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DOI
10.1016/j.psep.2020.05.024

Publication date
2020

Document Version
Final published version

Published in
Process Safety and Environmental Protection

Citation (APA)
Arzaghi, E., Chia, B. H., Abaei, M. M., Abbassi, R., & Garaniya, V. (2020). Pitting corrosion modelling of X80 steel utilized in offshore petroleum pipelines. *Process Safety and Environmental Protection*, *141*, 135-139. https://doi.org/10.1016/j.psep.2020.05.024

Process Safety and Environmental Protection 141 (2020) 135–139

Contents lists available at ScienceDirect

Process Safety and Environmental Protection

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

Pitting corrosion modelling of X80 steel utilized in offshore petroleum pipelines

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ARTICLE INFO

Article history:
Received 14 August 2019
Received in revised form 28 April 2020
Accepted 8 May 2020
Available online 19 May 2020

Keywords:
Pitting Corrosion
Deterioration
Offshore Structures
Bayesian Inference
Markov Chain Monte-Carlo

ABSTRACT

High strength steels such as X80 steels have recently been used more frequently in production of offshore structures. However, they may still be subject to degradation processes such as corrosion considering the conditions in marine environment. Pitting corrosion is a destructive form of corrosion which reduces the material resistance and may result in failure accidents with severe financial, human life and environmental consequences. The process of pitting corrosion is inconsistent and largely stochastic being influenced by a number of parameters with a high level of uncertainty. This makes it very difficult to predict corrosion in terms of its initiation time and spatial behavior. Therefore, it is vital to investigate pitting corrosion phenomena in offshore structures using a probabilistic approach for the assessment of structural reliability and operational safety. In this study, an in-situ experiment has been conducted on X80 steel in an NaCl solution in a laboratory environment to observe the generation and growth of corrosion pits. A probabilistic model based on Hierarchical Bayesian Approach (HBA) is developed for predicting the pitting corrosion growth rate using experimental results. In order to model the process more realistically, the proposed methodology considers the degradation process to be consisting of the time needed for pit initiation and propagation. The results indicate that the proposed methodology is capable of predicting the time required to reach a specific pit size. The methodology developed in this study can be applied to estimate the remaining useful life of subsea structures.

1. Introduction

Corrosion is defined as the degradation of a material due to a chemical and electrochemical reaction with its surrounding environment (Bhandari et al., 2015; Bhandari et al., 2017). As the operating time of these structures increases, material resistance will decrease due to the loss of thickness caused by corrosion. Corrosion may ultimately lead to structural failure if it is not predicted early enough and necessary integrity management actions are not taken. Corrosion damage is prevalent in process and marine and offshore industries due to high level of salinity and presence of aggressive corrosive agents in sea water (Arzaghi et al., 2018a, 2018b). High strength steels (HSS) have been widely used for construction of oil and gas pipelines. The total length of pipelines manufactured from X80 steel has exceeded 4000 km by 2012 (Zhang et al., 2012). This has helped reduce construction cost, however, pipelines made from HSS may still experience external corrosion which is a dynamic threat to the integrity of pipeline systems utilized in the petroleum industries (Wang et al., 2019). According to Bhandari et al. (2015), pitting corrosion is considered to be the most widespread and insidious form of all types of corrosion in marine and offshore structures. Abdel-Ghany et al. (2020) assert that pitting corrosion is classified as one of the most lethal forms of corrosion. This is due to its localized form of attack while being hard to detect. Difficulties of detection arise when pits, once nucleated, are usually covered with corrosion products. In addition to major economic impacts that corrosion directly imposes on the oil and gas industry, the environmental cost of corrosion can also be very high. According to the Offshore Hydrocarbon Release (HSR) statistics and analysis report 2002-2003, from a total of 2,313 hydrocarbon releases from offshore facilities in about 10 years, 1034 incidents were caused due to corrosion (Bhandari et al., 2015;

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https://doi.org/10.1016/j.psep.2020.05.024
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HSR, 2003; Khan and Howard, 2007). Preventing such impacts would not be possible without a good understanding of pitting corrosion processes.

Wang et al. (2016) suggest that pitting corrosion behaviour of HSS might be different from other materials even in similar environments and this is yet to be fully understood. Xie et al. (2017) investigated the corrosion behaviour of X80 pipeline steel exposed to HCO_3 – ion in simulated soil solutions. They suggest that ion concentrations highly influence and at times even disrupt corrosion reactions. Therefore, it is important to investigate pitting corrosion of HSS material in the marine environment particularly to model its growth rate. This is essential for predicting service life of pipelines as a part of asset integrity management of offshore petroleum structures.

McCallum et al. (2014) developed a series of Markov models to estimate accumulated damage density distributions as a function of a series of input parameters identified based on experimental and field observations. Their model requires data from long period of experimental tests. Field performance testing in relevant fields will provide the most reliable representation of the corrosion process, however, it may be several years before any useful data is obtained. Dai et al. (2020) have deterministically investigated the corrosion behaviour of carbon steel in high hydrofluoric acid concentration solutions reporting that a constant corrosion rate have been observed due to the loose structure of corrosion products. They also assert that such pits can transform to cracks when subjected to stress. Although their study provides a great insight into pitting corrosion and stress corrosion cracking in highly acidic environment, the entire process of pitting corrosion is influenced by a high level of randomness (e.g. due to the uncertainty of environmental conditions) that is not accounted for. It is necessary for any prediction tool to account for the level of uncertainty involved in the process. For instance, to predict the time to pit nucleation or pitting growth rate, a probabilistic approach must be adopted. Melchers (2009) recommended that predicting future pitting corrosion is essential to prevent severe consequences where the most suitable approach to this is by developing a probabilistic model based on experimental data and observations.

The aim of this research is to simulate pitting corrosion damage of X80 steel in a marine environment using NaCl solutions and to develop a probabilistic model for predicting the future health of the structures. A laboratory test is performed to allow the initiation and growth of pits on X80 steel while in-situ measurements of pit diameters are made. The recorded time-variable pit sizes are utilized for developing a probabilistic model of pit growth using a Bayesian technique. The methodology proposed in this study is a practical tool for better prediction of pit growth even with a limited number of observation data. The application of the framework is illustrated by considering various damage levels where probability distributions of time to reach critical damage are obtained. The presented framework is a useful tool for reliability assessment and maintenance planning of oil and gas pipelines using actual damage monitoring results.

1.1. Hierarchical Bayesian Analysis (HBA)

Statistical inference is defined as obtaining a conclusion based on the gained knowledge (Kelly and Smith, 2009). An extensive review of Bayesian statistics for probabilistic knowledge elicitation including a wide range of applications in risk and reliability analysis is provided by Barber (2012). HBA is an advanced probabilistic approach to performing inference based on real-world observations. Bayes' theorem is considered for carrying out Bayesian inference, given in Eq. (1):

$$\pi_1(\theta|x) = \frac{f(x|\theta)\pi_0(\theta)}{\int_\theta f(x|\theta)\pi_0(\theta)\,d\theta}, \quad (1)$$

Where θ is the unknown parameter of interest, $f(x|\theta)$ is the likelihood function, $\pi_0(\theta)$ is the prior distribution of θ and $\pi_1(\theta|x)$ is the posterior distribution of θ. The term hierarchical in HBA represents the use of multistage prior distributions. As suggested by Kelly and Smith (2009), the prior distribution for a parameter of interest is given in Eq. (2):

$$\pi(\theta) = \int_\Phi \pi_1(\theta|\varphi)\pi_2(\varphi)d\varphi, \quad (2)$$

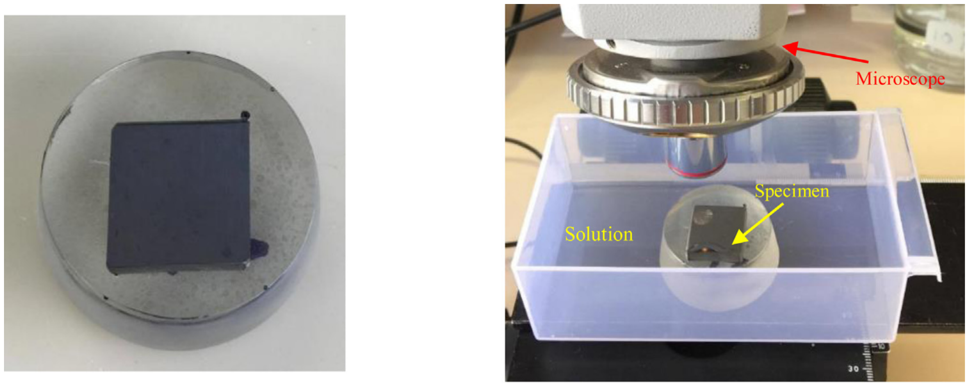
where $\pi_1(\theta|\varphi)$ is the first-stage prior representing the population variability in θ, given the value of φ; $\pi_2(\varphi)$ is the hyper-prior distribution representing the uncertainty of φ as a vector of hyper-parameters. HBA can assist in probabilistic analysis and risk modelling by propagating the uncertainties through complex models. Recently, a number of studies have been conducted to bring the application of Bayesian statistics to structural reliability assessment (Al-Amin et al., 2014; El-Gheriani et al., 2017), maintenance planning of engineering assets (Abbassi et al., 2016), probabilistic risk assessment (Abaei et al., 2018; Arzaghi et al., 2018a, 2018b; Yang et al., 2013; Yu et al., 2017) and multi-criteria decision making in engineering applications (Khakzad and Reniers, 2016). In the present paper, Bayesian inference is utilized to develop a methodology for predicting the pit growth rates using in-situ corrosion tests.

2. Methodology

In order to predict the growth rate of pitting corrosion, steel deterioration must be simulated in a laboratory experiment providing the required data for probabilistic analyses. The proposed method includes two main steps including executing an in-situ laboratory experiment and real time measurements of damage state as well as conducting a probabilistic assessment. Each step of the methodology is explained in detail in the following sub-sections.

2.1. Laboratory Experiment

The corrosion specimens were cut from an X80 steel sheet with final dimensions of 10 × 10 × 20 mm. This type of steel has a chemical composition (wt. %) of C 0.07, Mn 1.77, Ni 0.22, Mo 0.21, Si 0.30, P 0.02, S 0.05, Cu 0.22. In order to prepare the samples, the procedure of an in-situ corrosion test, suggested by Wang et al. (2016), was followed. Rust and scratches on the specimens were first removed by filing and subsequently they were ground with 400, 600 and 1200 grit abrasive paper. After a number of trials, it was concluded that the corrosion of other surfaces of the samples (except the one being monitored) must be limited. This was done to prevent the solution from becoming unclear due to the release of corrosion residuals (i.e if not controlled, it would make observation of pit growth very difficult). The specimens were therefore placed in a mold and sealed, on 5 sides, with wet system epoxy resin. In order to achieve a mirror finish, a few polishing options were examined before buffing. The available options were wet and dry sanding with abrasive paper and surface polishing with a variety of polishing products such as Brasso, Autosol, Silvo and metal polishing powders. After many trials, it was concluded that wet sanding is the most effective way for preparing the samples. The exposed surface of the specimens was wet ground with 600, 1500 and 2000-grit abrasive paper and mirror polished with diamond paste and buffing



a b

Fig. 1. (a) Specimen in epoxy resin mould and surface finished, (b) Experimental setup.

machine. The polished specimens were cleaned with distilled water and acetone and dried with air. This ensured generation of insidious pits on the sample and more chance of detecting and observing the degradation. One of the tested samples is presented in Fig. 1a and the setup of the experiment is illustrated in Fig. 1b. The specimen was immersed in 100 ml of 10% (wt.) NaCl electrolyte while an in-situ setup was capturing the surface using a microscope. Due to time limitations of the project, the concentration of NaCl was increased, as suggested by Wang et al. (2016), to accelerate the pitting corrosion. Application of similar environment for developing corrosion pits in laboratory conditions has been previously used by other researchers (Jafarzadeh et al., 2009; Nie et al., 2013). Other methods such as electrification of specimens have been previously used for conducting accelerated corrosion testing (Zhao and Fu, 2018). Fig. 1 illustrates the setup of the in-situ experiment.

Several preliminary tests were carried out to ensure the experimentation setup was able to simulate and record pit initiation and growth on the samples. For instance, to estimate the effectiveness of solution concentration, required test duration and settings of utilized microscope. Once test setup was confirmed, the degradation was recorded continuously using a microscope. During a 30-minutes period, the surface of the samples was captured at each 1-minute interval. It should be noted that the microscope was calibrated prior to the tests. Once a pit was detected from the first few observations, the recording focused on that specific site for monitoring pit growth. Observations of pit diameters were made by measuring the area of each pit. This provides the data required for probabilistic assessment of pit growth in HSS.

2.2. Probabilistic Analysis

In order to predict the structural reliability of an asset, often the time required for damage (corrosion or fatigue) to reach a certain extent is the parameter of interest. The present methodology therefore considers the limit state concept for analyzing the growth rate of pitting corrosion. That is, several damage sizes are specified representing critical damage levels and the times to reach these sizes were calculated for each observation. This results in obtaining a distribution for time which will be later probabilistically assessed. Based on the trial tests, the limit states that were considered included 0.01 mm, 0.02 mm and 0.03 mm pit sizes.

2.3. Hierarchical Bayesian model (HBM)

The HBM is developed based on the assumption that for any inter-arrival time $[t_i, t_{i+1}]$, the number of pitting observations in each specimen are not independent and identically distributed (iid). Therefore, the occurrence rate $\lambda(t)$ is dependent on time and pitting degradation process represents a Non-Homogeneous Poisson Process (NHPP). In this regard, a power law model as recommended by Kelly and Smith (2009) is adopted for modelling the random duration and nonlinearity of the corrosion process. The rate of this function is given by Eq. (3):

$$\lambda(t) = \frac{\alpha}{\beta}\left(\frac{t}{\beta}\right)^{\alpha-1} \tag{3}$$

The time to observe the first-passage event (reaching first damage size), given the power-law function follows a Weibull distribution. To estimate the parameters of α and β, HBM is employed for sampling the ith pit size observation from the experiment results. At each point of analysis, a conditional probability function must be defined to reflect the dependency of estimations on the previously observed pit size in the previous time interval, $[t_i, t_{i-1}]$. Kelly and Smith (2009), suggest that the appropriate likelihood function considering the power-law assumption can be found by Eq. (4):

$$f(t_i|t_{i-1}) = f(t_i|T_i > t_{i-1}) = \frac{f(t_i)}{Pr(T_i > t_{i-1})}\ , \quad i = 2, \ldots, n \tag{4}$$

where T_i is the observation time of pit size from experiment. Markov Chain Monte-Carlo simulations in OpenBUGS software have been carried out for sampling from the joint distribution of α and β and to obtain the posterior distribution of the hyper parameters. The MCMC sampling must be performed for using the entire range observations in the experiment in order to estimate the posterior distribution of hyper-parameters (α, β). The expected value (EV) of the hyper parameters distributions were then adopted for estimating the mean time to reach the critical damage sizes using Eq. (3). Although operating offshore structures will experience different environmental conditions representing different growth rates, by monitoring the extent of damage (which is normally performed on a continuous or regular basis), the Bayesian methodology presented here will account for the observations made and the predictions will reflect on the experienced conditions. It should be noted that corrosion damage is not a function of sudden and unstable changes in the influencing parameters (which do not usually occur in reality in the offshore environment), and mostly depends on the average of experienced conditions. It is anticipated that the developed methodology, once applied to actual operations and assets, in a condition monitoring framework, will account for any significant changes in environmental conditions.

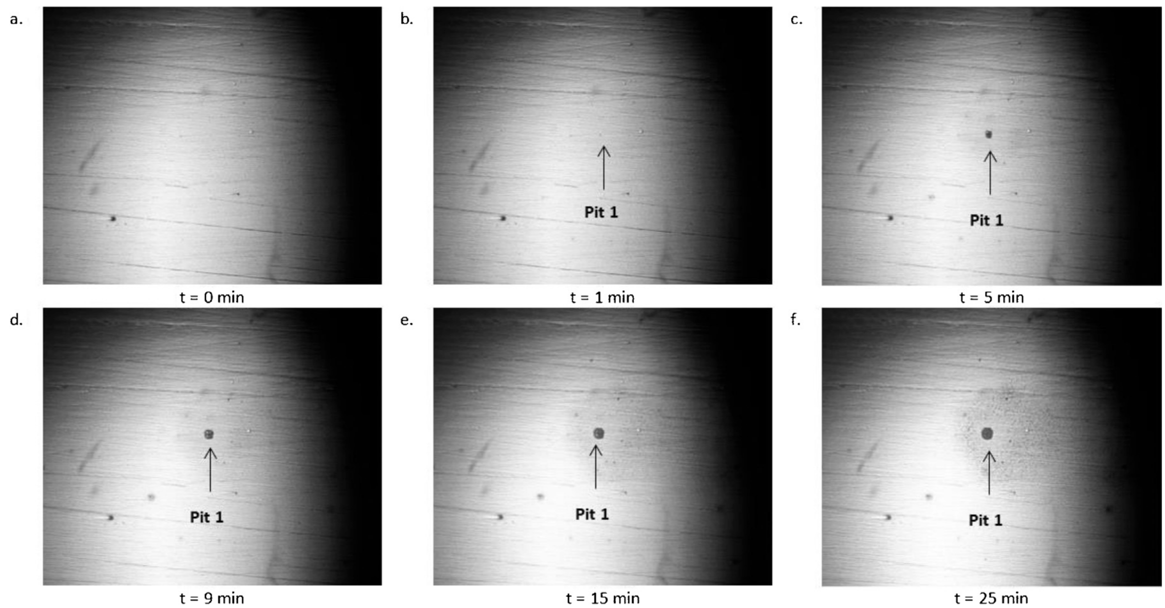


Fig. 2. Time evolution of pitting corrosion on X80 sample in 10% NaCl solution.

Three limit states are considered to obtain the required data for modelling the growth rate of pits. These limits are shown in Fig. 3 along with the measurements of damage. The data is analysed to identify the time of passage of each pit from the limit states. A total of 24 observations were made on the 0.01 mm limit while 19 and 9 observations were made for the 0.02 mm and 0.03 mm pit sizes, respectively.

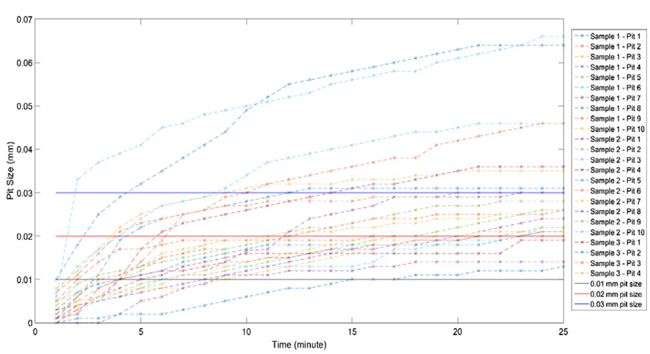


Fig. 3. Pit size growth on different X80 samples, a total of 24 growing pits were detected some of which grew to larger sizes in similar exposure time. The horizontal solid lines indicate the specified critical damage sizes introduced for the sake of probabilistic analysis of pitting growth rate.

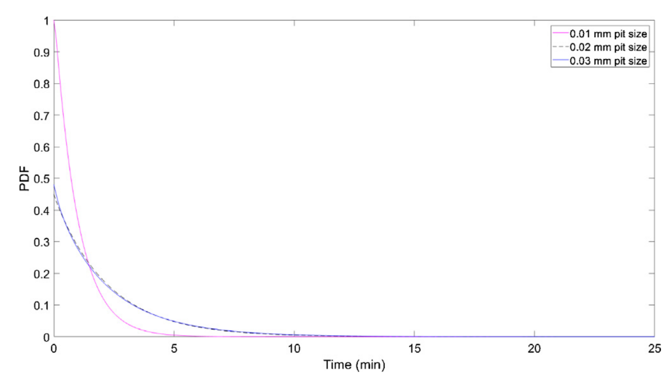


Fig. 4. The probability distribution of time to reach the three different pit sizes (0.01 mm, 0.02 mm, 0.03 mm).

3. Results and discussion

The process of pitting corrosion observed on one of the X80 samples during the in-situ test is illustrated in Fig. 2. The initial condition of the sample surface immediately after immersion is shown in Fig. 2a. Some minor scratches and defects can be seen on the surface of the specimen even though it has been mirror polished. Fig. 2b illustrates the pit initiation at one minute after starting the experiment at a site in proximity of a defect. Wang et al. (2016) states that the surface roughness will affect the pitting behavior and the initiation of pitting corrosion will depend on the surface condition of the material. Five samples have been polished and used to conduct this experiment. It is found that most of the pits initiated from the defects, however, it should be noted that the extent of imperfection in surface finish was maintained reasonably consistent for all the samples. Figs. 2c to 2f depict the propagation of the damage during the experiment. It can be confirmed that the pit grew constantly in the first few minutes, but the growth rate decreased with time of exposure increasing. The obtained results are in a good agreement with the experimental tests conducted by Wang et al. (2016). That is, a comparison with the results presented in their study confirms that within the first 30 minutes of exposure to solution most growing pits had a diameter of 0.02 mm-0.04 mm. Fig. 3 represents the growth of detected pits on all tested samples. A total of 24 growing pits were detected of which some have reached larger sizes than others in similar exposure times.

The observations are used for Bayesian inference in OpenBUGS to obtain the posterior distribution of the hyper parameters, alpha and beta, as explained in Section 3.2. The estimated mean values of alpha and beta are 0.9587 and 0.7946 for 0.01 mm pit size, 0.9978 and 2.245 for 0.02 mm pit size and 0.966 and 2.277 for 0.03 mm pit size, respectively. The mean alpha and beta values are used to obtain the probability distribution of time using Equation (3). These distributions are presented in Fig. 4 showing that almost every pit is likely to initiate and reach the pit size of 0.01 mm within 5-minute exposure time. The PDF for 0.02 mm and 0.03 mm pit size are very similar as they have similar alpha and beta values and pits are expected to reach these sizes before 10 minutes. This is mainly due to the capacity of the monitoring system used in the experiment. However, it is expected to notice a more different trend between these two curves should there be a more powerful damage monitoring system available. The results highlight the applicability of the proposed methodology in predicting the distribution of time to reach various structural degradations. The damage state (pit size thresholds) can be defined by the standards (e.g. those defined by DNV guidelines for subsea pipelines) or by in-house asset managers for improvement of decision-making. This is particularly useful in development of condition monitoring systems where the most recent observations are used to improve the knowledge of asset health state in near future. That is, the more observations (monitoring or inspections) obtained throughout the operation, the less uncertainty is present in the resulting deterioration model. The method can be used for estimation of remaining useful life of structures subject to pitting corrosion including offshore oil and gas and petroleum pipelines. More importantly, the application of this structural reliability assessment framework can be extended by utilizing data from real life condition monitoring systems. Operators and risk managers of process facilities can adopt this method for optimizing asset integrity management plans based on observations of structure health state.

4. Conclusion

In this paper, experimental tests were performed to simulate accelerated pitting corrosion phenomena on HSS and the growth of pit damage was probabilistically assessed. The proposed methodology adopts an HBA to predict the pitting corrosion growth rate. An accelerated pitting corrosion experiment is conducted to obtain the time evolutions of damage on X80 steel in NaCl solution. Based on the obtained observations, the posterior probability distribution of time to reach certain degradation level is estimated. The results suggest that more than 70% of the pits reached 0.01 mm pit size within a 2-minutes exposure time. This is while the PDF of time to reach 0.02 mm and 0.03 mm pit size are very similar, confirming a slower pace of damage growth in higher exposure times. The developed methodology in this paper can be used to monitor the growth rate of pitting corrosion and predict reliability of offshore structures subject to deterioration.

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

Authors thankfully acknowledge the financial support provided by National Centre for Maritime Engineering and Hydrodynamic (NCMEH) at the Australian Maritime College (AMC) of the University of Tasmania.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.psep.2020.05.024.

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