Spatial and Temporal Corrosion Degradation Modelling with A Lévy Process based on ILI (In-Line) Inspections

Rafael Amaya-Gómez[a,c,*], Mauricio Sánchez-Silva[b], Emilio Bastidas-Arteaga[c], Franck Schoefs[c], Felipe Muñoz[a]

[a] Chemical Engineering Department, Los Andes University, Cr 1E # 19A-40, Bogota Colombia
[b] Department of Civil & Environmental Engineering, Los Andes University, Cr 1E # 19A-40, Bogota Colombia
[c] Research Institute in Civil and Mechanical Engineering GeM, UMR 6183 - University of Nantes, Centrale Nantes, BP 92208 - 44322 Nantes Cedex 3, France
r.amaya29@uniandes.edu.co

Corrosion defects affect the structural integrity of onshore pipelines making them prone to a Loss of Containment (LOC). LOCs may trigger significant consequences over the surrounding people and environment. Therefore, In-Line (ILI) inspections are commonly implemented to measure indicators of the metal loss along the pipe due to corrosion to support future intervention decisions. However, ILI tools are subject to detection uncertainties that hide the real number of defects because of the accuracy of the technique and the complexity of the spatially distributed corrosion degradation. This paper presents a framework in which a corroding pipeline is assessed spatially and temporally based on ILI measurements. This framework includes new defects generated over time, which are clustered with those already detected, degraded, and assessed regarding the reliability. To this end, the number of new defects is estimated with a Homogeneous Poisson Process. The defects are clustered with the DNV RP-F101 criterion, and their degradation is predicted using Lévy processes. Finally, reliability is assessed temporally and spatially using Monte Carlo simulations based on a dynamic segmentation and a failure region. Following a real case study, the approach results allow us to identify critical segments of the pipeline.

1. Introduction

Management of corroded pipelines is one of the main objectives for pipeline operators considering the possible threats a Loss of Containment (LOC) may pose to the surrounding people and environment. Pipeline integrity is a performance-based process that manages pipeline serviceability and failure prevention considering the hazardousness of the transported materials. This process includes pipeline inspection, integrity assessment, and pipeline maintenance. For corroded pipelines, In-Line (ILI) inspections are commonly used to follow corrosion evolution. ILI tests provide valuable geometric and localized information of the defects identified along the pipeline using tools such as MFL (Magnetic Flux Leakage) and UT (Ultrasonic) (POF, 2009).

Based on ILI inspections, a metal loss can be assessed by several approaches following deterministic, empirical, numerical or probabilistic models. However, ILI inspections are subject of uncertainties during the defect detection (i.e., non-detected defects and false alarms), location, and sizing (i.e., tool resolution), so probabilistic approaches are useful to deal with these uncertainties comprehensively. Available probabilistic approaches usually focus on plastic collapse, yielding, or leak failure criteria. The plastic collapse is evaluated through burst pressure approaches like ASME B31G, DNV RP-F101, CSA Z662 or the model proposed by Netto et al., (2005). Yielding criteria can be described based on longitudinal and circumferential stresses included in a Von Mises approach (Amirat et al., 2006). A leak failure criterion is based on a critical defect-depth, which is commonly taken as 85 % of the pipeline wall thickness (Kale et al., 2004). Overall, these failure criteria are assessed through safety margins -or limit states- using operating or mechanical parameters to estimate pipeline failure probability. Nevertheless, maintenance decisions require to identify critical

segments along the pipeline, which can be associated, for instance, with soil corrosivity (Sahraoui & Chateauneuf, 2016).

Segmentation is the process of defining pipe sectors with similar characteristics (external or internal) that can be used as units for integrity evaluation. Segmentation can be static (i.e., predefined distance), or dynamic - i.e., adaptable to mechanical/external conditions. Static segmentations use fixed distances defined arbitrarily (e.g., one mile) or they are defined by specific mechanical elements of particular interest such as valves. In static segmentation, there is considerable variability in the results of risk assessment and may increase intervention costs due to unnecessary evaluations. Furthermore, critical zones can be hidden if risks are weighted throughout a long segment. In the dynamic segmentation, the length is not relevant, but the feature on which the segmentation is evaluated remain constant (Muhlbauer, 2004). From these two approaches, static segmentations are commonly implemented; some examples of integrity evaluations can be found in Hasan et al. (2002); Teixeira et al. (2008); however, a dynamic segmentation seems to be more reasonable for corroded pipelines, where localized defects are common along the pipeline.

This paper presents a framework in which critical segments are obtained using information from ILI inspections. The framework starts with a generation of new (undetected) defects and a clustering process based on their closeness with those already detected. Afterwards, these clusters are deteriorated with continuous Lévy Processes, and their reliability is assessed using a pressure failure criterion. Finally, critical segments are found using a dynamic segmentation, a failure region, and acceptable predefined thresholds.

2. Proposed framework

2.1 Generation, location, and clustering of corrosion defects

Although Smart PIGs (Pipeline Inspection Gauges) cover pipelines extensively, their inspections as any other measuring device are not perfect. According to Dann & Dann (2017), one uncertainty that limits the assessment of the pipeline is a detection threshold. ILI sensors detect and measure defects above a given threshold, which is commonly taken as 10 % of wall thickness. Hence, the real number of defects would be higher than the reported from the ILI report, so a generation rate should be considered for the future reliability predictions. In this paper, the number and initiation time of new defects were determined based on the suggestions of Zhang & Zhou (2014). Denote the number of defects up to the time t by $N(t)$ with ($t = 0$ the time of installation). Consider also a continuous time-dependent function $\Lambda(t)$ that is associated with the expected number of defects generated over $[0, t]$. Zhang & Zhou (2014) suggested a general form of this function as $\Lambda(t) = \int_0^t \lambda(\tau)d\tau$ with $\lambda(t)$ the instantaneous rate of new defects; however, in this paper this function was estimated using the mean increment of the number of defects (per segment) from two consecutive ILI inspections. Given the function $\Lambda(t)$, the number of defects up to time t (N_t) follows a Poisson distribution with the mass probability shown in Eq(1).

$$f\left(N_t \mid \Lambda(t)\right) = \frac{\Lambda(t)^{N_t} \exp\left(-\Lambda(t)\right)}{N_t!}, \qquad for\ t > 0 \tag{1}$$

Once the number of defects is determined, the next steps are to calculate the time in which these defects initiate their degradation process and to locate them along the pipeline. The first step is explained in detail by Zhang & Zhou (2014). Regarding the location, it depends on two parameters, namely, abscissa and clock-position. The latter corresponds to the relative orientation of the pipeline using a 12 hour-clock analogy. In this paper, the new defects were randomly spread using the current location distributions along the abscissa and the clock position.

After the new and detected defects were obtained and located, these defects were clustered in the inner and outer walls of the pipeline using the DNV RP-F101 criterion. This criterion was selected because of its interesting results against other limit distance criteria and supervised/unsupervised learning methods reported in Amaya-Gómez et al. (2016). This criterion uses the following longitudinally (l_{lim}) and circumferentially (c_{lim}) limit distances between two defects as a function of the pipeline diameter (D): $l_{lim} = 2\sqrt{Dt}$ and $c_{lim} = \pi\sqrt{D\ t}$.

2.2 Degradation process and reliability assessment

For the degradation process, a Lévy process (LP) was considered per cluster. A LP is defined as follows: Given a filtered probability space $(\Omega, \mathcal{F}, \mathbb{F}, \mathbb{P})$, an adapted process $\{X_t\}_{t=0}^{\infty}$ with $X_0 = 0$ almost surely is a LP if (Riascos-Ochoa et al., 2016): (i) $\{X_t\}_t^{\infty}$ has independent increments from the past; namely, $X_t - X_s$ is independent of F_s with $0 \le s \le t \le \infty$. (ii) $\{X_t\}_t^{\infty}$ has stationary increments, namely, $X_t - X_s$ has the same distribution as X_{t-s} with $0 \le s \le t \le \infty$. (iii) X_t is continuous in likelihood, namely, $\lim_{t \to s}\mathbb{P}(X_t \in \cdot) = \mathbb{P}(X_s \in \cdot)$.

For systems that degrade continuously, the LP can be described by a deterministic drift and a Lévy measure, using the Lévy-Ito decomposition and neglecting the Gaussian quadratic process. Then based on its characteristic function and the corresponding characteristic exponent, the lifetime and its expected value (Mean Time To Failure, MTTF) can be determined (Riascos-Ochoa et al., 2016). For this paper, a Gamma Process (Lévy sub-process) was considered because the lifetime and MTTF can be easily calculated.

The pipeline reliability was evaluated through a burst pressure failure criterion by using the approach reported by Netto et al. (2005). This approach was chosen because is less conservative among other approaches such as ASMEB31G or CSA Z-662 (Amaya-Gómez et al., 2016). This criterion approximates the burst pressure of a pipeline based on the material yield strength, pipeline diameter, wall thickness, defect depth, and defect length (Netto et al., 2005). This burst pressure is then used in the limit state function: $g_P = P_{burst} - P_{op}$, where P_{burst} and P_{op} are the burst and operating pressures, respectively. A failure occurs when $g \leq 0$, whereas the pipeline is in a safe zone for $g > 0$. The failure probability was then calculated with Monte Carlo simulations by assuming the operating pressure is Gumbel distributed -following the recommendations of CSA (2007)- and the method discussed in Hasan et al. (2002) to estimate their parameters.

2.3 Dynamic segmentation and failure region

Consider a fix segment length d_{seg} in which the pipeline length L_n can be divided into $n = L_n/d_{seg}$ segments and estimate the failure probability of each segment. Once this task is carried out, segments are shifted a distance $\Delta d_{seg} < d_{seg}$; i.e., $\Delta d_{seg} = \zeta \cdot d_{seg}$, where for example $\zeta \approx 0.1$, and the failure probability is recalculated. Segments are shifted until they reach the location of an original segment; i.e., k times with $k = d_{seg}/\Delta d_{seg}$. Once the segment has been shifted k times and the failure probabilities are calculated, the largest and shortest probabilities are used in a secant interpolation approach to determine upper and lower envelopes (Figure 1a). To this end, Matlab® functions developed by (Martin, 2010) and (Garcia, 2014) are considered.
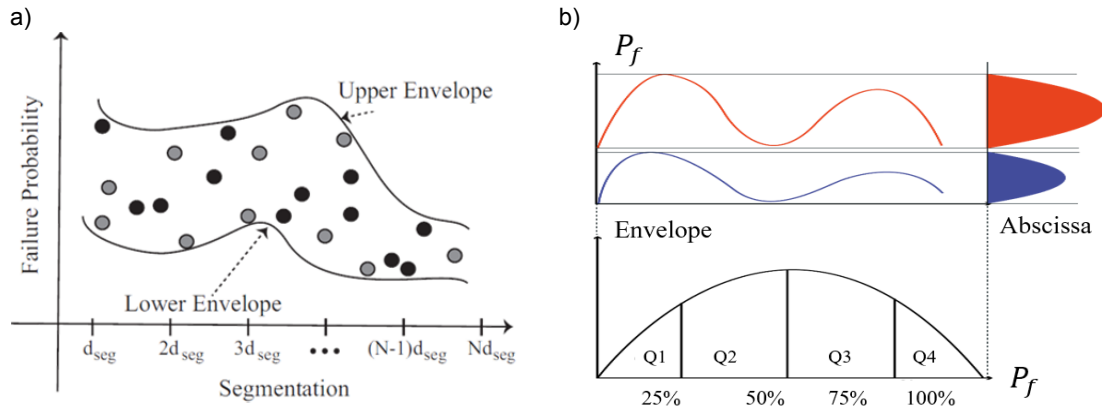

Figure 1: a) Dynamic Segmentation and b) Critical Region schemes

Segment length d_{seg} is determined by maximizing the mean difference between the failure probability without segmentation ($P_{f_{NS}}$) and both envelopes ($\mathcal{E}_u, \mathcal{E}_L$) for a given segment length $\mathcal{I}$:

$$\max_{\mathcal{I} \in S} \frac{1}{N} \sum_{j=1}^{N} \left| \mathcal{E}_U^j(\mathcal{I}) - P_{f_{NS}} \right| + \frac{1}{N} \sum_{j=1}^{N} \left| \mathcal{E}_L^j(\mathcal{I}) - P_{f_{NS}} \right| \tag{2}$$

where S is the set of possible segment lengths such that $\max S = \alpha < L_n$. Considering the entire joint replacement recommendation in case of a corrosion failure (ERCB, 2011), $\min S = \beta \geq \upsilon$ where υ is the minimum joint length reported of the pipeline. Based on these length segments for each evaluating year, a critical region is proposed for a spatial/temporal evaluation. This critical region is obtained from the upper/lower envelopes quartiles, i.e., 50 and 75 % of the data (Figure 1b). Then, two critical regions are proposed to illustrate the pipeline condition temporally along the abscissa.

3. Case study

This example aims to identify possible time and segments to intervene the pipe. The case study evaluates a carbon steel pipeline grade API 5L X52 alloy with an outer diameter of 273.1 mm (10-inch nominal diameter),

with a length of 44 km, a MAOP of 1500 psig, SMYS of 52 psig, SMTS of 60 psig, and an average wall thickness of 6.35 mm. Two corrosion data sets were obtained from ILI runs, 2 years apart. In the first run, 33,466 defects were identified and in the second 59,101. From these datasets, (i) almost 50 % of them are classified as pitting and the remaining are distributed mainly in circumferential slotting, and (ii) the metal loss defects are mostly located in the inner wall with around 80 % in both ILI measurements. Therefore, this paper focuses on the data obtained from the inner wall.

4. Results

4.1 Generation and degradation processes

Based on the two real ILI inspections, the number of new defects was predicted using Eq(1) with an expected number of defects up-to-time t (per kilometer) of $\Lambda(t) = 266.3 \, t$. To illustrate how these defects are generated and located, Figure 2 depicts the obtained results for a segment of the pipeline in the last inspection (Figure 2a) and 10 years after of generating defects (Figure 2b). Note that the distribution in Figure 2b is randomly placed with a predominant location where the defects have already existed; see for instance near 3800 km and a perimeter about 0.1 m. These figures show that new defects are more likely to be located close to the current defects of the pipeline, but a general or localized corrosion may also be incorporated.
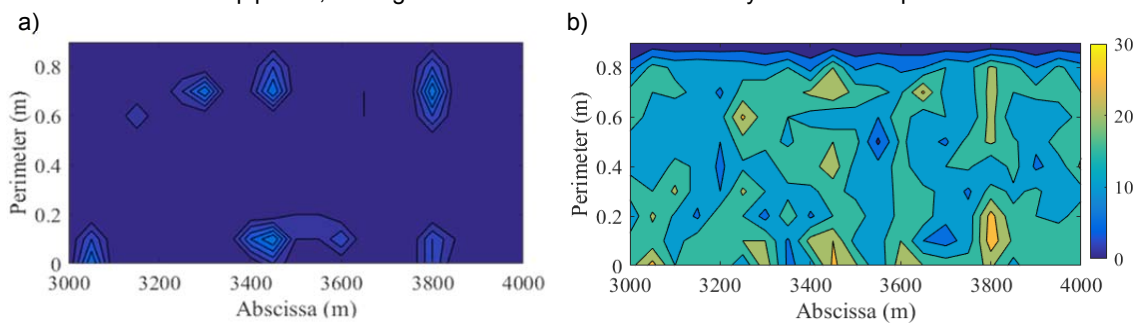

Figure 2. a) Initial (ILI) and b) after 10 years defect distribution

For the case study, a 5-year generation process was added to the already detected defects in the last ILI inspection. This timespan was selected because the time between inspections is about 4 to 6 years. After 5 years, a new inspection is expected to occur, updating the current number of defects. This new condition may trigger repair decisions that reduce $\Lambda(t)$; therefore, a higher generation time could be extremely conservative. From 113,677 defects in 44 km (over 59,000 defects generated), a total of 11,755 clusters were determined using the criterion of DNV, with an average number of 6 defects per cluster. Because of the amount of data, the degradation process was limited to homogeneous Lévy Processes for each cluster and another for isolated defects. For each cluster, their defect depths, the years of this inspection, and the installation year were used in a moment matching approach to calculate the degradation parameters, whereas for the isolated cases the mean degradation of the pipeline was used instead for this purpose (see van Noortwijk, (2009)).

The degradation process allows decision-makers to estimate the MTTF of each defect using a defect depth of 6.35 mm (i.e., the entire wall thickness) as the failure criterion. At the moment the pressure was not involved, so this failure represents a loss of the containment as in a leak, but it could also implicate a burst of the pipe. A preliminary result of the minimum MTTF along the pipeline every 50 m is shown in Figure 3. In this figure, two segments around 18 and 33 km have a MTTF about 10 years, whereas the remain defects depicted ranges near 20 to 50 years. Based on similar results, intervention decisions such as a monitoring or upcoming repairs could be supported in the next years to avoid a loss of containment in larger risk zones.
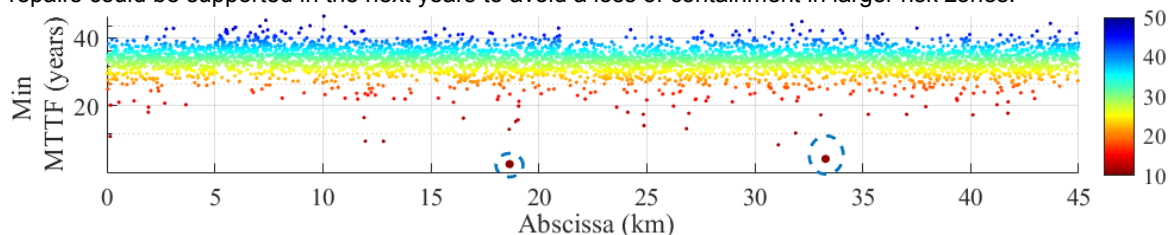

Figure 3. Minimum MTTF for every 50 m

4.2 Reliability-based results

The following parameters for the dynamic segmentation were considered based on the reported joints: $\beta = 5$, $\alpha = 100$, and $\Delta d_{seg} = 1$. Based on a sensitivity analysis of d_{seg} using the indicator of Eq(2), it was determined that the more significant results be found in a segment length between 10 to 15 m; a segment length that matches with the case study joint length range (almost 78 % are between 10 and 14 m). These results would suggest that a great focus of corrosion defects are located near the pipeline joints.
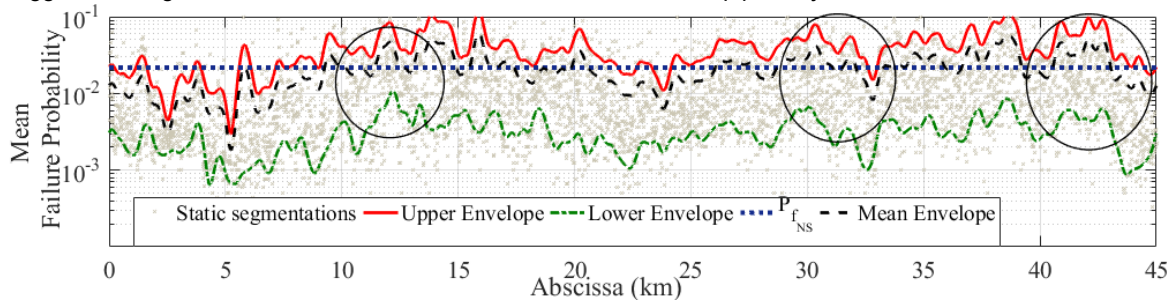

Figure 4. Dynamic Segmentation Results for 10 years and $d_{seg} = 9$.

To illustrate how this approach identifies critical zones along the pipeline, a dynamic segmentation at 10 years using $d_{seg} = 9$ m was obtained and depicted in Figure 4. This figure shows the failure probability without segmentation $P_{f_{NS}}$ around 0.02, the upper envelope as the solid red line, and the lower envelope as the dash-dot green line, and the mean between these envelopes in the black dash line. The results of this illustrative example show that relevant differences were obtained between the two envelopes (upper and lower) and $P_{f_{NS}}$ near segments such as 13-16 km, 31-34 km, and 40-43 km, as it can be evidenced with the mean of these envelopes. Note that these segments have at most differences of one order of magnitude and that $P_{f_{NS}}$ is not within the two envelopes (see the first 5km).
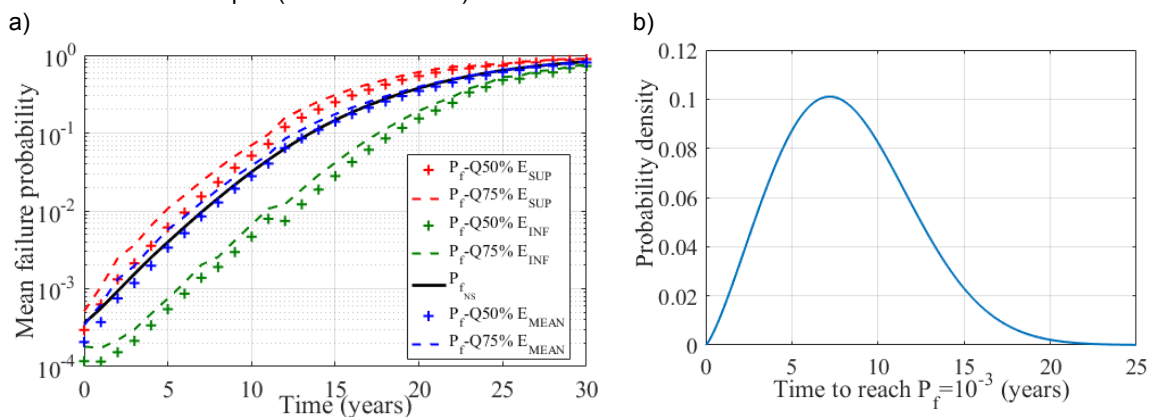

Figure 5. a) Critical Region Results and b) Density of the time to reach $P_f = 10^{-3}$

Finally, the critical region was defined to evaluate pipeline condition over time (see Figure 1). Quartiles of the envelopes were used to generate two critical regions depending on the concentration of data from the obtained envelopes: i) 50 % and ii) 75 % (Figure 5a). These critical regions expose an important variability throughout the pipeline obtaining ranges greater than one order of magnitude, particularly for the range of 10 to 15 years. To identify a possible time and segments to intervene, consider, for instance, the Low Safety Reliability level reported by DNV RP-F101 ($< 10^{-3}$) with the critical region. If the Lower Envelopes (50 % and 75 %) are used, an intervention can be recommended in the next 6-7 years of the inspection because these envelopes exceed this threshold, which almost matches with the mean time to reach $P_f = 10^{-3}$ if the defects were treated separately (Figure 5b). Then, critical segments can be identified using the dynamic segmentation along the pipeline as it was described with the example in Figure 4. The proposed critical region is an interesting alternative to integrity evaluations that are commonly based on fixed segmentations. This approach follows a continuous-reliability assessment based on a corrosion degradation process that can be used with acceptability thresholds to support decision-making in future interventions. This approach can be used with

other spatial evaluations that include, but are not limited to soil aggressiveness (Sahraoui et al., 2016), population density, and high environmental impact with the aim to support risk-based decisions.

5. Conclusions

An integrity evaluation was proposed for corroded pipelines based on a dynamic segmentation and a failure region based on information provided from ILI inspections. The proposed approach aims to identify critical segments temporally and spatially along the pipeline lifetime to support intervention decision-making process. The dynamic segmentation was developed based on upper and lower envelopes from a set of shifted static segmentations. The failure region was determined using the quartiles of the obtained dynamic segmentation. In both cases, a plastic collapse failure and the clustering criterion of DNV RP-F101 were considered with Lévy-based degradation processes. Based on a real case study, it was possible to identify that an intervention should be considered the next 6 to 7 years of the ILI inspection, and special attention should be focused on the kilometers 10 to 15 and 30 to 35.

References

Amaya-Gómez R., Sánchez-Silva M., Muñoz F., 2016, Pattern recognition techniques implementation on data from In-Line Inspection (ILI), Journal of Loss Prevention in the Process Industries, 44, 735-747.

Amirat A., Chateauneuf A., Chaoui K., 2006, Reliability assessment of underground pipelines under the combined effect of active corrosion and residual stress, International Journal of Pressure Vessels and Piping, 83(2), 107-117.

CSA, 2007. CSA Z662-07: Limit state equation for burst of large leaks and rupture for corrosion defect. Canadian Standard Association.

Dann M., Dann C., 2017, Automated matching of pipeline corrosion features from in-line inspection data, Reliability Engineering & System Safety, 162, 40-50.

ERCB, 2011, Directive 066: Requirements and Procedures for Pipelines. Calgary, Alberta, Canada: Energy Resources Conservation Board.

Garcia, D, 2014, Matlab File Exchange: SMOOTH1Q <mathworks.com/matlabcentral/fileexchange/37878-quick---easy-smoothing>

Hasan S., Khan F., Kenny S., 2012, Probability assessment of burst limit state due to internal corrosion, International Journal of Pressure Vessels and Piping, 89, 48-58.

Kale A., Thacker B., Sridhar N., Waldhart, J., 2004, A probabilistic model for internal corrosion of gas pipeline, International Pipeline Conference. Alberta, Canada. IPC2004-483

Martin, A, 2010, Matlab File Exchange: env secant <mathworks.com/matlabcentral/fileexchange/27662-env-secant-x-data--y-data--view--side->

Muhlbauer, W., 2004, Pipeline Risk Management Manual: Ideas, Techniques, and Resources, Elsevier Science.

Netto T., Ferraz U., Estefen S., 2005, The effect of corrosion defects on the burst pressure of pipelines, Journal of Constructional Steel Research, 61(8), 1185-1204.

POF, 2009, Specifications and Requirements for Intelligent Pig Inspection of Pipelines, Pipeline Operator Forum, Available <pipelineoperators.org/downloads-links/ >

Riascos-Ochoa J., Sánchez-Silva M., Klutke G.-A., 2016, Modeling and reliability analysis of systems subject to multiple sources of degradation based on Lévy processes, Probabilistic Engineering Mechanics, 45, 164-176.

Sahraoui Y., Chateauneuf A., 2016, The effects of spatial variability of the aggressiveness of soil on system reliability of corroding underground pipelines, International Journal of Pressure Vessels and Piping, 146, 188-197.

Teixeira A., Guedes Soares C., Netto T., Estefen S., 2008, Reliability of pipelines with corrosion defects, International Journal of Pressure Vessels and Piping, 85(4), 228-237.

van Noortwijk J., 2009, A survey of the application of gamma processes in maintenance, Reliability Engineering & System Safety, 94(1), 2-21.

Zhang S., Zhou W., 2014, Cost-based optimal maintenance decisions for corroding natural gas pipelines based on stochastic degradation models, Engineering Structures, 74, 74-85.