Multiscale framework for corrosion and reliability assessment of inspected pipelines

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ABSTRACT Corrosion attack is one of the main threats for onshore pipelines. Considering the wall reduction may lead to a leak, burst, or rupture of the pipe, the evolution of corrosion degradation is commonly monitored with In-Line Inspections (ILI). These inspections use a set of magnetic or ultrasonic sensors to detect and measure the metal loss at the pipe's inner and outer walls. These measurements are subjected to uncertainties during the detection, measurement, and location, which affect, in turn, the maintenance and repair decisions. This work proposed a framework that deals with and proposes innovative alternatives for these uncertainties to address the reliability assessment. The framework investigates the spatial variability of the corrosion defects, deals with new defects' appearance, and contributes with tools from a reliability perspective. This paper presents the proposed framework's principal elements and their results from a real case study of a 45 km long pipeline.

Keywords Reliability, spatial variability, corrosion, In-Line Inspection, onshore pipelines

I. INTRODUCTION

Onshore pipelines are the most widely used and cost-effective means for hydrocarbon transportation. However, they frequently experience inner and outer corrosion degradation due to the surrounding soil's aggressiveness, flaws in the protective coating, or the corrosiveness caused by the transporting fluid (Amaya-Gómez et al., 2021). The wall thickness reduction and the changes in the pipeline properties lead to either leak, bursts, or pipeline ruptures. Pipeline operators commonly use In-Line (ILI) inspections to follow the corrosion evolution of corroded pipelines. ILI tests provide valuable geometric and position information of the defects identified along the pipeline using smart PIGs (Pipeline Inspection Gauge) with a set of magnetic (MFL) or ultrasonic (UT) sensors, as illustrated in Figure 1.

Although smart PIGs cover the pipeline extensively, their inspection results are subjected to possible miss detections and erroneous measurements that can affect final management decisions. Some primary sources of uncertainty are (Dann & Dann, 2017): (i) *Detection*: ILI sensors can only detect defects above a given threshold, commonly taken as depths ≥10% of the wall thickness. (ii) *Detection error*: the detection of a defect is subjected to a Probability of Detection (PoD). (iii) *False errors*: the ILI tool may report a defect that does not exist. (iv) *Location error*: the actual and reported locations could differ. This shifted position complicates further complete monitoring (matching problem).

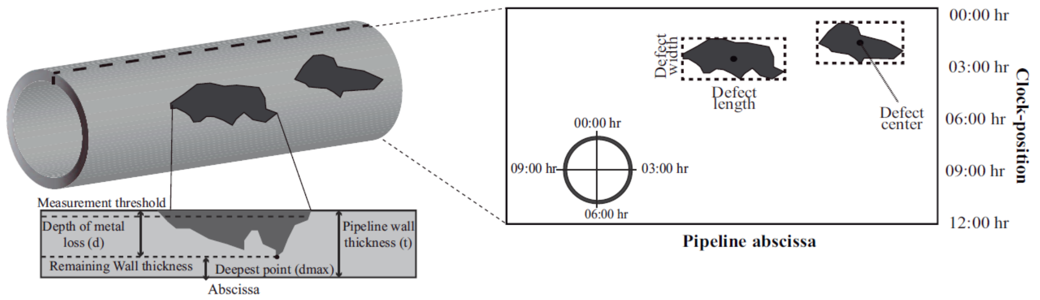

FIGURE 1 Scheme of the location of a corrosion defect. Modified from POF (2008)

This work seeks to support pipeline integrity programs of corroded pipelines, handling consecutive In-Line measurements' uncertainty. The work concentrates on how these measurements can be used in three main aspects: (i) the spatial variability of the corrosion defects at various scales, (ii) the modeling and identification of new defects, and (iii) the estimation of the reliability. This paper describes the proposed framework in a real 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 (10.34 MPa), and an average wall thickness of 6.35 mm. Two corrosion data sets were obtained from ILI runs two years apart. In the first run, 26,570 defects were identified, and in the second, 47,663. The defects are primarily located in the inner wall from these datasets, so this paper focuses on the data obtained from the inner wall.

II. UNCERTAINTY MODELLING OF A CORRODED PIPELINE

The proposed framework addresses how critical segments can be identified using information from ILI inspections. New defects will appear between consecutive inspections due to a miss-detection or the surroundings' aggressiveness. First, a matching approach was proposed, and further study their spatial distribution and interaction with already detected defects. The critical segments are evaluated from a reliability perspective, considering the possibility of "corrosion colonies" (i.e., clusters) following a stochastic corrosion degradation. Finally, it assesses how the failure probability changes spatially and temporally. The proposed framework is summarized in Figure 2.

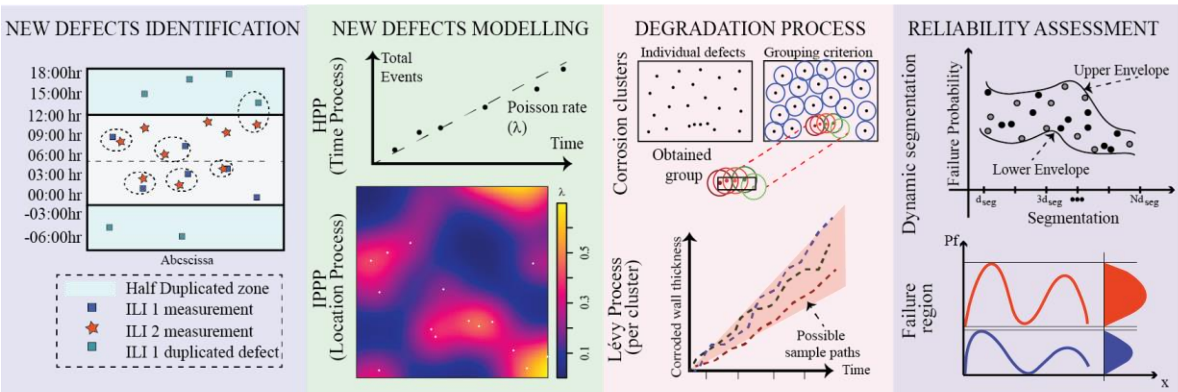

FIGURE 2 Scheme of the proposed framework

A. Identification of new corrosion defects

Consider two ILI measurements with m and n defects, respectively, denoted by $\mathcal{P} = \{p_i \in \mathcal{W}, i = 1, 2, \ldots, n\}$ and $\mathcal{Q} = \{q_k \in \mathcal{W}, k = 1, 2, \ldots, m\}$. In this case, p_i and q_k are vectors containing the location of the pipe, and $\mathcal{W} = (\mathbb{A} \times \mathbb{P}) \subset \mathbb{R}^2$ is the plane formed by the abscissa ($\mathbb{A}$) and circumferential position ($\mathbb{P}$) once the pipeline is unrolled axially (see Figure 3). The objective is to determine an affine transformation that matches the higher number of points between $\mathcal{P}$ and $\mathcal{Q}$.

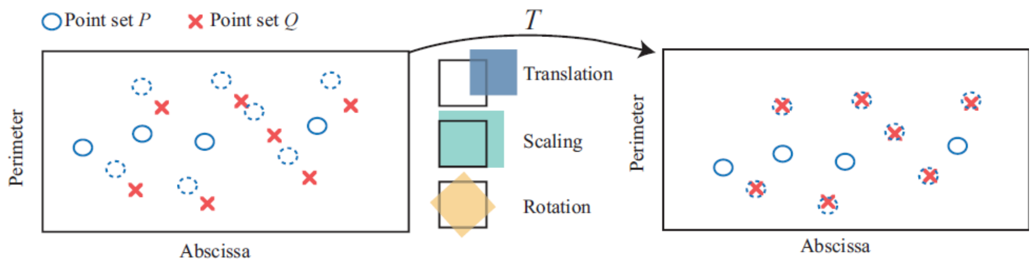

FIGURE 3 Schematic point matching problem

The matching problem was addressed following a nearest-neighbor criterion and an iterative approach. It considers an extended 2D plane to account for the pipeline continuity in the circumferential direction, as reported by Dann & Dann (2017), see Figure 2. The data processing begins by determining the Voronoi partition of each inspection. This partition defines regions or cells closer to each point for both set of points. These cells are identified and used to create tile lists that determine in which cell are located the points from the other set. The mixed nearest neighbor is then obtained considering the pairs that share being the nearest neighbor between each other. Although these pairs share being the closest neighbors, they can be extremely separated, like in the case of isolated corrosion defects. Clearly, this matching would not represent the reality, considering the defined location uncertainties. Therefore, pairs with a physical separation lower than the inspection accuracy are considered. Denote these accuracies by δ_x and δ_y, and consider only pairs with a separation shorter than $\delta = \sqrt{\delta_x^2 + \delta_y^2}$.

The next stage of the proposed methodology implements an iterative matching transformation using the best affine transformation from Chang et al. (1997). They found the affine transformation that minimizes the residual sum of squares from at least two sets of pairs. The proposed approach implements this transformation iteratively with the data processing until an arbitrary small difference of the residual sum of squares is obtained. Finally, a modified version of the correspondence and outlier approach of Dann & Dann (2017) is considered, see Eq. 1, after identifying the affine transportation $T(p_i)$ and letting $w_{ik} = \|q_k - T(p_i)\|^2$. Here $\mathbb{C} = [\mathrm{c_{ik}}]$ is a correspondence matrix, r and s are outlier vectors for each set, and α could be linked to the outliers' proportion in both sets. This problem is solved using linear programming, leading to binary outputs, i.e., each point is classified as a unique match or as an outlier.

$$\underset{\mathbb{C}, r, s}{\operatorname{argmin}} \sum_{i=1}^{2n} \sum_{k=1}^{m} c_{ik}(w_{ik} - \alpha) \tag{1}$$

subjected to ($\forall i = 1, \ldots, 2n, \;\; \forall k = 1, \ldots, m$):

$$0 \le c_{ik},\, r_i,\, s_k \le 1, \qquad \textstyle\sum_{k=1}^{m} c_{ik} + r_i = 1, \qquad \sum_{i=1}^{2n} c_{ik} + s_k = 1$$

B. New defects modelling

Because the actual number of defects would be higher than the reported from the ILI report, a generation rate should be considered for future reliability predictions. In this case, the number and initiation time of new defects were determined based on the suggestions of Zhang & Zhou (2014). Consider a continuous time-dependent function Λ(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 λ(t) the instantaneous rate of new defects. This function was estimated using the mean increment of the number of defects (per segment) from two consecutive ILI inspections. Given Λ(t), the number of defects up to time t follows a Homogeneous Poisson process (HPP).

Once the number of defects is determined, the following 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) using Monte Carlo simulations. Regarding the position, new defects are usually located following a uniformly random or Complete Spatial Randomness (CSR) distribution (Miran et al., 2016); however, it may be conservative considering that corrosion clusters are commonly reported near welded joints. Indeed, this clustered pattern was validated using the case study with different CSR tests based on nearest-neighbor and functionals methods recommended by Dettloff (2014) and Baddeley et al. (2016), e.g., Byth & Rypley, Maximum deviation, and the Diggle-Cressie-Locsmore tests. Consequently, the locations are simulated using an Inhomogeneous Poisson Point Process (IPPP) that depends on an intensity $\tilde{\lambda}(x)$ (i.e., the density of points) upon to a given location x. The intensity is determined using a kernel smoothing estimator, which can be thought of as a chocolate bar over the points that melt and form an undulating surface, depending on the points' density (see Figure 2). A Gaussian Kernel with the Diggle edge correction was implemented for this work, considering that many authors commonly recommended it. Further details are available in Baddeley et al. (2016).

C. Stochastic Degradation process for the corrosion clusters

If the defects are located close to each other - known as "corrosion colonies"- the chances of failure causing loss of containment become critical; in this case, the interaction of individual defects acts as a single larger defect (Figure 2). There are several grouping criteria between adjacent corrosion defects, where the most used are those from standards. The *corrosion colonies* relevance lies in the fact that they affect reliability predictions such as the Mean Time to Failure (MTTF), which in turn, are useful to support further decision-making processes (Amaya-Gómez et al., 2016). The DNV RP-F101 criterion was selected for this work because of its interesting results against other limit distance criteria and supervised/unsupervised learning methods (Amaya-Gómez et al., 2019c).

Each of these clusters follows a stochastic degradation based on a Lévy process (LP). 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: (i) $\{X_t\}_t^{\infty}$ has independent increments from the past, (ii) it has stationary increments, and (iii) X_t is continuous in likelihood. 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. Based on its characteristic function and the corresponding characteristic exponent, the lifetime, and its expected value (MTTF) can be determined (Amaya-

Gómez et al., 2019a). For this paper, a Gamma Process (Lévy sub-process) was considered because the lifetime and MTTF can be easily calculated.

D. Spatiotemporal Reliability Assessment

The pipeline reliability was evaluated through a burst and stress failure criteria by using the models reported by Netto et al. (2005) and Amirat et al. (2006). Netto's model was chosen because it is less conservative among other approaches for a moderate toughness pipe (Amaya-Gómez et al., 2019b). This criterion approximates the burst pressure based on the material yield strength, pipeline diameter, wall thickness, defect depth, and defect length. Amirat et al. (2006) considered a model based on longitudinal and circumferential stresses that incorporates residual contributions from the metal loss. The longitudinal stresses depend on load and support conditions throughout the pipeline, whereas circumferential stresses on the propagation of the applied load at the top of the pipe and the propagation of the support reaction at the bottom. Both models are evaluated from a limit state perspective: $g_P = P_b - P_{op}$ and $g_S = \sigma_u - \sigma_{eq}$, where P_b and P_{op} are the burst and operating pressures and σ_u and σ_{eq} are the ultimate strength and the Von Mises Stress, respectively. A failure occurs when $g \leq 0$, whereas the pipeline is in a safe zone for $g > 0$. The failure probability is then calculated with Monte Carlo simulations using a combined criterion for each defect as follows. Let $\mathcal{A}$ and $\mathcal{B}$ be the pressure and stress failure events, respectively, then the combined failure is estimated by the union of these two events, i.e.,$\mathbb{P}(\mathcal{A} \cup \mathcal{B}) = \mathbb{P}(\mathcal{A}) + \mathbb{P}(\mathcal{B}) - \mathbb{P}(\mathcal{A} \cap \mathcal{B})$.

A dynamic segmentation and a Failure Region are proposed to address the spatial and temporal variabilities. Consider a fixed segment length d_{seg} in which the pipeline length L_n can be divided into $n = L_n/d_{seg}$ segments and estimate each segment's failure probability. 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 (see Figure 2). Segment length d_{seg} is determined by maximizing the mean difference between the failure probability without segmentation and both envelopes for a given segment length. Finally, 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 2).

IV. MAIN RESULTS

Modelling of new defects and the degradation process

The matching approach outperformed other approaches, such as the annealing method proposed by Dann & Dann (2017). As a matter of an example, 50 simulations were compared using $n = m = 30$ and $\mathcal{P} := \{(p_{xi}, p_{yi})\}_{i=1}^{30}$ uniformly random distributed in $[0,1]^2$ and $\mathcal{Q} := \{(p_{xi} + \Delta_x, p_{yi} + \Delta_y)\}_{i=1}^{30}$ where Δ_x and Δ_y are uniform random variables associated with the location uncertainties. The results indicated a mean matching ratio of 84.8% against the 60.7% for the annealing process. In fact, it was obtained similar true matching ratios for the solver KNITRO, which is a solver specialized for non-linear optimization problems under an AMPL language in the NEOS server.

Based on the two ILI inspections, the expected number of defects up-to-time t (per kilometer) was Λ(t)=266.3 t. 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 Λ(t); therefore, a higher generation time could be extremely conservative. From 92,691 defects in 44 km (over 49,000 defects generated), a total of 9,023 clusters were determined using the DNV criterion, with an average number of 4 defects per cluster. The degradation process was limited to homogeneous Lévy Processes for each cluster and another for isolated defects because of the amount of data. 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; for the isolated defects, the mean degradation of the pipeline was considered instead (Amaya-Gómez et al., 2019a).

Reliability-based results

For the dynamic segmentation, it was considered a shifted distance of 1 m (Δd_{seg}) and a range of static segments from $d_{seg} = 5$ to 100 m. Based on a sensitivity analysis of d_{seg}, 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 is located near the pipeline joints.

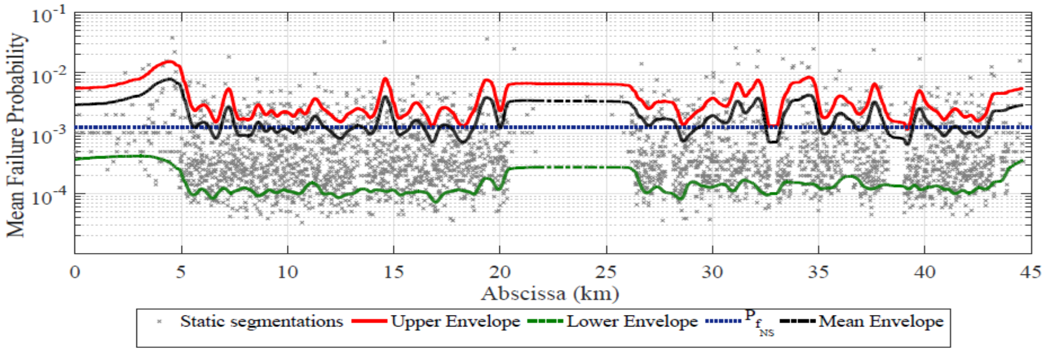

FIGURE 4 Dynamic Segmentation Results for 10 years and $d_{seg} = 9$

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 $P_{f_{NS}}$ near 0.0012, 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.

Finally, the critical region was defined to evaluate the pipeline condition over time (Figure 5a). Quartiles of the envelopes were used to generate three critical regions depending on the concentration of data: 25%, 50%, and 75%. These critical regions expose an important variability throughout the pipeline, 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. Considering the Lower Envelopes for 50% and 75%, an intervention can be recommended in the next 8-10 years of the inspection because these envelopes exceed this threshold. Besides, these years match the mean-time-to reach $\mathbb{P}_f = 10^{-3}$ if the defects were treated separately (Figure 5b). Then, the dynamic segmentation along the pipeline can identify critical segments, as described with the example in Figure 4. The proposed critical region is an interesting alternative to integrity evaluations 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 and population density to support risk-based decisions.

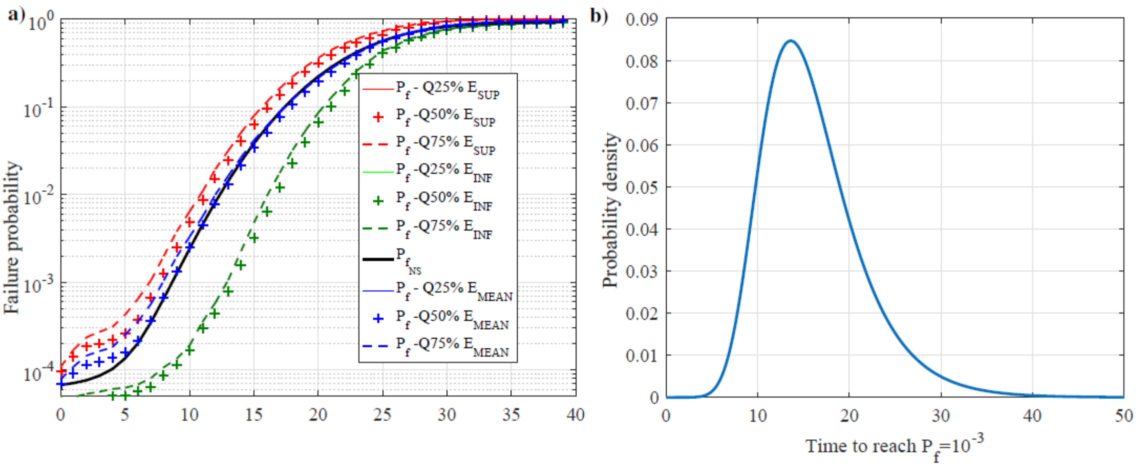

FIGURE 5 a) Critical Region Results and b) Density of the time to reach $P_f = 10^{-3}$

V. CONCLUSIONS

A framework is proposed to address the uncertainty obtained from In-Line Inspections and support further maintenance/repair decisions. This framework contemplated the appearance of new defects, which do not follow the Complete Spatial Randomness assumption (i.e., uniformly distributed). They were identified with a nearest-neighbor approach (i.e., Voronoi tessellation) using an iterative matching and correspondence optimization, outperforming other available approaches. These new defects would interact with already detected ones (i.e., corrosion clusters) depending on their separation, favoring a space-dependent degradation process that was evaluated with different Lévy Processes. Finally, an integrity evaluation was proposed for corroded pipelines based on a dynamic segmentation and a failure region to identify critical segments temporally and spatially along the pipeline lifetime. 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 combined failure criterion from a plastic collapse and a stress failure were considered using the model proposed by Netto et al. (2005), after an extensive review, and Amirat et al. (2006) because it also contemplates residual contributions. Based on a real case study, it was possible to identify that an intervention should be considered the next 8 to 10 years of the ILI inspection, and special attention should be focused on the kilometers 13 to 16 and 31 to 35. The main objective behind these decisions is to prevent any failure from the wall thinning, unnecessary repair, or shutdown of the flow.

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