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Markov chain modelling for time evolution of internal pitting corrosion distribution of oil and gas pipelines

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ABSTRACT

A continuous time non-homogenous linear growth pure birth Markov model was used to predict the future pit depth distribution of internally corroded oil and gas pipelines. A negative binomial distribution was used for calculating the transition probability functions of the pit depths whilst pit depth growth was estimated for low, moderate, high and severe pitting corrosion rates using field measured data of pit depths, temperatures, CO_2 partial pressures, pH and flow rates. The Markov predicted results agreed well with field measured pit depth data from X52 grade pipeline and L-80 and N-80 grades offshore well tubing.

1. Introduction

Pitting process can be metastable in nature — a situation in which a pitting process starts and stops after a while or immediately [1,2] or it can be a stable pitting that nucleates and grows indefinitely. Stable pits generally show stochastic behaviour [1,3] and are the focus of many researches. Pitting corrosion is initiated due to:

i. Electrochemical reactions of the carbon steel surfaces with the environment resulting in the formation of surface layers;
ii. discontinuity of the carbon steel material as a result of inclusions; and
iii. removal of an already formed surface layer due to erosion [4].

Forecasting of pitting corrosion rate has been done by modelling, extrapolation or using expert judgement [5]. Modelling technique can follow either probabilistic, deterministic or both approaches and has widespread application as exemplified by numerous publications [1,6–7,8,9]. Yusof et al. [6] studied pitting corrosion of offshore pipelines with Markov chain model and discovered that the prediction was not conservative due to the assumption that the model is linear. The data for the analysis was from repeated in-line inspection (ILI) of internal corroded offshore pipelines.

The authors assumed time of initiation of internal pitting corrosion as 2.9 years (after Velazquez et al. [10]) which is time of initiation of underground pipeline external pitting corrosion. This assumption may invalidate the result of these authors since the environmental condition of the soil is definitely different from that inside the pipeline. Although the future predicted pit depth distribution in this work was based on the exponential parameter (V_p) of power law being 1, the authors proposed Eq. (1) for

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predicting the value of V_p for future pit depth distribution if the initial pit depth (P_{d1}) and time (t_1) and future pit depth (P_{d2}) and time (t_2) are known with the pitting initiation time (t_{int}).

$$V_p = \frac{\log\left(\frac{P_{d2}}{P_{d1}}\right)}{\log\left(\frac{t_2 - t_{int}}{t_1 - t_{int}}\right)} \tag{1}$$

The work of Valor et al. [1] focused on pitting corrosion of underground pipelines and corrosion coupons. The authors used discrete pit depths in non-homogenous, continuous time Markov chain modelling to determine the transition probability function by correlating the stochastic mean pit depth with the empirical deterministic pit depth. They used Weibull process for simulation of the pitting induction time. Other researchers such as Bolanos-Rodriguez et al. [11], Valor et al. [12] and Rodriguez III et al. [13] also applied non-homogenous, continuous time pure birth Markov chain modelling to estimate the pit depth distribution of pipelines by using a closed form of Kolmogorov forward equation for computation of the transition probability function whilst assuming that the pit depth follows a stochastic process. Similarly, Camacho et al. [14] applied Fokker–Planck equation for transition probability function estimate of pitting corrosion of underground pipelines based on a continuous time, non-homogenous pit depth evolution and Hong [15] worked on pit initiation and growth processes by modelling pit initiation as a homogenous Poisson process whilst estimating the pit growth with time as a non-homogenous, continuous time Markov process.

Pipeline failures resulting from pitting have been attributed to pin-hole type pit [8] hence, the need for extreme value modelling of maximum pit depths of corroded pipelines to predict the distribution in the future. Valor et al. [8] applied a stochastic modelling approach to estimate the extreme value distribution of corroded low carbon steel using API-5L X52 pipeline corrosion coupons experimental data. Melchers [16] showed that extreme value analysis can be carried out with limited data if it is combined with Bayesian approach and demonstrated this feat with carbon steel coupons exposed to marine environment. Similarly, Melchers [17] used a bi-modal probability density function to represent the maximum pit depth distribution of mild steel exposed to marine environment and concluded that maximum pit depth distribution is better represented with Fretchet distribution for a long-time exposure of the material than Gumbel distribution that is traditionally used for the extreme value distribution plotting [1–3,5,18–19] however, Sheikh et al. [9] showed that the initial pitting corrosion followed a normal distribution and lognormal distribution for long-time exposure of carbon steel material to a corrosive environment.

Sulphate Reducing Bacteria (SRB) are the most active contributor to pitting in long-time exposure of carbon steel materials to marine environment [2] because their metabolic activities results in sulphate ion reduction to hydrogen and sulphide. The sulphide ion attacks the steel electrochemically causing more pitting corrosion due to an increase in anodic/cathodic reactions necessitated by sulphate reduction. Other researchers also found out experimentally that sulphur reducing bacteria starved of organic energy sources cause severe pitting corrosion of carbon steel materials [20]. Although cathodic protection and other forms of coating have the ability of protecting marine infrastructures like pipelines from external pitting corrosion, ageing infrastructures exposed to marine environment have serious problem of pitting corrosion which can predominantly cause assets failures. Rivas et al. [3] used block maxima and peak over threshold approach for extreme value analysis of laboratory simulated field data of buried carbon steel pipeline and concluded that the peak over threshold approach was more robust in estimating the maximum pit depth of the samples. In their own work, Valor et al. [21] described pit initiation and propagation as a stochastic process of non-homogenous Poisson process and non-homogenous continuous time Markov process respectively. They used extreme value statistics for modelling maximum pit depth growth for data obtained from literature. Although the work produced better results than those obtained from available literature (see ref. [21]), however, the assumption that the entire pits tested nucleates instantaneously may not always be the case practically.

Corrosion can result in unscheduled downtime especially for pitting corrosion, crevice corrosion, stress corrosion cracking and fatigue corrosion since they occur without outward signs on the facilities [22]. Hence, corrosion modelling is used for integrity management *via* prediction of expected time of pipeline failure so that mitigation actions that could include inspection and repairs will be initiated [7–8,23–24]. To establish the time dependent reliability of corroded high pressure offshore pipelines, Zhang and Zhou [25] determined the expected future internal corrosion wastage distribution due to internal pressure using Poisson square wave process. The authors established the time of pipeline failure with respect to small leak, large leak and rupture by using in-line inspection data after modelling stochastic pit depth growth with homogenous gamma distribution according to Eq. (2):

$$f_G(P_d(t)|\alpha(t-t_{int}),\beta) = \frac{\beta^{\alpha}(t-t_{int}) * P_d(t)^{\alpha(t-t_0)-1} * e^{-P_d(t)^{\beta}} * I(t)}{\Gamma(\alpha(t-t_{int}))} \tag{2}$$

where $f_G(P_d(t)|\alpha(t\text{-}t_0),\beta)$ is the probability density function of the pit depth at time t, $\alpha(t\text{-}t_0)$ is the time dependent shape parameter, $\Gamma(.)$ is the gamma function, $I(t)$ is an indicator function with values given in Eq. (3).

$$I(t) = \begin{cases} 1 & \text{if} \quad t > t_{int} \\ 0 & \text{if} \quad 0 \le t \le t_{int} \end{cases} \tag{3}$$

Bazán and Beck [26] also used Poisson square wave process to model external pitting corrosion of underground pipelines and concluded that power model gave a more conservative estimate of the future corrosion wastage than random linear model after