therefore, the influence of the start value needs to be reduced by ignoring the first part of the sample. This period is referred to as the burning-in period. The burning-in period is the time it takes the chains to be stabilized, which means therefore that there is not up and down drifting over time by ignoring the sample in the burning-in period. Afterward, the sample can be used for Bayesian inference of the parameters. There are some important algorithms that are commonly utilized to perform an MCMC, such as, but not limited to "Metropolis random walk Hastings", "Slice sampling", and "Gibbs's sampling". To get more details about MCMC methods and corresponding algorithms, one can refer to the following references (Banerjee et al., 2014; Congdon, 2020; Ntzoufras, 2011; Robert, 2007).

2. Methodology

It is important to predict the rate of MIC as well as pit depth growth in the early stage of subsea pipeline development to provide appropriate management practice(s), which can prevent, mitigate, and control the occurrence of pipeline failure caused by MIC. However, MIC management is a challenging task for decision-makers due to a lack of information in probabilistic risk analysis. The rate of MIC and pit depth growth can be estimated by utilizing modeling techniques such as Bayesian network. Such Bayesian network modeling techniques have a number of shortfalls which result from some degree of uncertainty. As can be seen from Fig. 2, the proposed six step methodology enables consideration of both types of data and model uncertainties by modeling CBN and HBA. In the proposed methodology, CBN and HBA can deal with the model and data uncertainties, respectively.

Step 1: Constructing the mechanistic model of MIC

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

Step 2: Collecting all the required information

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

Collecting data is the key step in any kind of statistical inference. Data can be defined as an observation value in a stochastic domain which may have different sources of uncertainty. However, assessing, evaluating, manipulating, and organizing any form of data is referred as information. Knowledge, in its general form, is assembled from the information. The inference is referred to as the process of obtaining a conclusion according to what is known for us (Kelly and Smith, 2009).

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

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

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

$x_i \sim$ Poisson (λ_i, t_i) as likelihood function,
$\lambda_i \sim$ gamma (α, β) as the first state of prior,
$\alpha \sim$ gamma $(0.0001, 0.0001)$ diffusive hyperprior,
$\beta \sim$ gamma $(0.0001, 0.0001)$ diffusive hyperprior.

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

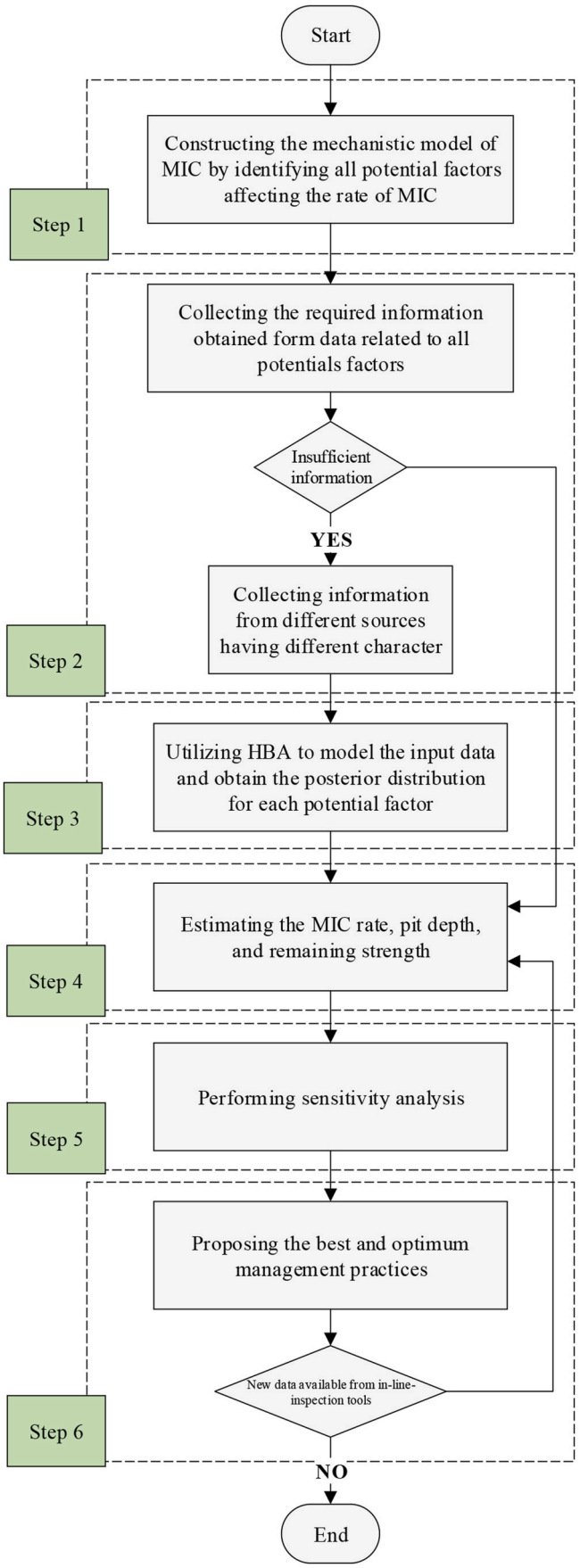


Fig. 2. The developed methodology framework.

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

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

To compute the pit depth growth over time, it is assumed that the actual depth of an MIC defect follows a power-law path. It is further assumed that the parameters of power-law growth are constant by time and quantified for each specific defect. Therefore, it is also considered that the pit depth growths of different defects are spatially independent. According to the power-law path model, the pit depth growth of the defect i at time j can be estimated in the following equation (Al-Amin et al., 2014; Zhang et al., 2014):

$$da_{ij} = a_i\left(t_j - t_{0i}\right)^{b_i} + \eta_{ij} \tag{4}$$

where the parameter a_i $(a_i > 0)$ is an indication of pit depth growth for defect i in one year from the initiation time of defect, the parameter t_j is the proceed time (elapse time in a year) from installation date until time j as the reorganization of a defect, the parameter t_{0i}represents the MIC initiation time (the proceed time from installation date to the time when defect i starts to grow), in practice $t_{0i} > t_j$, the parameter b_i $(b_i > 0)$ denotes the MIC rate of growth path, in which $b_i = 0, b_i > 0$, and $b_i < 1$ representthe linear, acceleration, and deceleration pit depth growth path, respectively, η_{ij} denotes the model error of the pit depth growth connected with defect i at time j.

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

$$a_i \sim N\left(\mu_a, \sigma_a^2\right) \tag{5a}$$

$$t_{oi} \sim U(0, t_1) \tag{5b}$$

$$\eta_{ij} \sim N_i\left(\mu_a, \sigma_{\eta i}^2\right) \tag{5c}$$

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

The prior distribution of parameter of b_i is obtained from the MIC

mechanistic model using CBN. The prior distribution parameters for a_i and η_{ij} are assigned another level of prior, named hyper-prior as they deal with the random variables. To treat the random variables, the normal and inverse-gamma distributions are considered for mean μ_a, and standard deviation $\sigma_a^2$and $\sigma_{\eta i}^2$ as prior distributions, respectively. The normal and inverse-gamma distributions are well-known conjugate priors of a normal distribution and using conjugate priors further provides posterior distributions without numerical integration (Zhang and Zhou, 2014). Keeping the above mentioned explanations, the hyper-priors can be defined as the following:

$$\mu_a \sim N(A, B) \tag{6a}$$

$$\sigma_a^2 \sim IG(C, D) \tag{6b}$$

$$\sigma_{\eta i}^2 \sim IG(E, F) \tag{6c}$$

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

The fully hierarchical Bayesian model for pit depth growth is established in Fig. 3 with respect to the aforementioned hyper-priors.

Step 5: Performing sensitivity analysis

The sensitivity analysis is carried out to study how the output uncertainty of the pit depth growth model can be separated into the different sources of input uncertainties (Saltelli, 2002). In addition, sensitivity analysis helps to validate the model by using different methods such as, but not limited to, the conditional variances-first path, conditional variances second path, higher-order sensitivity indices, total effects, *etc*. To obtain more details, one can refer to (Saltelli et al., 2008).

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

Step 6: Proposing the best and optimum management practice

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

3. Application to a case study

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

According to the first step of the developed methodology, the mechanistic model of maximum pit depth growth influence by MIC appears in Fig. 4. The mechanistic model of MIC is drawn with consideration to (i) environmental conditions, including salinity, CO_2 partial pressure, pH, O_2, temperature, water cut, and Sulphides, (ii) operational conditions including fluid velocity and pressure, (iii) material conditions including steel composition and Carbon content, (iv) biofilm, and (v) exposure duration.

In the second step, the pipeline operational data and information, according to the operational environment, are provided in Table 1 based on the combination of discrete and continuous variables. The provided data is based on literature (Adumene et al., 2020b; Arzaghi et al., 2018; Bhandari et al., 2015; Bhardwaj et al., 2020a, 2020b; Dawuda et al., 2021; Dubois, 2010; Palencia et al., 2019; Teixeira et al, 2008, 2019) and mean value of continuous variables are based on operational and chemical analysis from SeaRose FPSO. It is assumed that the pipeline contains multiple defects throughout. The non-informative distributions (i.e. distributions with small means and very large variances) are allocated as hyper-priors to the pit depth growth factors a_i , t_{oi} , and η_{ij} . To obtain pit depth growth, Bayesian updating software such as OpenBugs (www.openbugs.net) using MCMC methods is utilized by 1000000 iterations within interval 2 tinning, in which the estimated parameters of the growth models were then used to estimate the depth of a defect. Table 2 provides a chemical analysis of produced water showing the total number of microorganisms using the qPCR (quantitative Polymerase Chain Reaction) method, different types of microorganisms percentage as well as sulfate reduction rate (SRR), which further means that the defect in the pipeline is influenced by MIC. In addition, the sulfate reduction rate is used in the mechanistic model of MIC.

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

In the third step, testing data are provided from Table 1 with HBA as described in Section 3 (Preliminary of Hierarchical Bayesian Analysis) which provides a probability distribution (i.e. a predictive posterior distribution for each node in CBN) as shown in Fig. 5. The mean value of the distributions represents an adequate value of each node. After obtaining the Description and probability value of all nodes in CBN, it will then be used as prior belief in CBN to estimate the rate of MIC and

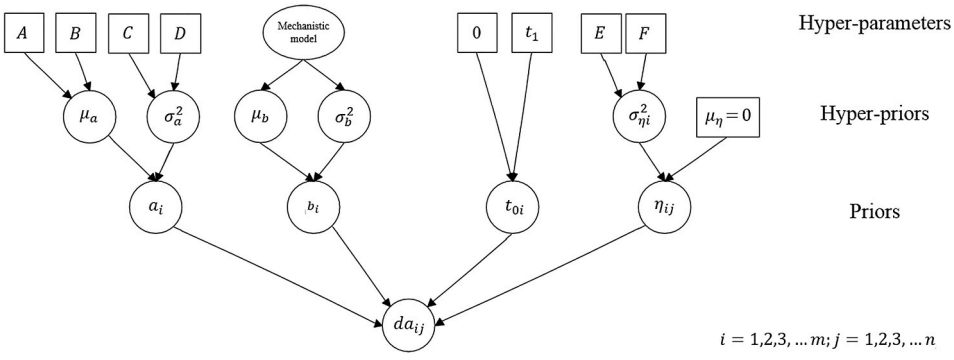


Fig. 3. The schematic representation of a fully hierarchical Bayesian model for pit depth growth (rectangular nodes and circle nodes represent the constant and stochastic (uncertain) components of the model, respectively and arcs show the relationships between the nodes which can be deterministic or stochastic).

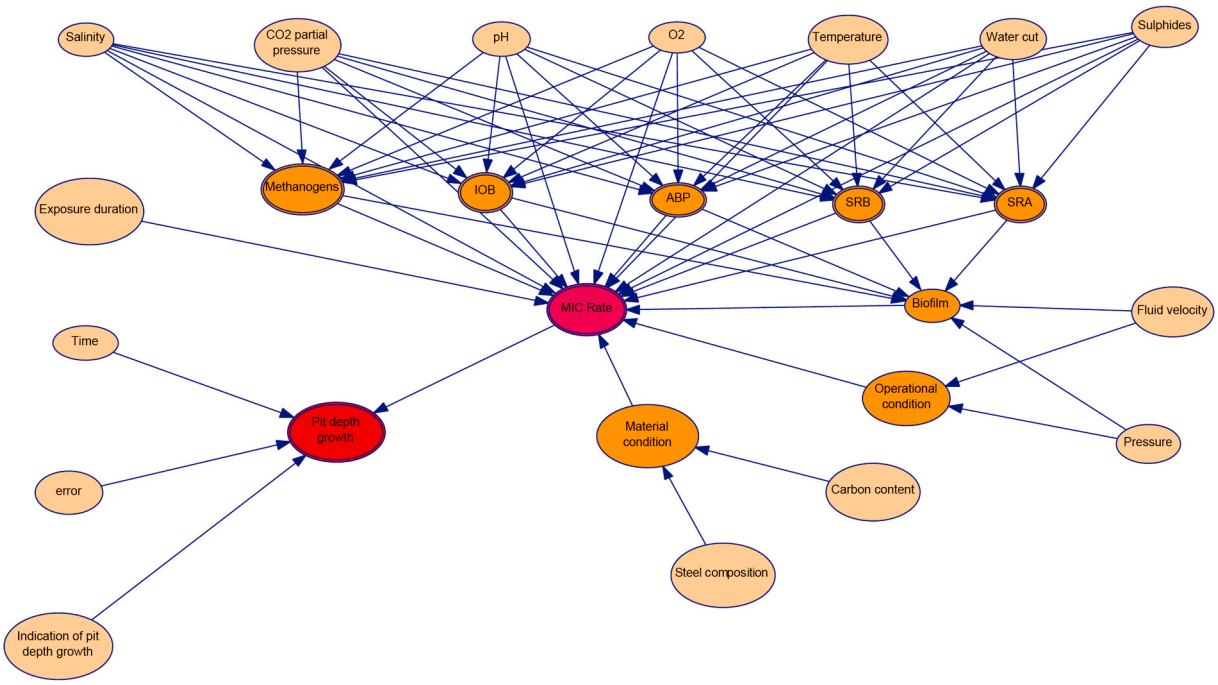


Fig. 4. The influence diagram of the mechanistic model of maximum pit depth growth influence by MIC (SRB (sulfate-reducing bacteria), SRA (sulfate-reducing Archaea), and IOB (iron-oxidizing bacteria).

Table 1
The pipeline operational parameters' data range.

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

further pit depth growth as shown in Fig. 6. As it can be seen from Fig. 6, the node "pit depth growth" is constructed based on an equation, representing that time-varying characteristics of pit depth growth considered in the BN prediction mode. In addition, it should be highlighted that parameters such as pit indication of pit depth growth using gamma distribution represent the randomness in the BN model.

In the fourth step, the probability of pit depth growth gained from the previous analysis can further be utilized to estimate the probability of pit depth growth over a period, considering that only t_j and t_{0i} are varied by time. Fig. 7 depicts the approximation of pit depth growth over a period showing mean, median, and 10 percent error.

For the fifth step, sensitivity analysis is performed as a forward propagation to understand how proposing a management practice can properly prevent, mitigate, and control MIC. In addition, it can increase the lifetime of the pipeline by decreasing the pit depth growth path over a period. Fig. 8 presents the possible management practice for the subsea pipelines influenced by MIC (Javaherdashti and Alasvand, 2019b).

The first two management practices are assumed that they are already considered in the pipeline installation. It is known as a method to prevent, or at least limit, internal contamination. The cathodic protection and coatings would be the least difficult, most economically

Table 2
Characteristic of microorganisms affecting the MIC (Chemical analysis was performed from produce water after separator (PW-Terra Nova SC003, F2-P (2019).

Category	Name of organism	Value %
SRB	Desulfacinum	0
	Desulfobulbaceae	0
	Desulfonauticus	0
	Desulfomicrobium	0
	Desulfoplanes	0
	Desulfovibrio	8.72
	Desulfuromonas	0
	Desulfuromonadaceae	0
	Dethiosulfatibacter	10.14
	Dethiosulfovibrio	0
	Fusibacter	0
	Marinitoga	0
	Sulfurospirillum	0
SRA	Archaeoglobus	38.36
	Caminicella	0
	Kosmotoga	0
	Petrotogaceae	0
	Thermacetogenium	0
	Thermoanaerobacter	1.35
	Thermoanaerobacteraceae	0
	Thermococcus	9.9
	Thermosipho	3.6
Methanogen	Methanosarcinaceae	0
	Methanothermococcus	0
	Methanolobus	0
	Methermicoccus	4.79%
IOB	Unknown	–
ABP	Unknown	–
Sum		76.86%
qPCR	3.19E+06 (16S copies/mL sample)	
SRR in situ		0.52

SRB (sulfate-reducing bacteria), SRA (sulfate-reducing Archaea), IOB (iron-oxidizing bacteria), and ABP (Acid-producing bacteria), qPCR (quantitative Polymerase Chain Reaction), SRR (sulfate reduction rate).

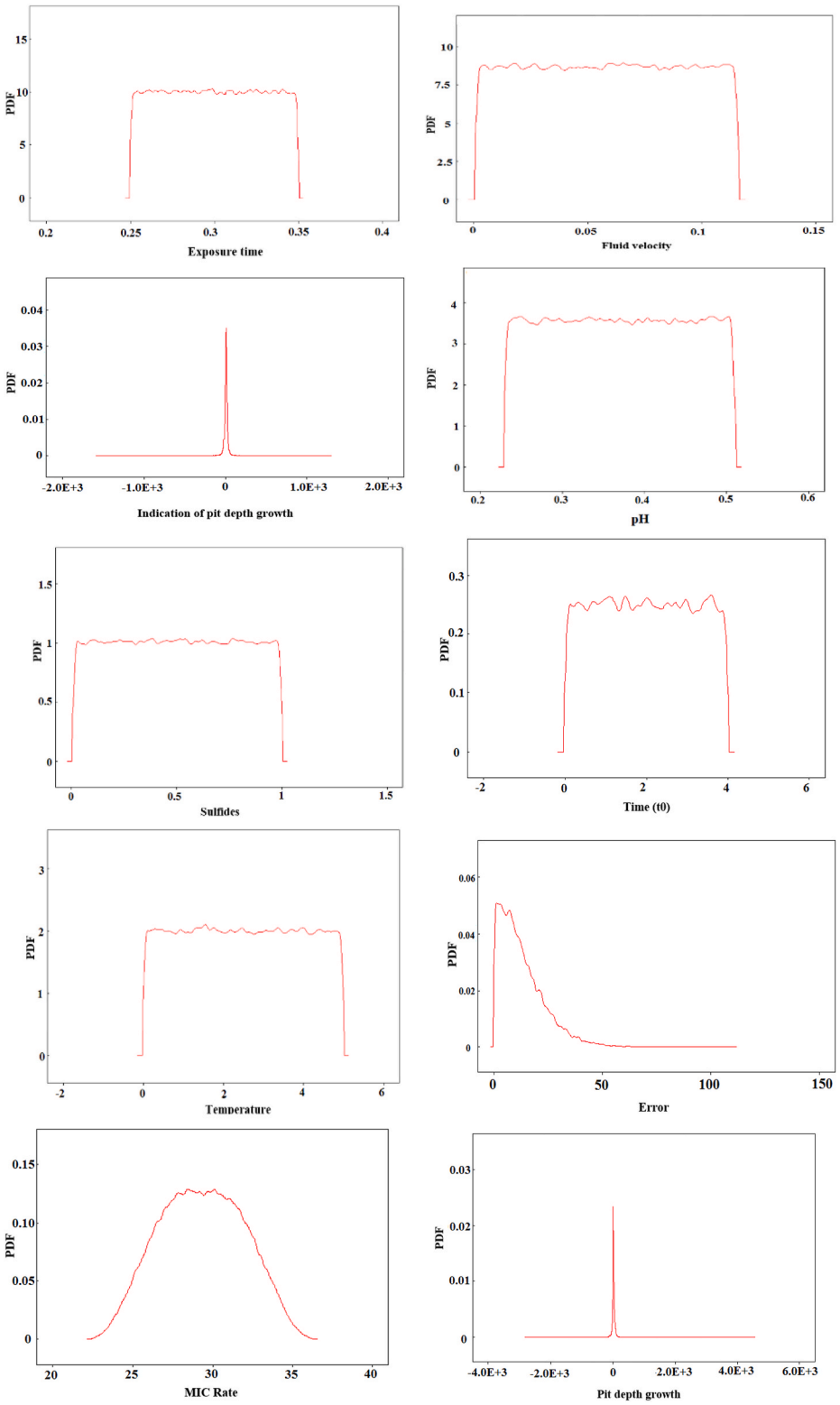


Fig. 5. Posterior predictive distribution for each root node.

friendly, and proficiently and preventively proactive to deal with MIC (Skovhus et al., 2017). The majority of offshore pipelines have coatings. The Fusion-bonded epoxy (FBE) is the most popular applied coating for North America (Orazem, 2014). Cathodic protection systems are divided into two methods (i) the sacrificial anode, and (ii) the impressed current system. In the latter, an external DC current is used to cathodically polarize the pipeline. This method of cathodic protection can be used to protect bare or poorly coated pipelines because of high current capacity. In the majority of subsea pipelines, the sacrificial anode technique is used.

As a first practice, continuous injecting inhibitors are evaluated. MIC inhibitors are those chemicals that influence anodic (chromates (CrO_4^{2-}), nitrites (NO^{2-}), phosphate, and molybdate), cathodic (Zinc salts ($ZnSO_4$), Polyphosphates ($Na_4P_2O_7$), and Phosphonates), or both types

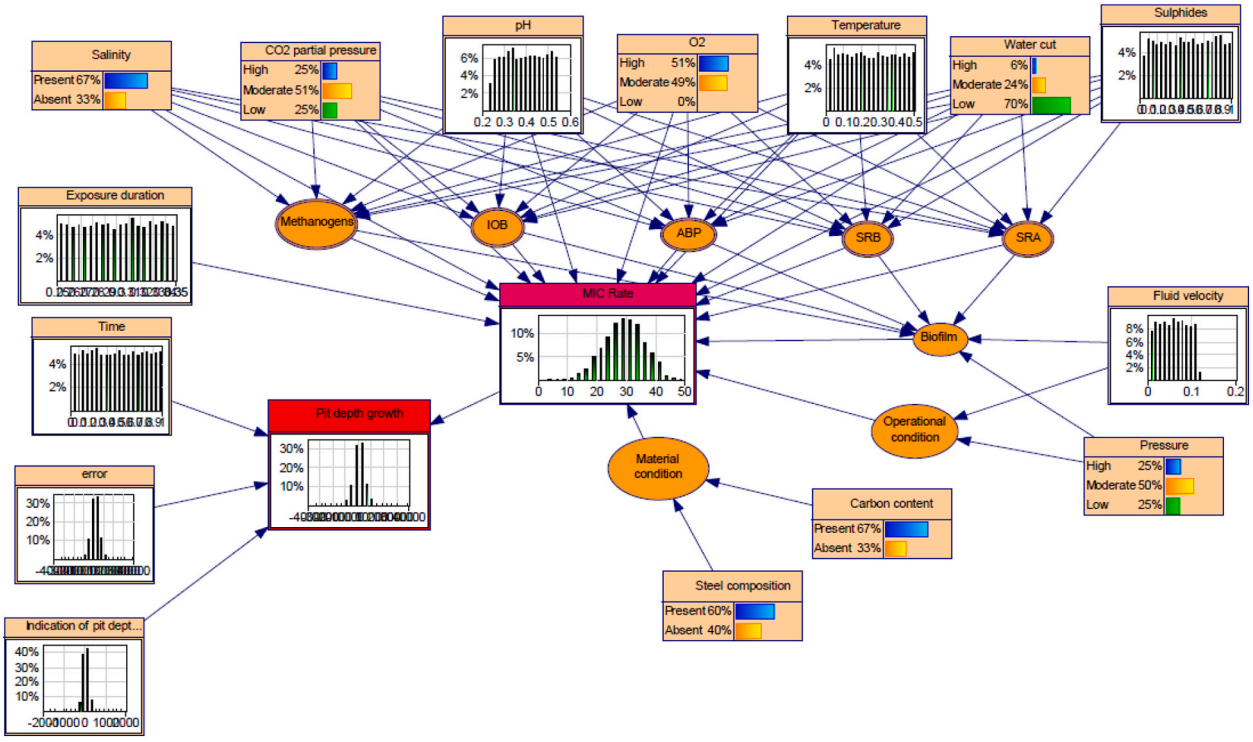


Fig. 6. The CBN for obtaining a pit depth growth.

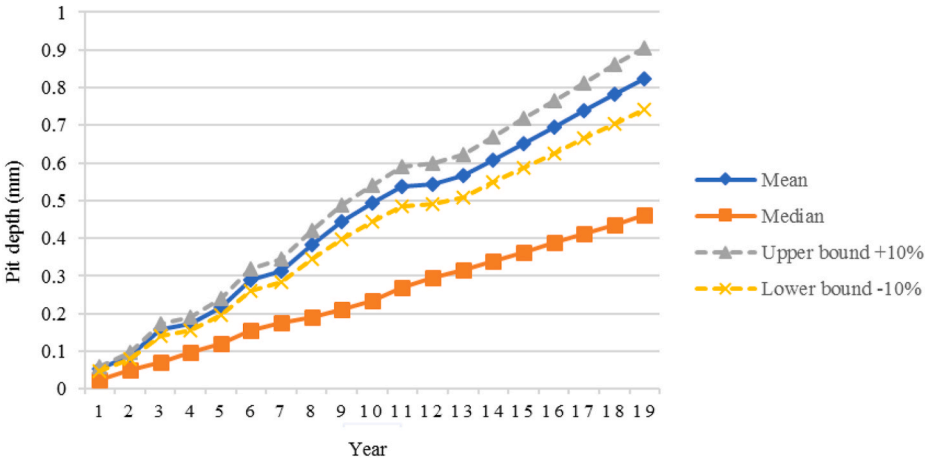


Fig. 7. The predicted pit depth growth path for the defect.

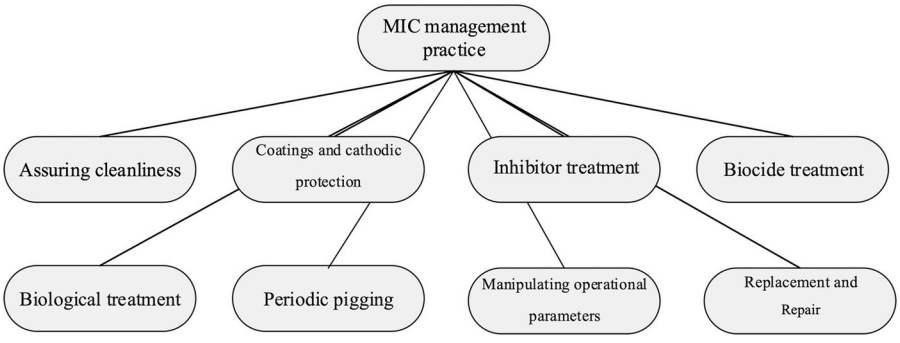


Fig. 8. MIC preventive, mitigative, and control management practice.

of reactions (polyphosphates, phosphates, silicates, and benzotriazole) to considerably reduce the rate of corrosion, in this case MIC (Chugh et al., 2020). The selection of MIC inhibitor is a difficult task for subsea industries as different types of aspects need to be taken into consideration such as, but not limited to, partitioning effect, compatibility of MIC inhibitors and other injected chemicals, the composition of produced water, the content of CO_2 and/or H_2S, for example (Sonke and Grimes, 2016, 2017). Inhibitors can control MIC in three ways (i) increasing the anodic or cathodic polarization behavior, (ii) reducing the movement or diffusion of ions to the metallic surface, and (iii) increasing the electrical resistance of the metallic surface. Inhibitors can be generally classified as passivating inhibitors, cathodic inhibitors, precipitation inhibitors, organic inhibitors, volatile corrosion inhibitors. In the subsea industry, three types of chemical injection are typically used as inhibitors, 1) Hydrate Inhibition, 2) Paraffin Inhibitors, and 3) Asphaltene Inhibitors (Bai and Bai, 2010). In this study, a value of 80% for inhibitor efficiency is considered and assumed that the efficiency of inhibitors would be present in the system at the required dosage through the entire pipeline. In such cases, the efficiency of the inhibitor is considered in mechanistic model in which parent node leading to rate of MIC and further pit depth growth are updated. As an example, if a management practice has a specific target such as biofilm, the efficiency of the practice could improve the target parent node. To estimate the pit depth growth path over a period, HBA within the MCMC method is utilized. Fig. 9 shows the efficiency of selected inhibitors on the pit depth growth path.

As a second practice, continuous injecting biocide is evaluated. Biocides mean the killer of those living things which may endorse the mitigation mechanism of MIC. The biocides can be single or a mixture of two or more compounds to kill microbes (NACE, 2006). To select the biocides in subsea industries, it is necessary to consider the following issues (i) selectivity against target microbes, (ii) biodegradability, and (iii) effectiveness in the presence of different chemical compounds such as inhibitors. The biocides can be categorized into two classes, oxidizing and non-oxidizing biocides. The oxidizing biocides such as chlorine, chlorinating compounds, chlorine dioxide, and bromine are used in water systems. The non-oxidizing biocides use synthetic molecules, which can be used in different environmental conditions. In addition, this type of biocide can reduce hydrocarbon contents. Formaldehyde, Glutaraldehyde, Quaternary amine substances, Carbamates, Metronidazole, and Isothiazolone which all have advantages and disadvantageous, are the common biocides in subsea industries,. Among all industry-based biocides, as an example, Formaldehyde is economical, but it is carcinogenic, large quantities are needed, and combines with ammonia, oxygen scavengers, and hydrogen sulfide. In this study, Formaldehyde (CH_2O (H−CHO)) is considered for evaluation, since it is economical and adequate for Desulfo-based microorganism (SRB category) and SRA category (Cheung and Beech, 1996; Dawson, 2010), which together constitute approximately 60% of available microbes in the system. In this study, a value of 60% for laboratory-based biocide efficiency is considered, since it can have efficiencies in the field of >99.9% (Dawson, 2010). It also assumed that Formaldehyde would be present in the system at the required dosage through the entire pipeline. To estimate the pit depth growth path over a period, HBA within MCMC method is utilized. Fig. 10 shows the efficiency of selected inhibitors on the pit depth growth path based on Equation (4).

As a third practice, launching periodical pigging is evaluated. Periodical pigging as a mechanical strategy is a way of MIC mitigation. In pipelines, a mechanical pig is used to clean garbage from the interior portion of the pipeline and can be used for investigation purposes. Its mechanism is removing a piece of the biofilm and keeping solid particles (Javaherdashti, 2008). According to the laboratory study, the efficiency of pigging in the rate of MIC is approximately 65% (Mand et al., 2019). Fig. 11 shows the efficiency of periodically launching pig within 3 years on the pit depth growth path based on Equation (4).

As a fourth practice, biological treatment is evaluated. The biological treatment is using a different type of bacteria against the primary bacteria responsible for MIC (Javaherdashti and Alasvand, 2019b). Several attempts have been made to use nitrate-reducing bacteria (NRB) fighting against SRB subsea industries. Two examples of methods for NRB against SRB are (i) bio-competitive exclusion and (ii) bio-augmentation. Nitrate induce the heterotrophic NRB (hNRB) sulfide-oxidizing NRB (SO-NRB) development as NRB. The hNRB fights against SRB to obtain a similar carbon variant. The SO-NRB are autotrophs and do not compete for SRB for electrons' donation (DiChristina, 1994; Nemati et al., 2001). A study demonstrated that the practicability of persevering with NRB as a treatment for MIC mitigation can reduce the rate of MIC up to 40% (Bødtker et al., 2008) in the presence of biocides and 50% without the presence of biocides (Sunde et al., 2004). To estimate the pit depth growth path over a period, HBA within MCMC method is utilized. Fig. 12 shows the efficiency of NRB with and without biocides on the pit depth growth path based on Equation (4).

As a fifth practice, manipulating operational parameters including pH, temperature, and fluid velocity are evaluated. In literature, scholars have made numerous efforts to determine the optimum pH value to reduce the rate of corrosion (Javaherdashti, 1999). In a laboratory study, the rate of corrosion for carbon steel coupled with the influence of SRB have been studied (Ismail et al., 2014). The obtained results suggest that the value of pH = 6.5 can highly influence the rate of corrosion because of the presence of sulfates within bacterial activities. Thus, the optimum value of pH is considered in the mechanistic model (Fig. 6) to update the model. To estimate the pit depth growth path over a period, HBA within the MCMC method is utilized. Fig. 13 shows the effect of the optimum value of pH on the pit depth growth path according to Equation (4). The parameter temperature also highly influences corrosion behavior. The pit depth growth path is a function of temperature and it can be concluded that it would increase with temperature. According to Melchers studies, the temperature in value of 17.5 has influenced the lowest rate of corrosion and further metal loss (Melchers, 1994). Thus, the optimum value of 17.5 is considered for the temperature in the mechanistic model (Fig. 6) in order to update the model. To estimate the pit depth growth path over a period, HBA within the MCMC method is utilized. Fig. 13 shows the effect of the optimum value of pH on the pit

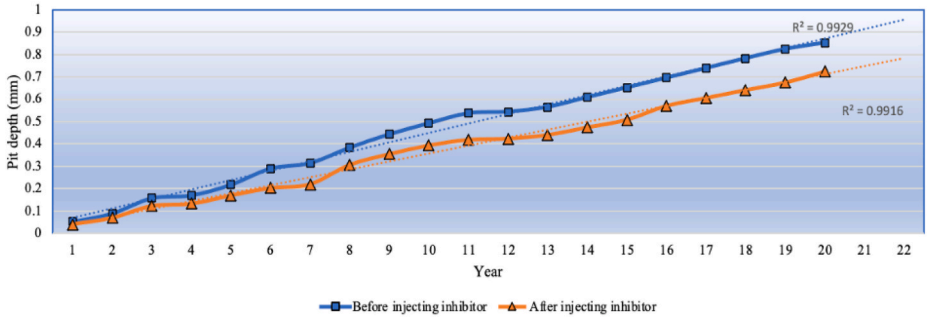


Fig. 9. The efficiency of selected inhibitors on the pit depth growth path.

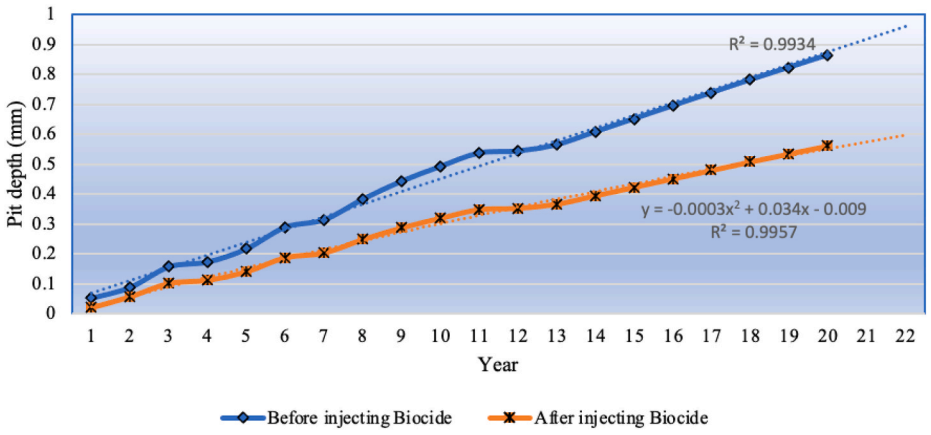


Fig. 10. The efficiency of Formaldehyde as a biocide on the pit depth growth path.

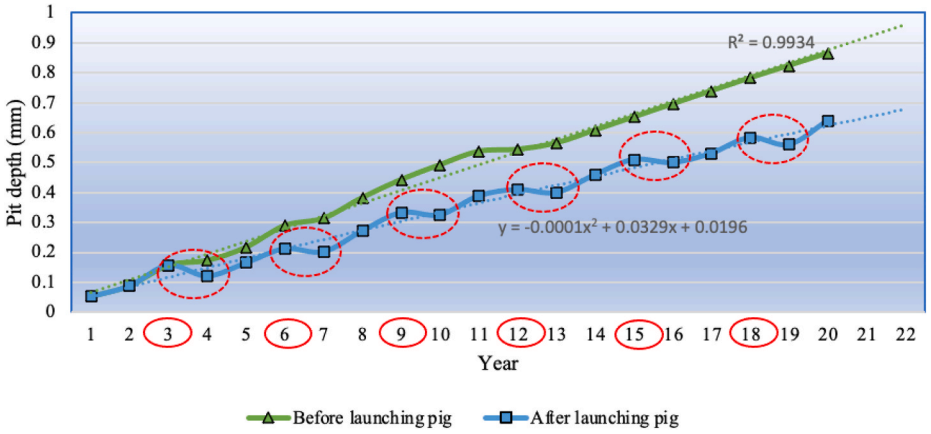


Fig. 11. The efficiency of periodically launching pig within 3 years on the pit depth growth paths.

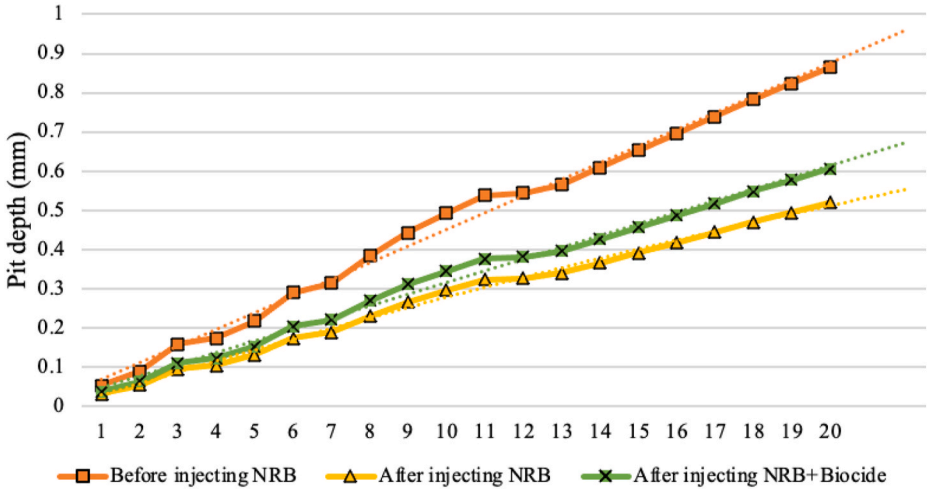


Fig. 12. The efficiency of NRB with and without biocide on the pit depth growth path.

depth growth path according to Equation (4). The parameter velocity also has a high influence on corrosion behavior. The pit depth growth path is a function of velocity and Melchers reported that the velocity nonlinearly increases the rate of corrosion, (Melchers, 2004). The higher level of velocity increases the rate of corrosion. According to the study of Soares et al. (2011), the minimum value velocity of 0.1 m/s has the maximum effect on the rate of corrosion in the marine environment, 0.12 mm/yr. Thus, to update the model,the optimum value of 0.1 m/s is considered for the velocity in the mechanistic model (Fig. 6). To estimate the pit depth growth path over a period, HBA within the MCMC method is utilized. Fig. 13 shows the effect of optimum value of pH on the pit depth growth path based on Equation (4).

In the last practice, Replacement and Repair of the corroded pipeline are evaluated. It is considered that once the maximum pit depth growth

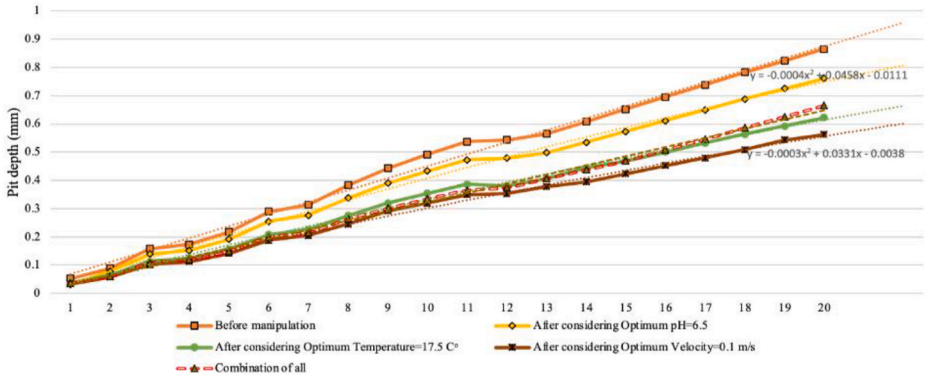


Fig. 13. The efficiency of operational parameters' manipulation with and without manipulation operational parametrs on the pit depth growth path.

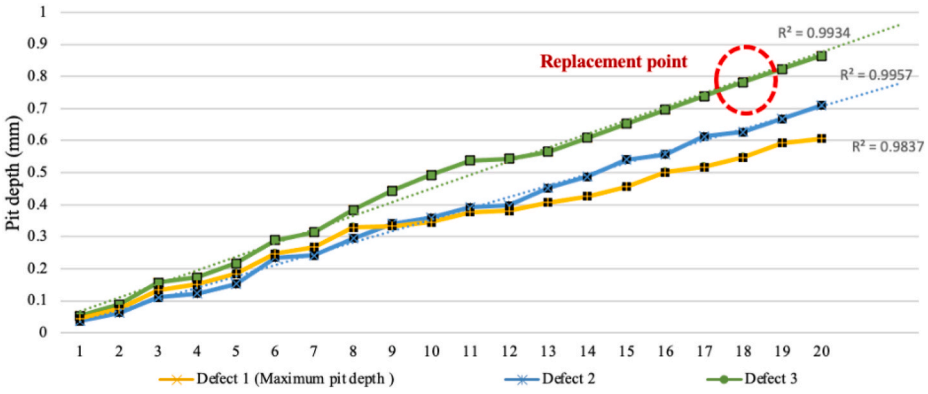


Fig. 14. The pit depth growth of three different defects.

path reaches 80% of wall thickness, replacement methods (such as grouted clamp, coupling, sleeve, cladding, welding, *etc*) are required. To evaluate the replacement, as can be seen in Fig. 14, three defects ($i = 1, 2, 3$) through the pipeline with the different indications of pit depth growth are considered. As can be seen, the replacement point of maximum pit depth would be in year 18. Replacement is done by using double block isolation tools installed locally on both sides of the defect having maximum depth and depressurizing the entire section of the pipeline to allow safe removal, and repair by installing a new pipeline section. After installing a new section, the defect having maximum pit depth has disappeared, and defect 2 will have maximum pit depth growth and is predicted to need a replacement at year 22. In addition, repair such as grouted clamp can be used instead of the replacement method. Assuming that, the grouted clamp can increase the thickness of the pipeline up to 50%, subsequently, pit depth growth will sharply decrease and defect 2 will have maximum pit depth growth. The pit depth growth considering the replacement and repair for defect 1 is depicted in Fig. 15.

In step six of our proposed framework, the efficiency of all singular management practice as well as different combinations in several time slices are considered. Thus, the best management practice would be based on optimum operational parameters (pH, temperature, and velocity), injecting NRB and biocide into the system at the required dosage in addition to launching periodical pig in order for the pipeline to survive for 40 years. As can be seen in Fig. 16, the period of launching pig increases to 5 years instead of 3 years as before, and the last pigging would be in year 30. In addition, if the pipeline still needs to be in operational condition, replacement and repair can be applied, and the second defect monitored within maximum pit depth growth.

Up to this point, a management practice was proposed at the time of

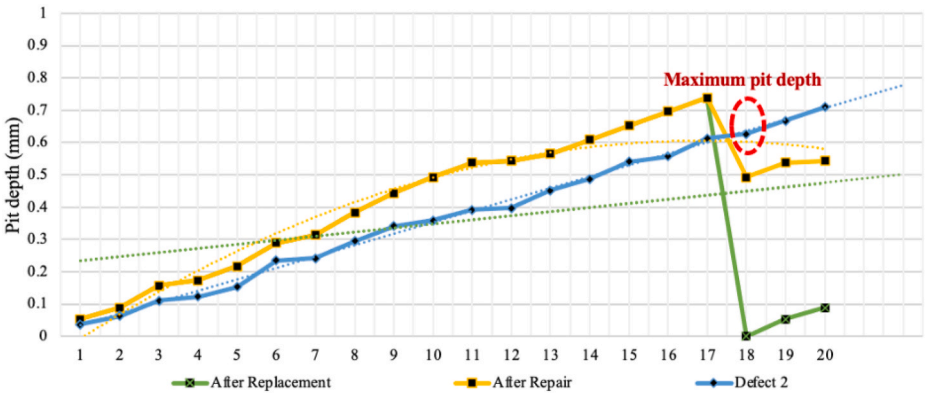


Fig. 15. The pit depth growth considering the replacement and repair for defect 1.

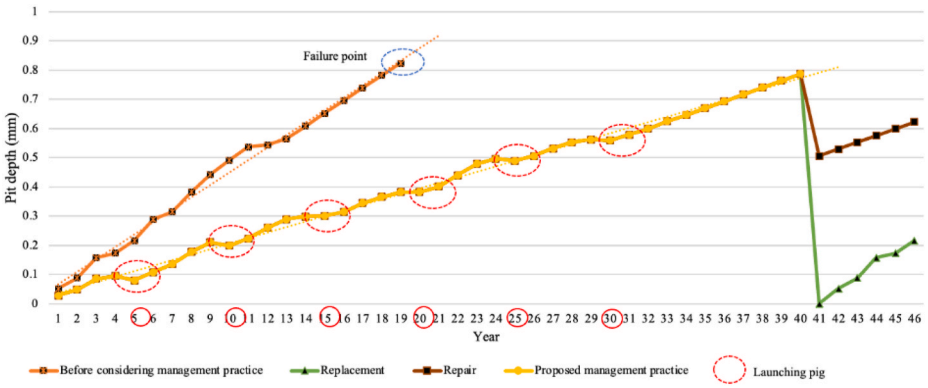


Fig. 16. The proposed management practice for the defect within maximum pit depth growth.

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

In the first case scenario, the in-line inspection tool is launched into the pipeline in year 3. Considering the measurement error of the in-line inspection tool (Al-Amin et al., 2014; Zhang et al., 2014), the actual pit depth of the defect is estimated (as an example 35 % wt), MIC rate (as an example 0.9 mm/yr), and biofilm thickness (High). As can be seen from Fig. 17, using new data as input into HBA, the pipeline will fail by the end of year 7. This sharp increase in the pit depth growth may be the result of the breakdown of the internal coating. Considering injection of NRB and biocide are in a highly effective manner, immediate launching pigging can be utilized. According to this practice, the pipeline can operate for the extra few years. Observing the efficiency of pigging, it is continued annually until year 13, with the pipeline close to failure point. According to this point, repair and replacement methods have been applied in years 13 and 19, respectively. Thus, the pipeline will work under operational conditions for a longer time.

In the second scenario, following the previous scenario, another in-line inspection tool is launched in the pipeline in year 5. The actual pit depth of the defect is estimated (as an example 55% wt), MIC rate (as an example 1.6 mm/yr), and biofilm thickness (high). As can be seen from Fig. 18, using new data as input into HBA, the pipeline will fail in the middle of year 6. According to the pit depth growth path, the proposed management practice seems to be ineffective. Therefore, the replacement of that area should be considered. After replacement, in year 6, the proposed management practice is continued.

4. Conclusions

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

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

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

During the study however, some important challenges have arisen. These are necessary to mention and can be improved in further studies. Firstly, the growth of an individual internal defect is assumed to be influenced by MIC, while multiple defects' interactions need to be considered as much more practical. Second, there is a lack of information to understand corrosion growth behaviours under the combination of management practice. Thus, this requires further laboratory-based studies. Lastly, in the current study, the cost, which is an important factor for management strategies, is not considered. This can be

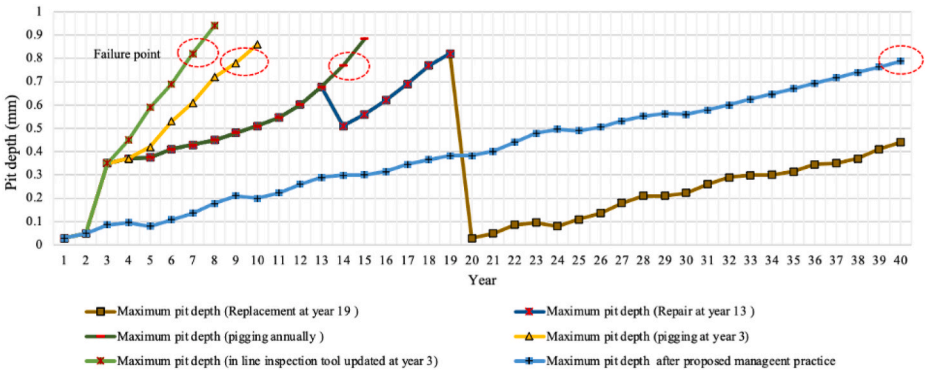


Fig. 17. Changing management practice based on collected new information by in-line inspection tools.

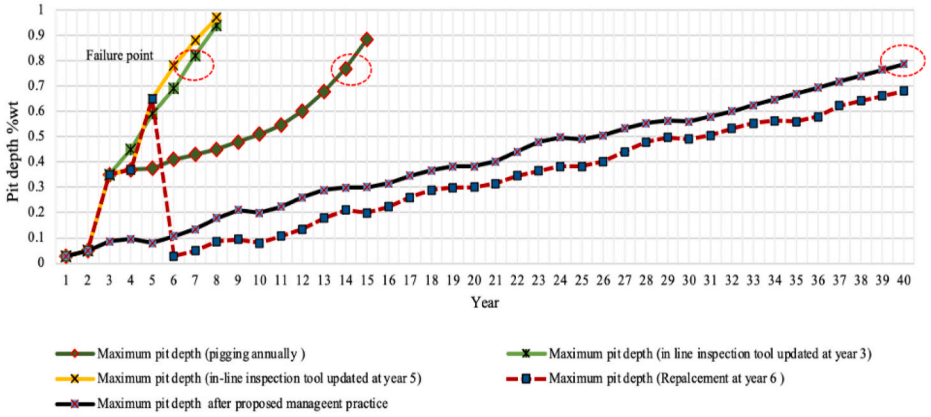


Fig. 18. Changing management practice based on collected new information by in-line inspection tools.

regarded as a future research activity. In addition, the robustness of the proposed model can be further validated once new information from pigging becomes available.

CRediT authorship contribution statement

Mohammad Yazdi: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Faisal Khan:** Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Rouzbeh Abbassi:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors acknowledge the financial support provided by Genome Canada and their supporting partners, and the Canada Research Chair (CRC) Tier I Program in Offshore Safety and Risk Engineering.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.oceaneng.2021.108852.

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