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Time-dependent Reliability Assessment for Corroding Pipelines Based on Imperfect Inspection Data

Shenwei Zhang
Risk Engineer, TransCanada Pipeline Ltd, Calgary, Canada

Shahani Kariyawasam
Principle Engineer, TransCanada Pipeline Ltd, Calgary, Canada

Wenxing Zhou
Assistant Professor, Western University, London, Canada

ABSTRACT: This paper presents a methodology to evaluate the time-dependent system reliability of pressurized pipelines containing multiple active metal-loss corrosion defects and subjected to at least one inline inspection (ILI). The methodology incorporates an inverse Gaussian process-based corrosion growth model, and separates three distinctive failure modes, namely small leak, large leak and rupture. The hierarchical Bayesian method and Markov Chain Monte Carlo (MCMC) simulation are employed to evaluate the model parameters based on data obtained from high-resolution inline inspections. An example involving an in-service gas pipeline is used to validate the developed corrosion growth model and illustrate the proposed methodology for the system reliability analysis. The impact of the growth model on the reliability of pipelines is investigated through the comparative analysis in the example. The proposed methodology will facilitate the application of reliability-based pipeline corrosion management programs.

1. INTRODUCTION

Pipeline systems are the safest and most economical means of transporting large quantities of oil and gas world-wide. Metal-loss corrosion, as one of the identified hazards threatens the structural integrity and safety of underground steel pipelines. Over the last decade, the reliability-based corrosion management programs have been increasingly adopted by pipeline operators to manage the structural integrity of pipelines and allocate limited resources for maintenance (Kariyawasam and Peterson 2008). Three main tasks are involved in this program, including periodic inline inspection (ILI) using high-resolution tools, engineering critical assessment of corrosion defects based on the inspection data and defect mitigation. The corrosion growth model is critical for the various tasks included in the reliability-based corrosion management programs, for example, accurate estimate of the failure probability of a given pipeline over a certain period of time, development of phased corrosion mitigation actions and determination of the re-inspection interval. Therefore, developing a realistic corrosion growth model by incorporating the information implied in the ILI data is of great importance to the pipeline industry.

The corrosion process is inherently complex and involves both the temporal and spatial variability. The former implies that the growth path of an individual corrosion defect varies from time to time, whereas the latter indicates that the growth paths of multiple defects are different but might be correlated, e.g. if the defects are closely spaced. Both the non-stochastic process- and stochastic process-based probabilistic growth models, including the linear growth model, Markov process- and Gamma process- (GP-) based models, have been reported to predict the growth of corrosion defects on pipelines (e.g. Zhou et al. 2012; Zhou 2010; Caleyo et al. 2009). In particular, the Bayesian methodologies have been employed to evaluate the parameters of the GP-based corrosion growth models based on ILI data that are subjected to measurement uncertainties (Zhang et al. 2012; Zhang and Zhou 2013). Recently, the inverse Gaussian process- (IGP-) based degradation model was reported in the literature (Wang and Xu 2010; Zhang et al. 2013). The IGP consists of independent increments that follow the inverse Gaussian distribution, which enables the IGP to characterize the monotonic nature of the growth. Furthermore, the mathematical tractability of the IGP (Wang and Xu 2010) also facilitates incorporating the IGP-based corrosion growth model in a Bayesian framework to evaluate and update the model parameters based on inspection data.

The reliability analyses of corroding pipelines have been well-reported in the literature (e.g. Pandey 1998; Zhou 2010), which employed either non-stochastic process-based or stochastic process-based growth models for the depth (i.e. in the through pipe wall thickness direction) of the corrosion defect. The methodology to evaluate the system reliability of pipelines based on the imperfect ILI data has been reported (Zhang and Zhou 2013), whereby the GP-based corrosion growth model was used in the analysis. The comparison of the predictions from the IGP- and GP-based growth models was investigated (Zhang et al. 2013). Furthermore, the impact of growth model on the reliability of pipelines was also studied by Valor et al. (2013), where the growth models considered, however, are not Bayesian growth models.

This paper presents a methodology to evaluate the system reliability of onshore natural gas pipelines containing multiple active metal-loss corrosion defects subjected to internal pressure. The methodology employs the IGP to model the growth of depths of corrosion defects. The methodology further incorporates the hierarchical Bayesian method and Markov Chain Monte Carlo (MCMC) simulation to update the growth model for the defect depth based on data collected from multiple ILIs. The simple Monte Carlo simulation is used to evaluate the system reliability of the pipeline in terms of three distinctive failure modes, namely small leak, large leak and rupture (Zhou 2010). An example involving an in-service natural gas pipeline is used to validate the proposed growth model and illustrate the methodology. Furthermore, the impact of growth model on the system reliability of pipeline is investigated through the comparative analysis.

2. INVERSE GAUSSIAN PROCESS

Let $\{X(t);\ t \geq 0\}$ denote an inverse Gaussian process (IGP) over time t. Following Wang and Xu (2010), the probability density function (PDF) of $X(t)$ is given by

$$f_{X(t)}(x(t)|\Theta(t), \xi(\Theta(t))^2) = \sqrt{\frac{\xi}{2\pi}}\Theta(t)x(t)^{-\frac{3}{2}}\exp\left(-\frac{\xi\left(x(t)-\Theta(t)\right)^2}{2x(t)}\right)I_{(0,\infty)}(x(t)) \quad (1)$$

where $\Theta(t)$ and $\xi(\Theta(t))^2$ denote the mean and shape parameters of $X(t)$, respectively, with ξ denoting the scale parameter (Chikkara and Folks 1989), and $I_{(0,\infty)}(x(t))$ is an indicator function and equal to unity for $x(t) > 0$ and zero for $x(t) \leq 0$. Note that the variance and coefficient of variation (COV) of $X(t)$ equal to $\Theta(t)/\xi$ and $1/(\xi\Theta(t))^{0.5}$, respectively. It should be pointed out that $\Theta(t)$ must be a monotonically increasing function of time t to ensure the monotonically increasing feature of corrosion process.

The IGP defined by Eq. (1) has three properties (Wang and Xu 2010): (1) $X(0) = 0$ with probability of one; (2) $X(\tau)$-$X(t)$ follows an inverse Gaussian distribution with a PDF of $f_{X(\tau)-X(t)}(x(\tau)-x(t)|\Theta(\tau)-\Theta(t),\ \xi(\Theta(\tau)-\Theta(t))^2)$ for all $\tau > t \geq 0$, and (3) $X(t)$ has independent increments.

3. INSPECTION DATA AND GROWTH MODELS FOR MULTIPLE DEFECTS

Consider that m active corrosion defects on a given pipeline have been subjected to n

inspections over a period of time. The measured depth (i.e. in the through pipe wall thickness direction) of the i^{th} defect at the j^{th} inspection, y_{ij}, (i = 1, 2, …, m; j = 1, 2, …, n) can be related to the actual depth, x_{ij}, Eq. (2) (Fuller 1987):

$$y_{ij} = a_j + b_j x_{ij} + \varepsilon_{ij} \quad (2)$$

where a_j and b_j denote the constant and non-constant biases associated with the ILI tool used in the j^{th} inspection, and ε_{ij} denotes the random scattering error associated with the ILI-reported depth of the i^{th} defect at the j^{th} inspection, and is assumed to follow a zero-mean normal distribution (Al-Amin et al. 2012). It is further assumed that for a given inspection ε_{ij} associated with different defects are independent, whereas for a given defect ε_{ij} associated with different inspections are correlated (Al-Amin et al. 2012). Assuming ε_{ij} and ε_{ik} ($j \neq k$) to be correlated is based on the consideration that the ILI tools used to inspect a given pipeline at different times are typically based on the same technology (e.g. magnetic leakage flux or ultrasonic) and employ similar sizing algorithms. Denote $\boldsymbol{\varepsilon_i} = (\varepsilon_{i1}, \varepsilon_{i2}, \ldots, \varepsilon_{in})'$ with "′" representing transposition. It follows above assumptions that $\boldsymbol{\varepsilon_i}$ follows a multivariate Gaussion distribution with a mean of zero and a variance matrix of $\boldsymbol{\Sigma_{\varepsilon_i}}$. $\boldsymbol{\Sigma_{\varepsilon_i}}$ is an n by n matrix with the element equal to $\rho_{jk}\sigma_j\sigma_k$ (j = 1, 2, …, n; k = 1, 2, …, n), with ρ_{jk} denoting the correlation coefficient between the random scattering errors associated with the j^{th} and k^{th} inspections, and σ_j and σ_k denoting the standard deviations of the random scattering errors associated with the tools used at the j^{th} and k^{th} inspections, respectively. A Bayesian methodology has been developed (Al-Amin et al. 2012) to evaluate a_j, b_j, σ_j and ρ_{jk} (j = 1, 2, …, n; k = 1, 2, …, n) based on the ILI-reported depths for a set of static defects. In this study, a_j, b_j, σ_j and ρ_{jk} were assumed to be known and deterministic quantities.

It is assumed that the actual defect depth follows an IGP given by Eq. (1), where $\Theta(t)$ was assumed to be a linear function of time, i.e. $\Theta(t) = \alpha(t-t_0)$ with t_0 denoting the defect initiation time. This assumption implies that the mean growth path is a linear function of time.

It follows from Eq. (1) that the growth of the i^{th} defect between the $(j$-1$)^{th}$ and j^{th} inspections, ΔX_{ij}, is inverse Gaussian distributed and has a PDF given by $f_{\Delta X_{ij}}(\Delta x_{ij}|\Delta\Theta_{ij}, \xi(\Delta\Theta_{ij})^2)$, with $\Delta\Theta_{ij} = \alpha_i(t_{ij}-t_{i,j-1})$ (j = 1, 2, 3, …, n), where t_{ij} denotes the time of the j^{th} inspection (e.g. the time elapsed since the installation of pipe up to the j^{th} inspection) for the i^{th} defect; t_{i0} denotes the initiation time of the i^{th} defect, (i.e. the time interval between the installation of pipe and the time at which the defect initiates), and α_i denotes the average growth of the i^{th} defect over a unit time interval (i.e. Δt = 1). The actual depth of the i^{th} defect at the time of the j^{th} inspection, x_{ij}, is then obtained by $x_{ij} = x_{i,j-1} + \Delta x_{ij}$, where x_{i0} is assumed to equal zero with a probability of one. In the above-described model, it is further assumed that t_0 and α are defect-specific and ξ is common for all defects.

4. BAYESIAN UPDATING OF THE GROWTH MODEL

4.1. Likelihood function

4.1.1. Likelihood function of growth of depth

Denote $\boldsymbol{y_i} = (y_{i1}, y_{i2}, \ldots, y_{ij}, \ldots, y_{in})'$ and $\boldsymbol{\Delta x_i} = (\Delta x_{i1}, \Delta x_{i2}, \ldots, \Delta x_{in})'$. Consider defect i, it follows from Eq. (2) as well as the assumptions described in Section 3 that the likelihood of the growth, $\boldsymbol{y_i}$, conditional on the inspection data, $\boldsymbol{\Delta x_i}$, can be expressed as:

$$L(\boldsymbol{y}_i|\Delta\boldsymbol{x}_i) = (2\pi)^{-\frac{n}{2}}\left|\boldsymbol{\Sigma}_{\varepsilon_i}\right|^{-\frac{1}{2}}\exp\left(-\frac{1}{2}\left(\boldsymbol{y}_i - (\boldsymbol{a}+\boldsymbol{b}\boldsymbol{x}_i)\right)'\left(\boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}_i}\right)^{-1}\left(\boldsymbol{y}_i - (\boldsymbol{a}+\boldsymbol{b}\boldsymbol{x}_i)\right)\right) \quad (3)$$

where $\boldsymbol{x_i} = (x_{i1}, x_{i2}, \ldots, x_{ij}, \ldots, x_{in})'$ with the j^{th} element, x_{ij}, equal to the summation of Δx_{ik} for k = 1, 2, .., j; $\boldsymbol{a} = (a_1, a_2, \ldots, a_n)'$ and $\boldsymbol{b}$ is an n by n full diagonal matrix with $b_{jj} = b_j$.

4.1.2. Likelihood functions of model parameters

Assume that the exchangeability condition (Bernardo and Smith 2007) is applicable to Δx_{ij} (i = 1, 2, …, m; j = 1, 2, …, n) for a given inspection j; in other words, Δx_{ij} and Δx_{lj} ($i \neq l$) are mutually independent for given inspection j conditional on α, ξ and t_0. It then follows from Section 2 that the joint probability density function of $\boldsymbol{\Delta x_i}$ is

$$f_{\Delta \boldsymbol{x}_i}\left(\Delta \boldsymbol{x}_i | \Delta\Theta_{ij}, \xi\left(\Delta\Theta_{ij}\right)^2\right) = \prod_{j=1}^{n} \sqrt{\frac{\xi}{2\pi}} \Delta\Theta_{ij} \Delta x_{ij}^{-\frac{3}{2}} \exp\left(-\frac{\xi\left(\Delta x_{ij}-\Delta\Theta_{ij}\right)^2}{2\Delta x_{ij}}\right) \quad (4)$$

Further denote $\boldsymbol{\Delta x} = (\boldsymbol{\Delta x}_1, \boldsymbol{\Delta x}_2, \ldots, \boldsymbol{\Delta x}_m)$, $\boldsymbol{\alpha} = (\alpha_1, \alpha_2, \ldots, \alpha_m)$ and $\boldsymbol{t_0} = (t_{10}, t_{20}, \ldots, t_{m0})$. Assume that the growths of different defects are spatially independent; in other words, Δx_{ij} and Δx_{lj} ($i \neq l$) are mutually independent for given inspection j conditional on α_i, ξ and t_{i0}. Given that α_i and t_{i0} are defect-specific and only depends on the growth of the i^{th} defect (i.e. $\boldsymbol{\Delta x_i}$) and ξ is common for the growth of all defects (i.e. $\boldsymbol{\Delta x}$), the likelihood function of $\boldsymbol{\Delta x_i}$ conditional on α_i, t_{i0} and ξ (i = 1, 2, …, m), as well as the likelihood function of $\boldsymbol{\Delta x}$ conditional on ξ, $\boldsymbol{\alpha}$ and $\boldsymbol{t_0}$ are therefore obtained from Eqs. (5a) and (5b), respectively.

$$L(\Delta \boldsymbol{x}_i | \alpha_i, t_{0i}, \xi) = \prod_{j=1}^{n} \sqrt{\frac{\xi}{2\pi}} \Delta\Theta_{ij} \Delta x_{ij}^{-\frac{3}{2}} \exp\left(-\frac{\xi\left(\Delta x_{ij}-\Delta\Theta_{ij}\right)^2}{2\Delta x_{ij}}\right) \quad (5a)$$

$$L(\Delta \boldsymbol{x} | \boldsymbol{\alpha}, \boldsymbol{t}_0, \xi) = \prod_{i=1}^{m} \prod_{j=1}^{n} \sqrt{\frac{\xi}{2\pi}} \Delta\Theta_{ij} \Delta x_{ij}^{-\frac{3}{2}} \exp\left(-\frac{\xi\left(\Delta x_{ij}-\Delta\Theta_{ij}\right)^2}{2\Delta x_{ij}}\right) \quad (5b)$$

4.2. Prior distribution

In this study, the prior distributions of the basic parameters, i.e. α_i, t_{i0} (i = 1, 2, …, m) and ξ were defined as follows: $\alpha_i \sim f_G(p, q)$, $t_{i0} \sim f_U(l, u)$ and $\xi \sim f_G(r, s)$, where f_G (f_U) denotes the PDF of the gamma (uniform) distribution; p (r) and q (s) denote the shape and rate parameters of the gamma distribution, respectively, and l and u denote the lower and upper bounds of the uniform distribution, respectively. The rational of selecting the prior distributions has been addressed by Zhang et al. (2013).

4.3. Posterior distribution

Let $\boldsymbol{\theta}$ denote the uncertain model parameters, $\boldsymbol{\lambda}$ denote the distribution parameters of the prior distribution of $\boldsymbol{\theta}$ (denoted by $\pi(\boldsymbol{\theta}|\boldsymbol{\lambda})$), and $\boldsymbol{D}$ denote the inspection data. The joint posterior distribution of $\boldsymbol{\theta}$ and $\boldsymbol{\lambda}$, denoted by $p(\boldsymbol{\theta},\boldsymbol{\lambda}|\boldsymbol{D})$ can be obtained by combining the prior distributions of $\boldsymbol{\theta}$ and $\boldsymbol{\lambda}$ (denoted by $\pi(\boldsymbol{\lambda})$), with the likelihood, $L(\boldsymbol{D}|\boldsymbol{\theta})$, of the inspection data according to Bayes' theorem (Gelman et al. 2004):

$$p(\boldsymbol{\theta},\boldsymbol{\lambda}|\boldsymbol{D}) = \frac{L(\boldsymbol{D}|\boldsymbol{\theta})\pi(\boldsymbol{\theta}|\boldsymbol{\lambda})\pi(\boldsymbol{\lambda})}{\int \cdots \int L(\boldsymbol{D}|\boldsymbol{\theta})\pi(\boldsymbol{\theta}|\boldsymbol{\lambda})\pi(\boldsymbol{\lambda})\,\mathrm{d}\boldsymbol{\theta}\,\mathrm{d}\boldsymbol{\lambda}} \propto L(\boldsymbol{D}|\boldsymbol{\theta})\pi(\boldsymbol{\theta}|\boldsymbol{\lambda})\pi(\boldsymbol{\lambda}) \quad (6)$$

where "$\propto$" represents proportionality.

The MCMC simulation techniques (Gelman et al. 2004) were employed in this study to numerically evaluate the marginal posterior distributions of the parameters.

5. TIME-DEPENDENT RELIABILITY EVALUATION OF PIPELINE SEGMENT WITH MULTIPLE DEFECTS

A corroding natural gas pipeline typically contains multiple defects and can fail by three different failure modes, i.e. small leak, large leak and rupture, under internal pressure (Zhou 2010). The probabilities of small leak, large leak and rupture, denoted by P_s, P_l and P_r, respectivey, are defined as: $P_s = \mathrm{P}[(g_1 \leq 0) \cap (g_2 > 0)]$, $P_l = \mathrm{P}[(g_1 > 0) \cap (g_2 \leq 0) \cap (g_3 > 0)]$, and $P_r[(g_1 > 0) \cap (g_2 \leq 0) \cap (g_3 \leq 0)]$, where P[•] denotes the probability of event •, $\cap$ represents a joint event, and g_1, g_2 and g_3 are three limit state functions and defined by Eqs. (7a), (7b) and (7c), respectively.

$$g_1 = 0.8wt - d \quad (7a)$$

$$g_2 = r_b - p \quad (7b)$$

$$g_3 = r_{rp} - p \quad (7c)$$

where wt denotes the pipe wall thickness; d denotes the defect depth; r_b represents the burst pressure of a pipe containing a part-through wall corrosion defect; r_{rp} is the rupture pressure, and p is the maximum operation pressure. The use of 0.8wt as opposed to wt in Eq. (7a) has been addressed in Zhang and Zhou (2013). The three limit state functions were detailed in Zhou (2010). A simulation-based methodology to evaluate the probabilities of small leak, large leak and rupture over a forecasting period starting from the most recent inspection has been developed, details of which can be found in Zhang and Zhou (2013).

6. EXAMPLE

6.1. General

The example involves an in-service underground natural gas pipeline. The pipeline was inspected by high-resolution magnetic flux leakage (MFL) tools in 2000, 2004 and 2007. The calibrated biases, the random scattering errors associated with individual ILI tools as well as the correlations between the random scattering errors of different ILI tools used in 2000, 2004 and 2007 are as follows: $a_1 = a_2 = 2.04$ (%*wt*) and $a_3 = -15.28$ (%*wt*); $b_1 = b_2 = 0.97$ and $b_3 = 1.4$; $\sigma_1 = \sigma_2 = 5.97$ (%*wt*) and $\sigma_3 = 9.05$ (%*wt*); $\rho_{12} = 0.82$, $\rho_{13} = \rho_{23} = 0.7$ (Al-Amin et al. 2012), where the subscripts '1', '2' and '3' denote the parameters associated with the ILI data obtained in 2000, 2004 and 2007, respectively, and %*wt* represents the percentage of wall thickness and is the unit of the ILI reported depth by MFL tool.

A pipe segment was selected from this pipeline to carry out the reliability analysis. The selected pipe segment has a nominal outsider diameter of 508 mm (20 inches), an operating pressure of 5.66 MPa, a length of 560 m and a nominal wall thickness of 5.56 mm. The segment is made from API 5L X52 steel with a specified minimum yield strength (SMYS) of 359 MPa and a specified minimum tensile strength (SMTS) of 456 MPa.

6.2. Validation of the growth model

The growth model was first validated by comparing the field-measured depths with the corresponding depths predicted by the growth model for 62 defects, which were excavated, field measured and recoated in 2010. The field-measured depths were assumed to be free of measurement errors (Al-Amin et al. 2012). The three sets of ILI data obtained in 2000, 2004 and 2007 were used to carry out the Bayesian updating and evaluate the probabilistic characteristics of the parameters of the growth models for each of the 62 defects.

The values of p, q, l, u, r and s of the prior distributions as defined in Section 4.3 were specified as follows: $p = 1$, $q = 1$, $l = 0$ (year), $u = 28$ (year), $r = 1$, $s = 1$. A comparison between the predicted depths in 2010 with the corresponding field-measured depths for the 62 defects is shown in Fig. 1.

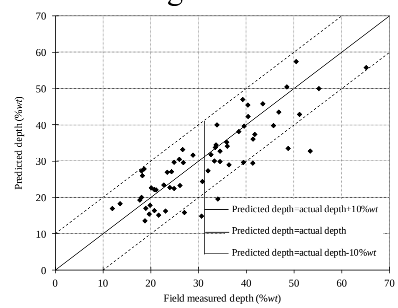

Figure 1 Comparison of the predicted depths in 2010 with the corresponding field-measured depths

Figure 1 suggests that the proposed model can provide reasonably good predictions for majority of the defects considered, as the predicted depths for 90% of the 62 defects fall within the region bounded by the two lines representing actual depth ±10 %*wt*. The predicted depths show significant deviation (defined as the absolute difference between the predicted and actual depths being greater than 10 %*wt*) from the corresponding actual depths for only six defects, with the maximum absolute deviation being approximately 15 %*wt*.

6.3. Reliability analysis results

The time-dependent system reliability was evaluated for the selected pipe segment described in Section 6.1. This segment contains 10 active external corrosion defects.

The PCORRC model (Leis and Stephens 1997) was adopted in this study to calculate the burst pressure of the pipe at a given corrosion defect, i.e. r_b in Eq. (7b). The burst pressure is calculated as follows:

$$r_b = \xi \frac{2\sigma_u wt}{D}\left[1 - \frac{d}{wt}\left(1 - \exp\left(-0.157L/\sqrt{D(wt-d)/2}\right)\right)\right] \quad (8)$$

where σ_u is the pipe ultimate tensile strength; D is the pipe diameter; L is the defect length, and ξ is a multiplicative model error term. Equation (8) is applicable for $d/wt \leq 0.8$ and $L \leq 2D$ (Kiefner et al. 1973).

The model developed by Kiefner et al. (1973) for pressurized pipes containing through-wall defect was used to calculate the rupture pressure, r_{rp}, as follows:

$$r_{rp} = \frac{2\sigma_f wt}{MD} \quad (9)$$

where M is the Folias factor and equals $(1+0.6275L^2/D/wt-0.003375(L^2/D/wt)^2)^{0.5}$ if $L \leq (50Dwt)^{0.5}$ and $3.3+0.032L^2/D/wt$ otherwise, and σ_f is the flow stress and defined as $0.9\sigma_u$. The model error associated with Eq. (9) was ignored due to a lack of relevant information in the literature. The probabilistic characteristics of the random variables involved in calculating r_b and r_{rp} are summarized in Table 1. All the random variables in Table 1 were assumed to be mutually independent.

Table 1 probabilistic characteristics of the random variables

Random variable	Nominal value	Unit	Mean/Nominal	COV (%)	Distribution type	Source
D	508	mm	1.0	0.06	Normal	CSA 2007
wt	5.56		1.0	0.25/mean	Normal	Jiao et al. 199
σ_u	455	MPa	1.08	3	Normal	Jiao et al. 199
P	5.66		1.05	2	Gumbel	Zhou 2010; CSA 2007
ξ_b	1.0	N/A	1.079	26.4	Gumbel	Zhou and Huang 2012

Due to a lack of the ILI-reported lengths of the 10 defects in the ILI of 2007, the lengths of the 10 defects, denoted by L_i (i = 1, 2, …, 10), were assumed to be independent and follow an identical lognormal distribution with a mean of 30 mm and a coefficient of variation (COV) of 50% based on the information summarized in Annex O of CSA Z662 (CSA 2007).

The probabilities of small leak, large leak and rupture over a ten-year forecasting period, were shown in Fig. 2. Results shown in Figure 2 indicate that, over the entire forecasting period, the probability of small leak (large leak) at a given time point is about one magnitude higher than the probability of the large leak (rupture) at the same time point. Furthermore, the growth of the corrosion defect has a slight impact on the probabilities of small leak, large leak and rupture; for example, the probability of small leak at the end of the forecasting period is about twice of that at the beginning of the forecasting period. Similar observations were made on the probabilities of large leak and rupture.

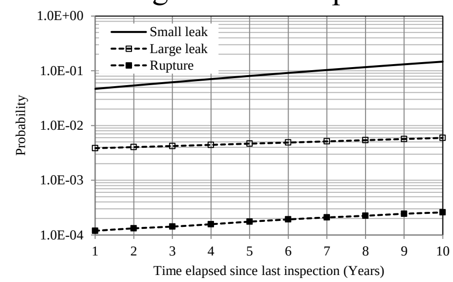

Figure 2 Probabilities of small leak, large leak and rupture based on the IGP-based growth model

6.4. Comparative study

In this section, the impact of the corrosion growth models on the reliability of the pipe segment was investigated. The same segment as described in Section 6.3 was used in the comparative study. Three growth models were considered in this study, namely the IGP-, homogeneous gamma process- (HGP-) and nonhomogeneous gamma process- (NHGP-) based models. Details of the HGP- and NHGP-based models can be found in the literature (Zhang and Zhou 2012, Zhang et al. 2014). A comparison between the field-measured and predicted depth from the three growth models indicates that the absolute values of deviations between the predicted and field-measured depths for the 10 defects are reasonably small (e.g. <5%wt). The similar prediction for the 10 defects allows the comparison of the failure probabilities corresponding to different growth models to be founded on a common basis.

The probabilities of small leak, large leak and rupture, over a ten-year forecasting period, corresponding to the three growth models are depicted in Figs. 3(a) and 3(b), respectively.

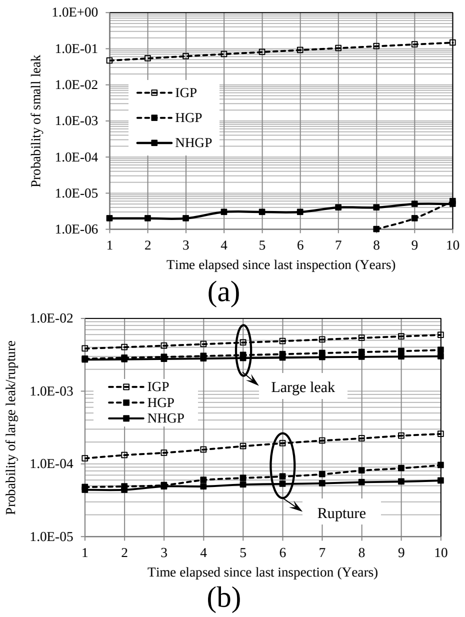

Figure 3 Time-dependent failure probabilities based on three growth models

Results shown in Figure 3(a) indicate that the probabilities evaluated using the IGP-based model are significantly higher than those evaluated using the GP-based models over the entire forecasting period, for example, the probabilities of small leak corresponding to the IGP-based model are about four orders of magnitude higher than those corresponding to the NHGP-based model over the entire forecasting period. It can be observed that the probabilities of small leak corresponding to the NHGP-based model differ significantly from those corresponding to the HGP-based model especially for $\tau \leq 8$ years. Figure 3(a) implies that the probability of small leak is very sensitive to the growth model employed to characterize the defect depth. This is expected because only two random variables (i.e. *d* and *wt*) are included in the limit state function given by Eq. (7a).

Results shown in Fig. 3(b) illustrate that the IGP-based model leads to the most conservative estimate of the failure probability over the 10 year forecasting period, which is similar as that observed from Fig. 3(a). The probabilities of large leak (rupture) corresponding to the IGP-based model are about two (three) times those corresponding to the GP-based models. Furthermore, the difference between the probabilities of large leak/rupture corresponding to the NHGP- and HGP-based models is small. Figure 3(b) suggest that the impact of the growth model on the probabilities of large leak and rupture is less pronounced than that on the probability of small leak as reflected by Fig. 3(a). This observation is mainly attributed to the fact that the limit state functions for large leak and rupture as given by Eqs. (7b) and (7c) include a total of eight random variables (as opposed to a total of two random variables involved in the limit state function for small leak). The uncertainties in parameters (e.g. the internal pressure and model error for the burst capacity model) other than the defect depth can have a large impact on the failure probabilities.

7. CONCLUSIONS

This paper presents a methodology to evaluate the time-dependent system reliability of pressurized energy pipelines containing multiple active metal-loss corrosion defects. The methodology employs the IGP to characterize the growth of the depth of individual corrosion defect. The methodology further incorporates the inspection data in the reliability analysis by using the hierarchical Bayesian method and MCMC simulation to update the growth model for the defect depth based on data collected from multiple ILIs. The measurement uncertainties associated with the ILI data are taken into account in the Bayesian updating. The simple Monte Carlo simulation is used to evaluate the failure probability of the pipeline in terms of three distinctive failure modes, namely small leak, large leak and rupture.

The growth model was first validated by comparing the predicted depth with the corresponding field-measured depths for 62 defects, which suggests that the model characterizes the growth of the defect depth reasonably well.

The time-dependent system reliability analysis was then carried out for a pipe segment that contains 10 defects by incorporating the proposed models for corrosion growth. The results indicate that the probabilities of small leak over the entire forecasting period are the highest, which are about one (two) order of magnitude higher than the probabilities of large leak (rupture).

Finally, the system reliability analysis was performed using the NHGP- and HGP-based models to investigate the impact of the growth model on the reliability of pipeline. Analysis results suggest that the growth models have a significant impact on the probability of small leak, but a smaller impact on the probabilities of large leak and rupture. The proposed model provides a viable alternative to predict the corrosion growth on energy pipelines based on imperfect inspection data and will facilitate the corrosion management of pipelines.

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