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Bayesian inferences of generation and growth of corrosion defects on energy pipelines based on imperfect inspection data

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ABSTRACT

Stochastic process-based models are developed to characterize the generation and growth of metal-loss corrosion defects on oil and gas steel pipelines. The generation of corrosion defects over time is characterized by the non-homogenous Poisson process, and the growth of depths of individual defects is modeled by the non-homogenous gamma process (NHGP). The defect generation and growth models are formulated in a hierarchical Bayesian framework, whereby the parameters of the models are evaluated from the in-line inspection (ILI) data through the Bayesian updating by accounting for the probability of detection (POD) and measurement errors associated with the ILI data. The Markov Chain Monte Carlo (MCMC) simulation in conjunction with the data augmentation (DA) technique is employed to carry out the Bayesian updating. Numerical examples that involve simulated ILI data are used to illustrate and validate the proposed methodology.

1. Introduction

The metal-loss corrosion involves two processes, namely the growth of existing defects and generation of new defects. Both processes are inherently random. The reliability-based corrosion management of steel oil and gas pipelines usually consists of inspections of pipelines using high-resolution inline inspection (ILI) tools to locate and size corrosion defects, evaluation of the time-dependent probabilities of failure of corroding pipelines and determination of suitable defect mitigation strategies to limit the probabilities of failure to acceptable levels. While the failure probability of a corroding pipeline is influenced by both the growth of existing defects and generation of new defects, the current practice generally focuses on the former but ignores the latter aspect. The present study is aimed at incorporating both aspects in the pipeline corrosion management to improve its accuracy and effectiveness.

Stochastic processes, e.g. the gamma process [1,2] and Markov chain [3,4], have been employed to model the growth of corrosion defects on pipelines. Recently, the gamma process-based corrosion growth models in conjunction with the hierarchical Bayesian methodology have been developed based on the data obtained from multiple in-line inspections (ILIs) of pipelines [5,6]. The Poisson processes, including the homogeneous and non-homogenous Poisson process (HPP and NHPP), have been used to characterize the generation of corrosion defects [7,8]. Hong [7] employed HPP to investigate the impact of newly generated defects on the evaluation of the failure probability of corroding pipelines. Valor et al. [8] develop an NHPP-based generation model and a Markov chain-based growth model for pitting corrosion.

Inspection data provide valuable information pertaining to the condition of corrosion defects. However, inspection data are subjected to the detecting uncertainty as reflected in the probability of detection and probability of false call, and the sizing uncertainty (i.e. the measurement errors) [9]. Yuan et al. [10] developed a Bayesian model to predict the number and depths of corrosion pits on steam generators in nuclear power plants based on in-service inspection data, by taking into account the probability of detection and measurement errors associated with the inspection data. The authors assumed that corrosion pits grow rapidly to stable sizes within a short period of time; as a result, all corrosion pits were treated as static in their study. The Markov Chain Monte Carlo (MCMC) simulation in conjunction with the data augmentation technique was used to carry out the Bayesian updating. In Refs. [11,12], the maximum likelihood method was employed to estimate parameters of probabilistic defect growth models using inspection data containing measurement errors. In particular, a linear growth model is established in a two-stage

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hierarchical structure in [11], and the gamma process-based growth model was adopted in [12] with the model parameters evaluated using a computationally-efficient maximum likelihood method that incorporates the Genz transform and quasi-Monte Carlo method. Note that the generation of defects over time was not considered in [11] or [12].

Kuniewski et al. [13] developed a sampling-inspection strategy for the reliability evaluation of corroding structures. They employed NHPP and the gamma process to characterize the defect generation and growth, respectively, and showed that the number of defects deeper than a certain threshold by a given time also follows NHPP. The formulation for Bayesian updating of the defect generation model based on the inspection data was derived; however, the updating of the defect growth model was not considered (the parameters of the growth model were assumed to be known). The probability of detection was considered in the updating, but the measurement errors were ignored.

The objective of the present study was to develop a probabilistic model to characterize the growth of existing defects and generation of new defects on pipelines based on the imperfect ILI data. The growth modeling was focused on the defect depth (i.e. in the through-pipe wall thickness direction), as this is the most critical defect dimension. The model was formulated in a Bayesian framework, which accounts for the inherent variability involved in the corrosion process as well as the detecting and sizing uncertainties associated with the ILI tool. The non-homogeneous gamma process was used to model the growth of defect depths, and the non-homogenous Poisson process was employed to model the generation of new defects. The MCMC simulation and data augmentation technique were used to carry out the Bayesian updating to evaluate the model parameters. Numerical examples involving simulated inspection data were used to illustrate and validate the proposed methodology. Compared with previous studies in the literature, the main contribution of this study is the proposed Bayesian framework for updating both the defect growth and generation models based on imperfect inspection data.

The rest of this paper is organized as follows. Section 2 briefly describes the uncertainties involved in the ILI data; Section 3 presents the probabilistic models for the defect generation and growth adopted in this study; the Bayesian methodology for evaluating the defect generation and growth models based on the inspection data is described in Section 4; numerical examples are given in Section 5, and conclusions are presented in Section 6.

2. Uncertainties in the ILI tool

Two types of uncertainties associated with the ILI tool were considered in this study, namely the measurement error and imperfect detectability. The former includes the biases and random scattering error, whereas the latter is characterized by the probability of detection (POD) and probability of false call (POFC).

2.1. Measurement error

The ILI-reported depth of the jth defect at the ith inspection, y_{ij}, ($i, j = 1, 2,\ldots$) can be related to the corresponding actual depth, x_{ij}, through the following equation [14,15]:

$$y_{ij} = a_i + b_i x_{ij} + \varepsilon_{ij} \tag{1}$$

where a_i and b_i denote the biases associated with the ILI tool used in the ith inspection ($a_i = 0$ and $b_i = 1$ corresponding to an unbiased tool), and ε_{ij} denotes the random scattering error associated with the ILI-reported depth of the jth defect at the ith inspection, and is assumed to be normally distributed with a zero mean and standard deviation σ_i. For ILI of oil and gas pipelines, it is common practice [16] to track the same defect in different inspections (i.e. the so-called defect matching) based on the longitudinal and circumferential positions of the defect reported by ILI tools. It is assumed that for a given inspection i, ε_{ij} and ε_{ik} ($j \neq k$) (i.e. the random scattering errors associated with the ILI-reported depths of the jth and kth defects) are independent, whereas for a given defect j, ε_{ij} and ε_{lj} ($i \neq l$) may be correlated with a correlation coefficient of ρ_{il} [16]. Let $\mathbf{E}_j = (E_{1j}, E_{2j},\ldots,E_{sj})'$ denote the vector of random scattering errors associated with s inspections for defect j, with "′" representing transposition. It follows from the above assumption that $\mathbf{E}_j$ is multivariate normal-distributed and has a probability density function (PDF) given by

$$f_{\mathbf{E}_j}(\boldsymbol{\varepsilon}_j) = \frac{1}{\left(\sqrt{2\pi}\right)^{n/2} |\boldsymbol{\Sigma}_{\mathbf{E}_j}|^{1/2}} \exp\left(-\frac{1}{2}\boldsymbol{\varepsilon}_j' \boldsymbol{\Sigma}_{\mathbf{E}_j}^{-1} \boldsymbol{\varepsilon}_j\right) \tag{2}$$

where $\boldsymbol{\Sigma}_{\mathbf{E}_j}$ denotes the $s \times s$ variance–covariance matrix of $\mathbf{E}_j$ with the element at the ith row and lth column equal to $\rho_{il}\sigma_i\sigma_l$. In this study, a_i, b_i and $\boldsymbol{\Sigma}_{\mathbf{E}_j}$ were assumed to be known quantities whose values can be evaluated by comparing the ILI-reported and corresponding field-measured depths for a set of benchmark defects [16] or inferred from the vendor-supplied specifications for the accuracy of the ILI tools. It should be pointed out that the random scattering errors conditional on a given set of ILI data must satisfy the constraint that the growth of the actual defect depth is non-negative, and consequently does not follow a multi-normal distribution.

2.2. Probability of detection and probability of false call

POD represents the ability of an ILI tool to detect a true corrosion defect. It is typically a function of the size of the defect and a set of parameters indicating the inherent detecting capability of the ILI tool. The following exponential POD function [17] was adopted in this study:

$$\mathrm{POD}(x) = \begin{cases} 1 - e^{-q(x - x_{th})} & x \geq x_{th} \\ 0 & x < x_{th} \end{cases} \tag{3}$$

where x denotes the actual depth of a given defect; x_{th} denotes the detection threshold, i.e. the smallest defect size that can be detected, and q is a constant that characterizes the inherent detecting capability of the ILI tool. If x_{th} and the POD value for a given defect depth are known, the value of q can be readily computed.

The probability of false call (POFC) is the probability of an ILI tool obtaining an indication of a defect that does not exist in reality. POFC was ignored in the present study; in other words, all the ILI-reported corrosion defects were assumed to be true corrosion defects.

3. Probabilistic models for defect generation and growth

3.1. Defect generation

The non-homogeneous Poisson process (NHPP) was employed to characterize the generation of new defects, as the model has been widely used in the literature (e.g. [8,13]). According to this model, the total number of defects, $N(t)$, generated within a time interval [0, t] (e.g. $t = 0$ denotes the time of installation of the pipeline) over a given segment of the pipeline follows a Poisson distribution with a probability mass function (PMF), $f_P(N(t)|m(t))$,