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# Developing a dynamic model for pitting and corrosion-fatigue damage of subsea pipelines

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ABSTRACT

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):

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

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:

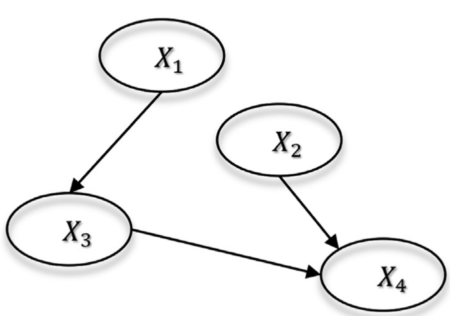


**Figure 1.** A conventional Bayesian network.

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

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”.

$$t_{fl} = t_{pn} + t_{pg} + t_{sc} + t_{lc} \tag{3}$$

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:

$$\frac{dc}{dt} = \frac{C_p}{2\pi c^2} \tag{4}$$