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A R T I C L E I N F O

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A B S T R A C T

Degradation of subsea pipelines in the presence of corrosive agents and cyclic loads may lead to the failure of these structures. In order to improve their reliability, the deterioration process through pitting and corrosion-fatigue phenomena should be considered simultaneously for prognosis. This process starts with pitting nucleation, transits to fatigue damage and leads to fracture and is influenced by many factors such as material and process conditions, each incorporating a high level of uncertainty. This study proposes a novel probabilistic methodology for integrated modelling of pitting and corrosion-fatigue degradation processes of subsea pipelines. The entire process is modelled using a Dynamic Bayesian Network (DBN) methodology, representing its temporal nature and varying growth rates. The model also takes into account the factors influencing each stage of the process. To demonstrate its application, the methodology is applied to estimate the remaining useful life of high strength steel pipelines. This information along with Bayesian updating based on monitoring results can be adopted for the development of effective maintenance strategies.

1. Introduction

One of the major causes of failure of offshore structures such as oil and gas pipelines is degradation of structural properties during their lifespan (Dey and Gupta, 2001; Sulaiman and Tan, 2014; Yang et al., 2017). Corrosion is the most well-known form of steel deterioration resulting in generation of pits or more extended damage (Bhandari et al., 2015b, 2016, 2017). Fatigue, on the other hand, is the disintegration of material due to cyclic loads applied on the structure. Coupled corrosion-fatigue results from applied cyclic stresses in tandem with presence of corrosive agents, where localized corrosion in the form of pits may provide the required conditions for initiation of fatigue crack initiation.

Many parameters including material properties and environmental conditions influence this process. These factors, each incorporating a level of uncertainty, may be adopted to estimate the remaining useful life of the structure. While these predictions will provide reliable measures for improving maintenance strategies, a dynamic framework is also required for updating the estimations based on new observations during the service life.

A great deal of research has been conducted to predict the state of damage and fatigue life in steel and aluminum alloy structures that are subjected to pitting and corrosion-fatigue. Kondo (1989) developed a model for the prediction of fatigue crack initiation time based on pit growth, however, the damage process was not entirely simulated. Goswami and Hoeppner (1995) proposed a seven-stage model that considers the effect of electrochemical processes on pit formation as well as the role of pitting in fatigue crack initiation. This model however, was conceptual and failed to provide a computational framework. A probabilistic model was developed by Harlow and Wei (1994) for prediction of corrosion-fatigue life comprising the time for crack initiation, surface crack growth and the growth of damage to the critical size. This model, however, does not consider the time of pit nucleation as well as the effect of short cracks in service life modelling. Kaynak and Baker (1996) assessed the effect of short cracks on fatigue life of steel structures concluding that the growth rates of short cracks are different (usually smaller) from those of long cracks. Shi and Mahadevan (2001) proposed a mechanics-based probabilistic model of the entire pitting and corrosion-fatigue process suggested by Goswami and Hoeppner (1995). They adopted Monte Carlo simulations and the First-Order Reliability Method (FORM) approach to conduct the probabilistic analysis.

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Although, their framework provides a guideline for estimating fatigue life, application of FORM may result in computational complications.

Alternatively, Bayesian network (BN) as an advanced probabilistic model has widely been applied to reliability analysis of complex systems. Application of BN significantly reduces the method complexity and computational time of inference, by factorizing the joint probability distribution of the parameters of interest based on local dependencies.

Various applications of BN in risk and reliability engineering can be found in Weber et al. (2012), Abbassi et al. (2016), Bhandari et al. (2015), Yeo et al. (2016) and Abaei et al. (2017). However, only a few studies adopted BNs for modelling deterioration processes in structures. Friis-Hansen (2000) studied the application of Dynamic Bayesian Network (DBN) in modelling fatigue crack growth of offshore jacket structures. The developed probabilistic network was also used to identify optimum inspection plans. Straub (2009) developed a generic computational framework using DBN for modelling deterioration processes with potential applications in inspection, maintenance, and repair planning. Arzaghi et al. (2017) developed a methodology for probabilistic modelling of fatigue crack growth using BN. The model was extended to an Influence Diagram for finding the optimum maintenance plan among multiple repair alternatives with different economic impacts.

In the present study, a probabilistic methodology is developed for modelling corrosion-fatigue deterioration in offshore structures. This methodology consolidates the entire damage process including pit nucleation, pit growth transited to short and long fatigue cracks, and the fracture of structure. To improve the accuracy of corrosion-fatigue life estimations, the model incorporates the randomness in the parameters influencing the process. For this purpose, DBN is adopted as an efficient probabilistic tool. The advantages of this methodology are illustrated through the remaining useful life assessment of an offshore pipeline subjected to pitting and corrosion-fatigue.

2. Bayesian networks

2.1. Conventional Bayesian network

BNs are directed acyclic graphs used for reasoning under uncertainty by considering the causal relationships (represented by directed edges) among a number of random variables (represented by chance nodes) (Pearl, 1988). BN estimates the joint probability distribution of a set of random variables based on the conditional independencies and the chain rule, as in Eq. (1):

$$P(U) = P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i | pa(X_i)) \quad (1)$$

where $P(U)$ is the joint probability distribution, and $pa(X_i)$ is the parent set of random variables X_i. Fig. 1 depicts a conventional BN comprising random variables X_1-X_4. The main advantage of Bayesian networks is that when new information about any of the chance nodes becomes available, the model can update the probabilities for a more efficient knowledge elicitation. For instance, if variable X_2 is observed to be in state e, the joint probability distribution is updated based on Bayes' theorem:

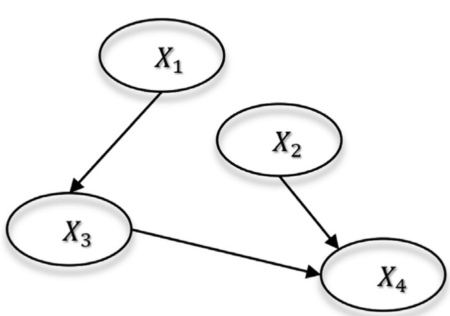

Figure 1. A conventional Bayesian network.

$$P(X_1, X_3, X_4 | e) = \frac{P(X_1, X_3, X_4, e)}{\sum_{X_1, X_3, X_4} P(X_1, X_3, X_4, e)} \quad (2)$$

Dynamic Bayesian networks (DBNs) particularly represent stochastic processes and enable explicit modelling of the evolution process of a set of random variables (Jensen and Nielsen, 2007). A DBN divides the time line into a discrete number of time slices $t \in [0, T]$ and allows a node in time slice $i+1$ to be conditionally dependent on a node in time slice i as well as its parents in time slice $i+1$. Fig. 2 illustrates a DBN in which the evolving process of the variable Y_t is modelled. This variable in time slice t is dependent on Y_{t-1} as well as X_t. In order to establish a DBN, the conditional probability tables for evolving nodes should be completed, for instance $P(Y_t | Y_{t-1}, X_t)$for variable Y_t in the DBN presented in Fig. 2.

The transition between two consecutive time slices may for instance be dependent upon the physical features of the stochastic process being modelled. A detailed explanation of inference algorithms developed specifically for DBN structures can be found in Murphy (2002).

3. Pitting and corrosion-fatigue modelling methodology

To develop the probabilistic model, it is first necessary to assess the entire damage process identifying the physics behind pitting and the corrosion-fatigue phenomena. This will also facilitate developing the computational framework for predicting damage states and establishing the DBN. The seven-stage model proposed by Goswami and Hoeppner (1995) is adopted as the basis for analyzing the service life in the present study. Fig. 3 illustrates the total corrosion fatigue life (t_{fl}) initiated with pit nucleation time (t_{pn}) and eventually resulting in fracture. This process also includes three damage growth times for pit (t_{pg}), short crack (t_{sc}) and long crack (t_{lc}) as well as two transition stages, i.e., "pit-to-crack transition" and "short-crack to long–crack transition".

$$t_{fl} = t_{pn} + t_{pg} + t_{sc} + t_{lc} \quad (3)$$

The proposed methodology models the entire deterioration process including pitting corrosion and fatigue damage growth. Fig. 4 presents an overview of the entire methodology and its key elements.

The computational methods for each component of the total failure time represented in Eq. (3) will be discussed in the following subsections:

3.1. Pit nucleation

The time for pit initiation has attracted a great deal of research, yet the dependence on many influencing factors such as materials and electrochemical has not been fully investigated. Hence, the developed model considers this stage of damage life as a random variable modelled by a lognormal distribution. The adopted distribution parameters, suggested by Shi and Mahadevan (2001) are provided later in the following sections.

3.2. Pit growth

According to Kondo (1989) and Harlow and Wei (1994), pits are assumed to remain in a hemispherical shape while growing at a constant volumetric rate. This yields a pit growth rate, given by:

$$\frac{dc}{dt} = \frac{C_p}{2\pi c^2} \quad (4)$$

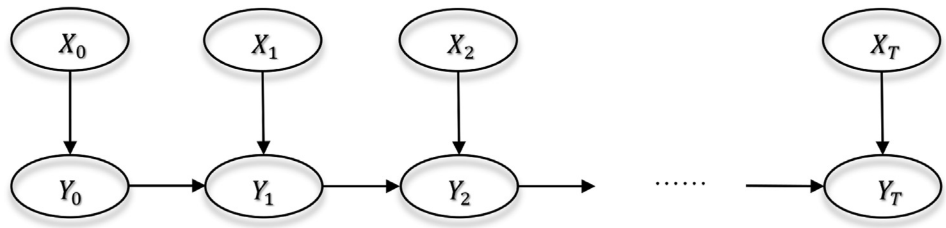

Figure 2. A Dynamic Bayesian network.

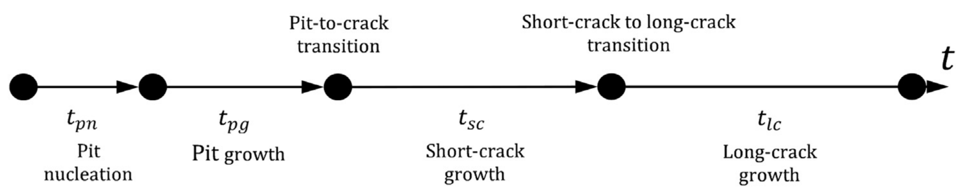

Figure 3. Different stages of pitting corrosion-fatigue life.

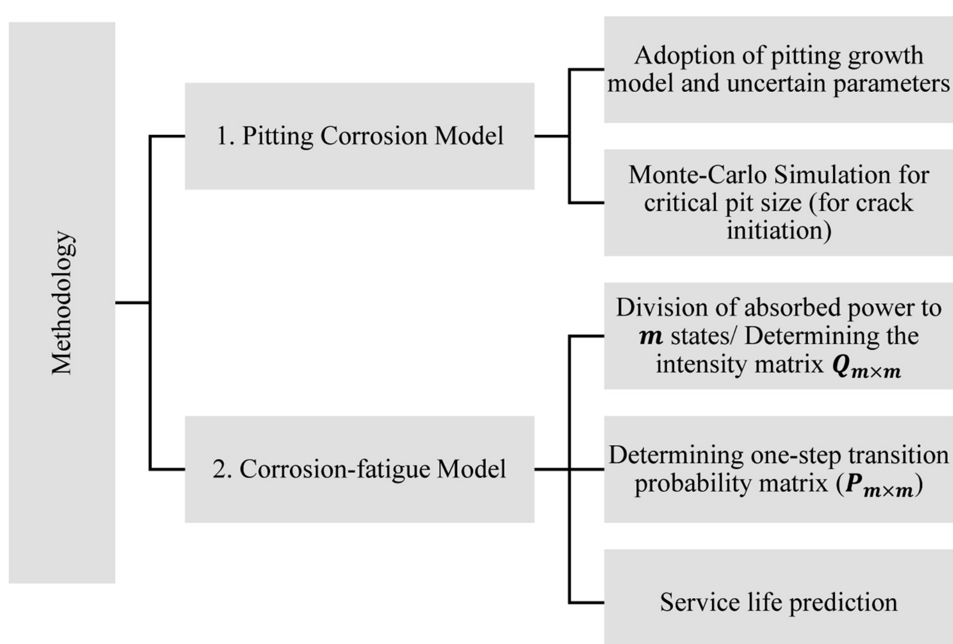

Figure 4. Developed methodology for service-life prediction of deteriorating subsea pipelines.

$$C_p = \frac{MI_{P0}}{nF\rho}\exp\left(-\frac{\Delta H}{RT}\right) \tag{5}$$

where c is the pit radius, M is the molecular weight of the material, I_{P0} is the pitting current constant, n is the valence number, $F = 96,514$ (c/mol) is Faraday's constant, ρ is density, ΔH is the activation energy, $R = 8.314$(J/molK) is the universal gas constant, and T is the temperature.

The transition from pit growth to crack initiation is dependent on mechanical characteristics such as stress intensity factor, ΔK. Two criteria are considered as the boundary conditions for crack initiation: (1) the stress intensity factor for the equivalent surface crack growth of the pit reaches the threshold stress intensity factor of the fatigue crack growth (Eq. (6)), and (2) the fatigue crack growth rate exceeds the pit growth rate.

$$\Delta K_{pit} = \Delta K_{crack} \tag{6}$$

Kondo (1989) suggests that the critical crack length (c_{cr}) that satisfies the conditions for transition from pit growth and crack initiation can be calculated as:

$$c_{cr} = \left(\frac{1}{2}\right)\left(\frac{2Q}{\pi\alpha}\right)\left[\frac{\Delta K_{cr}}{2.24\Delta\sigma}\right]^2 \tag{7}$$

where $Q = 1.464\alpha^{1.65}$ is the shape factor, $\alpha = \frac{a}{c} = 0.7$ is the aspect ratio of pit (c and a are half the length of the major and minor axes of pit shape), $\Delta K_{cr} = 2.4Mpa\sqrt{m}$ is the threshold stress intensity factor, and $\Delta\sigma$ is the stress range experienced by the structure.

3.3. Short and long crack growth

Long cracks are usually considered when using fracture mechanics for

Table 1
Random values used in pitting corrosion-fatigue model.

Variable	Description	Distribution	Mean	Standard Deviation
$\Delta\sigma$	Stress range (MPa)	Normal	60	10
T	Temperature (K)	Normal	293	1
A	Weibull scale parameter (MPa)	Normal	5.35	0.963
MU	Model uncertainty	Normal	1	0.18
C_0	Initial pit size (m)	Exponential	1.98×10^{-6}	0.99×10^{-7}
C_{cr}	Initial crack size (m) [from Monte Carlo sim]	Exponential	0.8×10^{-3}	-
C_{th}	Fatigue crack threshold (short to long) (m)	Normal	2.0×10^{-3}	

fatigue analysis, and Paris' law is widely used for estimating damage sizes. The effect of short cracks on fatigue life has attracted the attention of researchers, however, there is no explicit formula derived for short crack growth. According to Kaynak and Baker (1996) and (Shi and Mahadevan, 2001), a probabilistic model based on Paris' law that accounts for the uncertainty of parameters such as stress intensity factor, may be applied. Eq. (8) represents the empirical formula for damage growth:

$$\frac{da}{dN} = C(\Delta K)^3 \tag{8}$$

where N is the number of applied load cycles, c and m are material parameters specifically obtained for short and long cracks resulting in two identical growth rates from the equation. ΔK is the stress intensity factor, which can be expressed empirically as:

$$\Delta K = Y(c)\Delta\sigma\sqrt{\pi c} \tag{9}$$

where $Y(c)$ is the geometry function dependent on the crack depth, and $\Delta\sigma$ is the stress range. While the explicit solution of Eq. (8) is not possible, by assuming that the geometry function is independent of crack depth c and the stress range $\Delta\sigma$ follows a Weibull distribution, an analytical solution can be achieved (Madsen et al., 1986):

$$a_{t+1} = \left(a_t^{\frac{2-m}{m}} + M_U S A^m\right)^{\frac{2}{2-m}}, m \neq 2 \tag{10}$$

$$S = C\,N\Gamma\left(1+\frac{m}{B}\right)Y^m\pi^{\frac{m}{2}}\left(1-\frac{m}{2}\right) \tag{11}$$

where A and B are the scale and shape parameters of the Weibull distribution, respectively, and Γ is the gamma function. Eq. (10) enables the computation of crack size in current time step as a function of crack size in the previous time step and the material constants m and c, where these parameters are obtained from empirical models for short and long cracks. Different methods are developed to identify the transition size c_{th} from short crack growth to long crack growth. Kaynak and Baker (1996) suggested this value is about 1–2 mm for En7A steel. Similarly, in this study the critical size is regarded as a random variable with a mean value of 2 mm.

3.4. Probabilistic analysis and BN model

The probability analysis was performed using Monte Carlo simulations in tandem with implementation of a DBN. To estimate the time for the initial part of damage life where pitting corrosion is dominant, 10^4 samples where generated from random variables involved in Eq. (4), (5) and (7). The distributions of these variables are listed in Table 1. It should be noted that initial pit size (C_0) was considered as the initial condition when solving Eq. (4). The remainder of service life, where fatigue damage progresses, is estimated using a DBN. For this purpose, the generic DBN developed by Straub (2009) was adopted to model each of the two growth processes indicated in Fig. 5. The developed network qualitatively represents a deterioration process describing the state of damage over the life time divided into a discrete number of slices. That is, the damage size is a function of the initial condition (nodeC_{cr}) which is followed by the process of short crack growth (nodes C_1^{sc} to C_n^{sc}), transition to long crack at a critical crack size (node C_{th}) and eventually the long crack growth process (nodes $C_1^{lc}$to C_m^{lc}). The occurrence of failure event is assessed by defining a limit state G, as :

$$G = C_f - C_i \tag{12}$$

where $C_i$and C_f are the actual and critical crack size, respectively.

4. Application: corrosion fatigue damage of a subsea pipeline

To demonstrate the applicability of the developed method in predicating corrosion-fatigue service life, a numerical study is carried out on the failure of an offshore pipeline. The mechanical properties of the structure are listed in Table 2. It is assumed that $N = 10^6$ load cycles are experienced by the pipeline every year and critical size of damage for failure is $Cf = 10 \times 10^{-3}$m.

The results of Monte Carlo simulation showed that the critical pit size for transition to short crack has a mean of $E[C_{cr}] = 8 \times 10^{-4}$m. The cumulative probability distribution of this variable is presented in Fig. 6. This distribution was discretized into 20 exponentially growing intervals which form the upper bounds of states of damage size nodes in the DBN. This was performed to avoid rounding errors caused by uniform interval lengths in the last intervals where the probabilities are significantly low.

As illustrated in Fig. 5, the DBN model contained two consecutive periods corresponding to corrosion fatigue cracks with different growth rates. An adequate number of time slices were included in the short crack growth process so that the mean size of predicted damage equals the critical transition sizeC_{th}, before long crack growth is initiated. The long crack process was then extended for a number of time slices (each representing a year) until fracture occurred,$P(F = 1) = 1$.

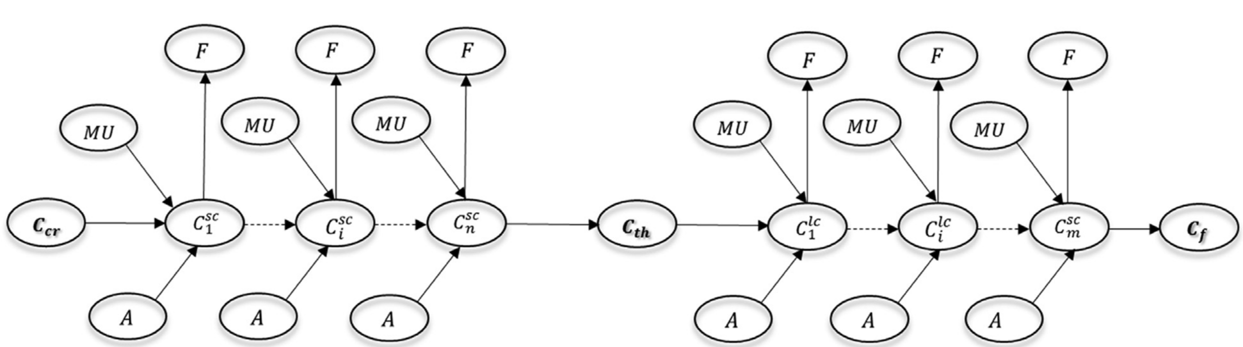

Figure 5. Developed Bayesian network for modelling corrosion-fatigue life.

Table 2
Deterministic values used in pitting corrosion-fatigue model.

Variable	Description	Mean
ρ	Density (gm/m^3)	7.8×10^6
n	Valence	2
M	Molecular weight (gm)	55.75
ΔH	Activation energy (KJ/mol)	5.0×10^4
m_{sc}, m_{lc}	Short/long crack growth exponent	3.0
C_{sc}, C_{lc}	Material parameter for short/long crack	2.17×10^{-13} 1.45×10^{-14}
Y	Geometry function	1
B	Weibull shape parameter	0.66
N	Load cycles	10^6/year

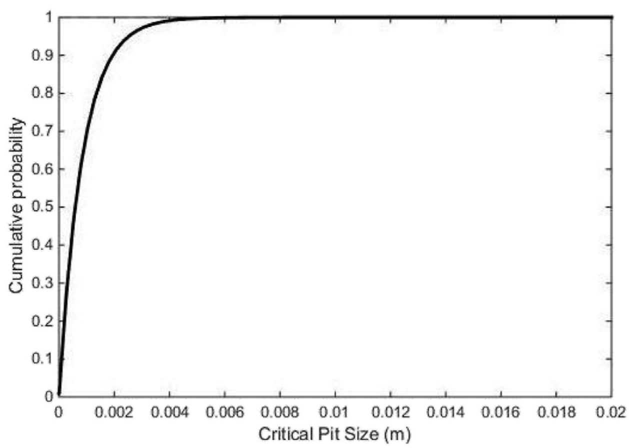

Figure 6. Cumulative probability distribution of critical pit size leading to the transition to short crack.

The results of the case study, presented in Fig. 7, suggest that within the third year of operation the grown pits will satisfy the conditions required for initiation of fatigue cracks and damage will be growing in the form of short cracks. The prediction of pipeline corrosion fatigue life indicates that the transition from short crack to long crack takes place in year 12 after which the damage develops at a significantly faster rate. 15 years after the start of the operation the extent of damage will be significantly increasing where the probability of failure is about 0.1 in the 20th year, given no repairs were performed. This probability will increase to almost 0.5 in the 25th year of operation and approximately 10 years later the structure is extremely close to failure event,$P(F=1)$«0.95.

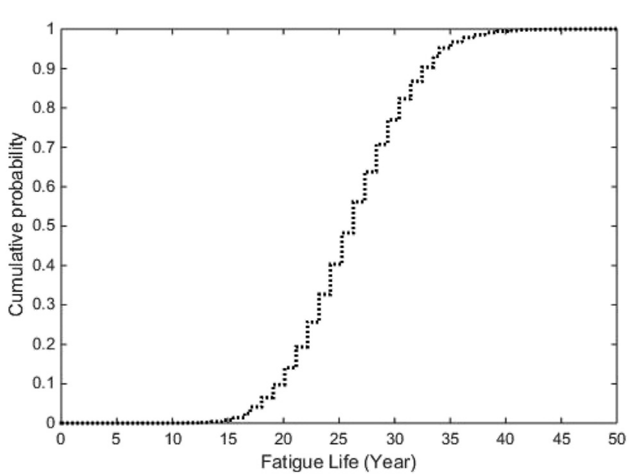

Figure 7. Cumulative probability distribution of corrosion-fatigue life for an offshore pipeline.

These results highlight the strength of the methodology for predicting the service life of a corroded subsea pipeline subjected to cyclic loads. The proposed methodology can be readily used to update the predictions based on new damage size inspection results and also provides a great potential for optimization of maintenance plans. Moreover, by enhancing the DBN model with a monitoring capacity, the predictions can be updated during the operation period with observation of influencing parameters.

5. Conclusion

This paper presents a probabilistic methodology for prediction of pitting and corrosion fatigue service life in offshore pipelines. For this purpose, Monte Carlo simulations are used to analyze the time of pit growth as well as estimating the size of pit in which transition to short crack growth occurs. It was observed that pits with mean size of about 0.8 mm have the required condition for crack initiation in steel pipelines. A DBN model was implemented for simulating short and long crack growth which may lead to fracture. The predictions suggest that in the 20th year of operation, probability of failure event is about 0.1 where this value reaches to about 0.95 in 15 years, given that no maintenance is performed on the pipeline. The results of this study highlights the capability of the method in prediction of corrosion fatigue life considering the randomness of the parameters involved in the problem. These capabilities can also be enhanced for efficient monitoring, inspection and maintenance planning strategies.

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References

Abbassi, R., Bhandari, J., Khan, F., Garaniya, V., Chai, S., 2016. Developing a quantitative risk-based methodology for maintenance scheduling using Bayesian network. Chem. Eng. Technol. 48, 235–240.
Abaei, Mahdi, Mohammad, et al., 2017. Developing a novel risk-based methodology for multi-criteria decision making in marine renewable energy applications. Renew. Energy 102, 341–348.
Arzaghi, E., et al., 2017. Risk-based maintenance planning of subsea pipelines through fatigue crack growth monitoring. Eng. Fail. Anal. 79, 928–939.
Bhandari, J., et al., 2015. Risk analysis of deepwater drilling operations using Bayesian network. J. Loss Prev. Process. Ind. 38, 11–23.
Bhandari, Jyoti, et al., 2015b. Modelling of pitting corrosion in marine and offshore steel structures – a technical review. J. Loss Prev. Process. Ind. 37 (Supplement C), 39–62.
Bhandari, J., Khan, F., Abbassi, R., Garaniya, V., Ojeda, R., 2016. Reliability Assessment of Offshore Asset Under Pitting Corrosion using Bayesian Network. Paper presented at the Corrosion 2016.
Bhandari, J., Khan, F., Abbassi, R., Garaniya, V., Ojeda, R., 2017. Pitting degradation modeling of ocean steel structures using Bayesian network. J. Offshore Mech. Arctic Eng. 139 (5), 051402.
Dey, P.K., Gupta, S.S., 2001. Risk-based model Aids Selection of pipeline inspection, maintenance strategies. Oil Gas J. 99, 54–60.
Friis-Hansen, A., 2000. Bayesian Networks as a Decision Support Tool in Marine Applications. PhD. Technical University of Denmark.
Goswami, T., Hoeppner, D., 1995. Pitting corrosion fatigue of structural materials. In: Chang, C., Sun, C. (Eds.), Structural Integrity in Aging Aircrafts. AMSE, New York, pp. 39–129.
Harlow, D.G., Wei, R.P., 1994. Probability approach for prediction of corrosion and corrosion fatigue life. AIAA J. 32 (10), 2073–2079.
Jensen, F.V., Nielsen, T.D., 2007. Bayesian Networks and Decision Graphs. Springer, New York.
Kaynak, C., Baker, T., 1996. Effects of short cracks on fatigue life calculations. Int. J. Fatig. 18 (1), 25–31.

Kondo, Y., 1989. Prediction of fatigue crack initiation life based on pit growth. Corrosion 45 (1), 7–11.

Madsen, H.O., Krenk, S., Lind, N.C., 1986. Methods of structural safety. In: Hall, W.J. (Ed.). Prentice-Hall, Englewood Cliffs, N.J., p. 403

Murphy, K.P., 2002. Dynamic Bayesian Networks: Representation, Inference and Learning. University of California, Berkeley.

Pearl, J., 1988. Probabilistic Reasoning in Intelligent Systems. Morgan Kaufmann, San Francisco, CA.

Shi, P., Mahadevan, S., 2001. Damage tolerance approach for probabilistic pitting corrosion fatigue life prediction. Eng. Fract. Mech. 68 (13), 1493–1507.

Straub, D., 2009. Stochastic modeling of deterioration processes through dynamic Bayesian networks. J. Eng. Mech. 135 (10), 1089–1099.

Sulaiman, N.S., Tan, H., 2014. Third party damages of offshore pipeline. J. Energy Challeng. Mech. 1 (1).

Weber, P., Medina-Oliva, G., Simon, C., Iung, B., 2012. Overview on Bayesian networks applications for dependability, risk analysis and maintenance areas. Eng. Appl. Artif. Intell. 25 (4), 671–682. https://doi.org/10.1016/j.engappai.2010.06.002.

Yang, Yongsheng, et al., 2017. Corrosion induced failure analysis of subsea pipelines. Reliab. Eng. Syst. Saf. 159 (Supplement C), 214–222.

Yeo, C., Bhandari, J., Abbassi, R., Garaniya, V., Chai, S., Shomali, B., 2016. Dynamic risk analysis of offloading process in floating liquefied natural gas (FLNG) platform using Bayesian Network. J. Loss Prev. Process. Ind. 41, 259–269.