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Bayesian analysis of small probability incidents for corroding energy pipelines

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ABSTRACT

This paper presents a new methodology for estimation of small posterior failure probabilities for underground energy pipelines, based on external corrosion inspection data. The analysis of the data is based on the BUS (Bayesian Updating with Structural reliability methods) that sets an analogy between Bayesian updating and a reliability problem. The structural reliability method adopted herein is Subset Simulation (SuS) and the whole analysis is referred to as BUS-SuS. Corrosion data obtained from multiple in-line inspections (ILI) of an underground natural gas pipeline are used to illustrate and validate the proposed methodology. The growth of the corrosion defects is modelled through an hierarchical Bayesian framework and the ILI associated measurement errors are comprehensively considered. Through this efficient method, it is ensured that the final samples have reached the posterior distribution. It is also more advantageous over other methods typically employed for Bayesian analysis of corroding pipelines, because it allows the estimation of small posterior failure probabilities directly within the same framework. The proposed methodology can be incorporated in a reliability-based pipeline integrity management program to assist engineers in selecting suitable maintenance strategies.

1. Introduction

During the operation of energy pipelines, some degree of degradation of their condition is considered inevitable and as a result, comprehensive maintenance and rehabilitation plans should be at hand, as part of structural reliability-based maintenance management programs [16]. According to incident data, metal-loss corrosion is the most predominant gradual deterioration process. A sudden breakdown can lead to loss of productivity or severe accidents like ruptures, with large environmental, economic and social implications. A typical industry strategy for reliability-based corrosion management includes high-resolution inline inspections (ILI) to measure defects on the pipeline body and estimate failure probabilities based on the inspection results. Bayesian data analysis is the most credible way of updating probabilistic models given observation data and has been considerably used in energy pipelines' literature over the past decade [21,26,2,29,40,7]. This study focuses on cases where observation data is available on the model response, where Bayesian analysis serves the requirement to inversely determine the probabilistic input parameters given output data. The analytical estimation of the high-dimensional integrals typically involved in Bayesian updating is not feasible in pipeline problems and therefore Markov Chain Monte Carlo (MCMC) sampling techniques are commonly adopted to numerically perform this task [2]. The limitations of these methods include the uncertainty around ensuring that the final samples have reached the posterior distribution and also the difficulty in ultimately quantifying small probabilities of rare failure incidents [34]; particularly rupture due to metal-loss corrosion in the setting of energy pipelines [40].

An alternative method to MCMC has been proposed recently, which sets an analogy between Bayesian updating and a reliability problem [33]. This formulation is termed BUS (Bayesian Updating with Structural reliability methods) and enables the use of established structural reliability methods (SRM) to conduct the Bayesian updating. It also facilitates the estimation of small posterior failure probabilities, directly within the same analysis framework without the requirement of either explicit knowledge or approximation of the posterior joint probability distribution of the random variables [34]. The SRM adopted herein is Subset Simulation (SuS), which was proposed by Au and Beck [4]. The whole methodology is referred to as BUS-SuS and it is considered to be an improved reinterpretation of the classical rejection sampling approach to Bayesian analysis with subset simulation. It is particularly advantageous for underground energy pipelines whose physical models contain many random variables and their failure probabilities are typically very small, especially against rupture [18,28].

Generally, when it comes to mechanical models, the uncertainties regarding material and geometrical properties, environmental factors

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and the models themselves should be accounted for probabilistically, in order to obtain realistic forecasts of failure probabilities [12,43,20]. The corrosion growth model is considered critical for the accuraccy and validity of underground energy pipelines mechanical models [35]. Most corrosion growth models reported in literature can be categorised as random-variable based, stochastic process-based models, fuzzy models, interval models and imprecise probability models [15,37,8,21,40,32,25,11,9,23,24,3]. In Maes et al. [21] and Zhang and Zhou [40] a stochastic process, namely gamma process, was employed to characterize the growth of corrosion defects on the pipeline. Then, hierarchical Bayesian approaches were used to update the gamma process model based on in-line inspection (ILI) data by means of MCMC simulation. The posterior failure probabilities were estimated using a crude Monte Carlo simulation approach. As mentioned above, except for the limitations of the MCMC (i.e. difficulty in ensuring stationarity of the Markov Chain) the estimation of small failure probabilities was not feasible based on the Monte Carlo simulation.

In the present study, BUS-SuS is applied in a real pipeline example subjected to internal pressure loading and is validated against field data. The growth of multiple active metal-loss corrosion defects is characterised through adopting a gamma process model and incorporating it into an hierarchical Bayesian framework based on multiple ILI data, with the associated measurement errors comprehensively considered. A Ferry-Borges stochastic process is employed to model the internal pressure in the subsequent reliability analysis [42]. The contributions of this paper include first the validation of BUS-SuS against an industry application, with subsequent insights on its efficiency and/or limitations and second the computation of small posterior failure probabilities, without the requirement to explicitly define or approximate the posterior joint probability density function.

The content of this paper is structured as follows. The formulation of the stochastic corrosion growth model is presented in Section 2. The hierarchical Bayesian method for updating the model parameters and the BUS-SuS methodology is described in Section 3. The internal pressure model along with the methodology for evaluating the time-dependent reliability of corroding pipelines containing multiple active corrosion defects are described in Section 4. The numerical application of the above is presented in Section 5. The results and discussions are also part of Section 5. Finally, some concluding remarks are presented in Section 6 on the basis of the outcomes of the study.

2. Stochastic growth model

2.1. Gamma process

ILI data may define either a detailed profile of each defect's depth as a function of its length or it may provide only an indication of the maximum defect depth and maximum defect length. When a detailed depth profile is defined, an effective surface defect can be determined from this profile using the procedures described in Kiefner and Vieth [17]. The effective area is defined by its effective length and actual cross-sectional depth. The depth of an elliptical defect of the same length and area as the effective defect is then used to determine the defect's effective depth. If a detailed profile is not available, the effective surface defect feature is defined as the semi-elliptically shaped feature with the measured maximum depth and maximum length. In this study, the growth of each active corrosion defect depth is modelled through both a homogeneous (HGP) and a non-homogeneous gamma process (NHGP). The gamma process is a non-decreasing stochastic process that consists of a series of independent and gamma distributed increments. The distribution of the depth of the corrosion defect (metal-loss in the through pipe wall thickness direction) at time t, $d_i(t)$ is given by [21,40]:

$$f_{d_i(t)}(d_i(t)|\alpha(t-t_{i0})^{\kappa},\beta_i) = \beta_i^{\alpha(t-t_{i0})^{\kappa}} d_i(t)^{\alpha(t-t_{i0})^{\kappa}-1} e^{-d_i(t)\beta_i} / \Gamma(\alpha(t-t_{i0})^{\kappa}) I_{G(0,\infty)}(d_i(t)) \tag{1}$$

where $\alpha(t\text{-}t_{i0})^{\kappa}$ and β_i represent the time-dependent shape parameter and rate parameter (or equivalently the inverse of the scale parameter) of defect i, respectively and t_{i0} the initiation time of the ith defect. Also, $I_{G(0,\infty)}$ $(d_i(t))$ denotes an indication function which equals one if $d_i(t) > 0$ and zero otherwise and $\Gamma(x) = \int_0^{\infty} s^{x-1}e^{-z}dz$ for $x > 0$ [39].

Eq. (1) denotes the probability density function (PDF) of a gamma distributed random variable $d(t)$ with mean equal to $\alpha(t-t_{i0})^{\kappa}/\beta_i$ and variance equal to $\alpha(t-t_{i0})^{\kappa}/\beta_i^2$. For the growth of the ith defect within one year, the incremental depth is a gamma distributed random variable with a mean value of α/β_i and a variance of α/β_i^2, when it comes to homogeneous gamma process (HGP). For the non-homogeneous gamma process (NHGP), the aforementioned values refer only to the first unit increment of time since t_{i0} [40]. For the rest of the increments, the mean and variance are $\alpha(t_{(in+1)}^{\kappa} - t_{in}^{\kappa})/\beta_i$ and $\alpha(t_{(in+1)}^{\kappa} - t_{in}^{\kappa})/\beta_i^2$ respectively. It should be noted that Eq. (1) is a HGP when the shape parameter (i.e. $\alpha(t-t_{i0})^{\kappa}$ for $t \geq 0$) is a linear function of time ($\kappa = 1$) and a NHGP when non-linear ($\kappa > 1$, $\kappa < 1$). In this study, α_i and κ are assumed to be common for all the defects of a pipeline segment, while β_i and t_{i0} are assumed to be defect specific. It was further assumed that the prior distributions of β_i and t_{i0} associated with different defects are identical and mutually independent (iid). Both the NHGP and HGP are considered in the analyses conducted in this study.

2.2. Uncertainties associated with the observation data

The multiple ILI inspections provide observation data that can be incorporated in the corrosion growth probabilistic modelling by means of Bayesian updating. In this study, the probability distributions of the parameters of the gamma process model will be updated based on the observation data. However, the ILI data are subject to measurements errors and sizing uncertainties associated with the ILI tools [1]. Herein, k metal-loss corrosion defects of a pipeline segment are considered, which have been inspected l times over a given period and the measurement errors of the observations are taken into consideration extensively. As a result, the measured depth y_{ij} of the ith defect ($i = 1, 2, \ldots, k$) at inspection j ($j = 1, 2, \ldots, l$) has the following relationship with the actual depth d_{ij}:

$$y_{ij} = c_{1j} + c_{2j}d_{ij} + \varepsilon_{ij} \tag{2}$$

The parameters c_{1j}, c_{2j} are the constant and non-constant biases associated with the ILI tool of the jth inspection, which are assumed to be deterministic quantities. For instance, for $c_{1j} = 0$ and $c_{2j} = 1$ the tool is considered unbiased. Furthermore, ε_{ij} denotes the random scattering errors with respect to the measured depth, which are assumed to have zero means and known standard deviations (i.e. from the inspection tool's specifications). Herein, it is assumed that ε_{ij} are spatially independent and identically distributed for a given inspection j. For a specific defect i, ε_{ij} are considered correlated and follow a multivariate normal distribution with a zero mean and known covariance matrix $\mathbf{\Sigma}_{\varepsilon}$ of the random scattering errors associated with different inspections [1].

The PDF of $\boldsymbol{\varepsilon}_i = (\varepsilon_{i1}, \varepsilon_{i2}, \ldots, \varepsilon_{il})^{\mathrm{T}}$, with "T" denoting transposition, is given by:

$$f_{\varepsilon_i}(\varepsilon_i\,|\mathbf{\Sigma}_{\varepsilon_i}) = (2\pi)^{-\frac{l}{2}}|\mathbf{\Sigma}_{\varepsilon_i}|^{-\frac{1}{2}}\exp\left(-\frac{1}{2}\varepsilon_i^{\mathrm{T}}\mathbf{\Sigma}_{\varepsilon_i}^{-1}\varepsilon_i\right) \tag{3}$$

where $\mathbf{\Sigma}_{\varepsilon}$ is an l-by-l matrix with elements equal to $\rho_{fq}\sigma_f\sigma_q$ ($f = 1, 2, \ldots, l$; $q = 1, 2, \ldots, l$), with ρ_{fq} being the correlation coefficient between the random scattering errors associated with the fth and the qth inspections and σ_f, σ_q denoting the standard deviations of the random scattering errors associated with the tools used in inspections f and q, respectively.