

Probabilistic prediction of external corrosion fatigue life in buried steel pipes

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ABSTRACT

This research investigates a methodology for probabilistic life prediction of buried steel pipelines subjected to external corrosion. A unified methodology is developed considering multiple stages of degradation related to external corrosion (due to soil) and fatigue. These stages include corrosion pit nucleation, pit growth, transition from pit to short crack, short crack growth, transition from short to long crack, stable long crack growth, and unstable fracture. The methodology is useful in obtaining stage-specific forecasts for the fatigue life of buried steel pipelines subjected to external pitting corrosion fatigue. State-of-the-art computational models are used to predict damage initiation and evolution at each stage. The variability in environmental, material, and loading parameters is propagated through these models to obtain a probabilistic estimate of the remaining service life (RSL) of the pipe. Insights from probabilistic RSL prediction highlight the influence of soil type and pipe coating material on corrosion fatigue life. Global sensitivity analysis is then employed to quantify the relative importance of environmental factors (pH, pipe/soil potential, and chloride concentration), material properties (threshold stress intensity factor), and the range of cyclic stress experienced by the pipe.

1. Introduction

Buried pipelines play a pivotal role as a critical civil infrastructure [1], and are widely employed across various sectors for transporting materials [2,3]. Steel pipelines are susceptible to external as well as internal corrosion. In external corrosion, the outer surface of the pipe degrades due to environmental factors such as soil composition, moisture content, and corrosive agents [4]. Conversely, internal corrosion is driven by chemical reactions affecting the pipeline's interior and is influenced by factors like fluid composition, temperature, and flow rate [5]. The US Department of Transportation's Pipeline and Hazardous Materials Transport Administration maintains a database of all undesirable incidents for in-service pipelines [4,5]. According to this data [4–6], external corrosion accounts for approximately 8% of all pipeline incidents, whereas internal corrosion is responsible for around 12% of the incidents. External corrosion-induced failure mechanisms manifest in various forms such as hydrogen-induced cracking (HIC) [7], stress corrosion cracking (SCC) [8], combined HIC and SCC [9,10], microbiologically induced corrosion (MIC) [11], and corrosion fatigue (CF) [12].

Corrosion fatigue [12,13], defined as *fatigue in corrosive environment*, is the focus of this study. The soil provides a corrosive environment, which contains moisture, salts, and other potentially corrosive agents [14–16]. Fatigue is induced by cyclic loading exerted on the pipeline material over time. This cyclic loading can arise from soil

movement [17], service loads [18], or traffic loads [19]. External surface deformation due to stress cycles helps break passive films, thereby promoting corrosion. This creates an environment conducive to the initiation and propagation of corrosion pits on the external surface of the pipeline [20,21]. The corrosion pits are conducive to the initiation and propagation of short fatigue cracks, which grow over time into long fatigue cracks. The progression of external corrosion fatigue thus involves breakage of passive films, nucleation and growth of corrosion pits, nucleation as well as repeated opening and closing of microscopic cracks, crack growth, and structural deterioration [22]. This phenomenon is of significant concern as it can potentially compromise the mechanical properties of the pipeline, ultimately resulting in leaks, fractures, or other structural failures [23]. Therefore, addressing external corrosion and corrosion fatigue is essential in ensuring the longevity and reliable operation of buried steel pipelines. This involves two important aspects: (a) developing comprehensive remaining useful life (RSL) models and (b) conducting sensitivity analysis using the RSL model to identify the environmental, material, and loading parameters that significantly influence the RSL.

External pitting corrosion fatigue consists of seven damage initiation or evolution stages (Fig. 1): pit nucleation (Stage 1), pit growth (Stage 2), transition from pit to short crack (Stage 3), short crack growth (Stage 4), transition from short crack to long crack growth (Stage 5), stable long-crack growth (Stage 6), and unstable fracture (Stage 7). A

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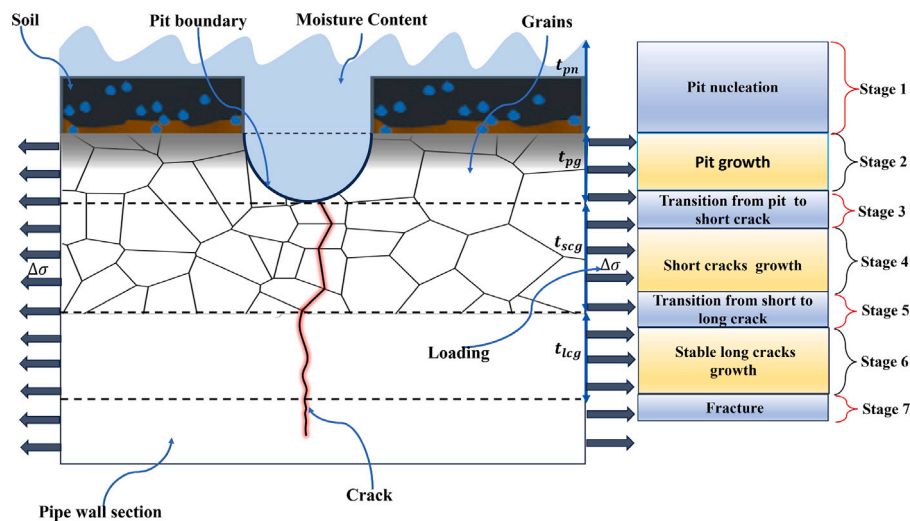


Fig. 1. External pitting corrosion fatigue for buried steel pipelines: Stages of damage initiation and evolution.

comprehensive RSL prediction model thus needs to consider all these stages as well as the uncertainty in environmental factors, material properties, and loading to estimate RSL. A brief review of previous research on predictive modeling of different stages in external corrosion fatigue is provided next.

Extensive research has been reported on the prediction of soil corrosion (Stages 1 and 2) in buried steel pipelines [24–26]. Researchers have considered various factors affecting the corrosion process, such as soil properties [27–30], soil compositions and pipe materials [31,32], environmental conditions [33–35], and pipeline-specific characteristics [36]. Both empirical and mechanistic modeling approaches have been explored to capture the intricate interplay between compositional, thermal, chemical changes in soil, corrosive agents, and pipeline materials [37–41]. Katano et al. [38] developed a regression model for pit growth in underground pipes to predict pitting depth based on environmental factors. Velázquez et al. [39] incorporated soil and pipe properties to forecast the pitting depth and rate of pit growth (depth increase) over time. Caleyó et al. [40] identified suitable probability distributions for pitting corrosion rate and depth in underground pipelines depending on the age of the pipeline. Wang et al. [41] trained data-driven regression models that consider the influence of soil ion content and aeration to predict corrosion pit growth in buried steel pipes. Azoor et al. [42] developed a coupled electro-chemical-soil model to assess the impact of soil aeration on underground metal pipe corrosion. They found that macro-cells are formed due to differential aeration and significantly influence pipeline deterioration. They validated their model prediction with corrosion data from the United States National Bureau of Standards [43].

Considerable attention has been given to understanding how soil corrosion affects pit growth in pipelines, but only a few studies have explicitly addressed the impact of fatigue loads during various stages of external corrosion cracking in pipelines [20,21]. Currently, there is a scarcity of models and data on CF in pipeline steel. CF of pipeline steel has been investigated only in a few specific environments, for example, near-neutral pH stress corrosion cracking (NNpHSCC) in dilute carbonate/bicarbonate environments following coating disbonding [20, 21]. Studies by Yu et al. [44] and Zhao et al. [45,46] have suggested that CF significantly influences NNpHSCC crack growth. They have also proposed models for predicting steel pipeline service life based on integrated SCC and fatigue analysis that considers crack initiation, early-stage growth, and steady-state growth. Many of the available models often focus on a specific stage of the degradation process, such as crack initiation or steady-state growth, and do not

consider all the stages of pipeline degradation. Furthermore, corrosive environments other than dilute carbonate/bicarbonate are not comprehensively addressed in existing models.

Many of the past studies do not account for the variability in environment, material, and loading properties and do not provide a probabilistic RSL prediction for buried steel pipes. Probabilistic corrosion fatigue prediction frameworks have been developed for other materials (e.g., aluminum alloys) and other applications (e.g., aircraft). Goswami and Hoepfner [47] outlined a framework spanning seven stages from corrosion initiation to fatigue fracture. Harlow and Wei [48,49] presented a probability-based life prediction method for aluminum alloys that showed qualitative agreement with experimental data. Zhang and Mahadevan [50] developed a reliability updating approach for aluminum alloy lap-sheets based on field data. Shi and Mahadevan [51] investigated a probabilistic approach to predicting the pitting corrosion fatigue life of aluminum alloys. They considered the seven stages of the corrosion fatigue evolution mentioned above, and utilized analytical as well as Monte Carlo simulation methods to evaluate the reliability of aging aircraft structures exposed to multiple site damage (MSD). While these investigations contribute significantly to understanding corrosion fatigue in aluminum alloys, they do not consider external corrosion fatigue of buried steel pipes. A probabilistic model for the fatigue life of buried steel pipelines that considers all steps in the multi-stage degradation process and the variability in environmental, material as well as loading parameters is thus not available in the literature.

A probabilistic RSL prediction model could also be used to evaluate the relative influence of environmental, material, and loading parameters on RSL by conducting a sensitivity analysis that includes the uncertainties in various factors. Previous efforts have mainly focused on local sensitivity analysis, which neglects the uncertainty in model inputs/parameters and considers the change in model output at a particular input point. Velázquez et al. [39] computed the derivative of pit depth with respect to various model parameters. They found that the pit depth is affected, in decreasing order of importance, by pH value, pipe-to-soil potential, pipe coating type, bulk density, water content, and dissolved chloride concentration. Nguyen et al. [52] performed feature importance studies using machine learning surrogate models for external corrosion. They found that the corrosion rate of carbon steel is most influenced by temperature and chloride concentration. Gu et al. [53] computed the change in model output for a unit change in model input to assess gas pipelines with corrosion defects under landslide conditions. They found the following order of importance (descending): landslide displacement, axial position of the corrosion

defect, soil cohesion, depth of the corrosion defect, pressure, and length of the corrosion defect. Demissie et al. [54] developed a Bayesian belief network for soil corrosivity index (SCI). They performed variance reduction (VR) analysis and found that soil resistivity has the highest influence on the variance of SCI. These studies did not consider all stages of corrosion fatigue and conducted *local* sensitivity analyses. They also did not identify which factors most significantly affect the transition from pit-to-crack.

These limitations in corrosion fatigue modeling, incorporation of uncertainty quantification, and sensitivity analysis are addressed in this work. First, a probabilistic modeling methodology aimed at predicting the RSL for steel pipes deteriorating due to external pitting corrosion and fatigue is developed. Leveraging the conceptual framework discussed in [51], a unified methodology that combines the influences of soil corrosion and fatigue for buried steel pipelines is proposed. To the best of the authors' knowledge, this is the first effort to address the problem of steel pipeline external corrosion fatigue in a comprehensive manner. Second, a probabilistic global sensitivity analysis (GSA) of corrosion fatigue models is conducted to identify the dominant inputs and uncertainty sources that affect the probabilistic life prediction. GSA examines the entire input space and captures interactions as well as non-linear effects. Local sensitivity analyses, on the other hand, rely on computing local gradients and can capture only the local behavior of the model. GSA thus helps in identifying the key inputs and supports effective model simplification and uncertainty quantification in complex systems. In this work, Sobol' global sensitivity indices are computed to quantify the influence of each input on the variance of the model output. RSL and the critical pit size for pit-to-crack transition are considered as the two output quantities of interest.

In this study, the Remaining Service Life (RSL) prediction model includes the corrosion pit nucleation phase to provide a comprehensive understanding of the degradation process from initiation to failure. This comprehensive RSL definition has been used in previous works [50,51] and is intended to capture the full lifecycle of corrosion progression. However, it is recognized that in practical applications, RSL predictions often commence after the detection of pitting corrosion. In practical applications of the proposed methodology, the nucleation phase can be neglected.

The main contributions of this work are:

1. Development of a probabilistic methodology for predicting RSL of buried steel pipes that considers various stages of external corrosion fatigue (Fig. 1).
2. Incorporation of state-of-the-art computational models at each stage.
3. Explicit consideration of the interaction between soil corrosion and fatigue in the modeling of damage growth.
4. Global sensitivity analysis to evaluate the impact of environmental, material, and loading parameters on fatigue life and to identify factors that affect the transition from pit-to-crack.

The rest of the paper is organized as follows. The probabilistic RSL prediction methodology is discussed in Section 2.1. The methodology considers pit nucleation and growth (Section 2.1.1), transition from pit to short crack (Section 2.1.2), short crack growth (Section 2.1.3), transition from short crack to long crack (Section 2.1.4), stable long crack growth (Section 2.1.5), and unstable fracture (Section 2.1.6). The uncertainty propagation and sensitivity analyses are discussed in Section 2.2. A numerical example is discussed in Section 3 to demonstrate the proposed methodology. Results are presented in Section 4. Conclusions drawn from the study are summarized in Section 5.

2. Methodology

This section develops a probabilistic framework for RSL prediction that considers all the phases of external corrosion fatigue in buried steel pipes and incorporates variability in soil properties, material properties, and loading. We first describe the computational models for damage evolution.

2.1. Computational models for multi-stage damage evolution

The total fatigue life is modeled to consist of seven stages (Fig. 1). These include pit nucleation (Stage 1), pit growth (Stage 2), transition from pit to short crack (Stage 3), short crack growth (Stage 4), transition from short to long crack growth (Stage 5), stable long crack growth (Stage 6), and unstable fracture (Stage 7). The total fatigue life (t_f) is given as

$$t_f = t_{pn} + t_{pg} + t_{scg} + t_{lcr} \quad (1)$$

where t_{pn} denotes the time for pit nucleation, t_{pg} denotes the time for pit growth till it transitions into a small crack, t_{scg} represents the time for short crack growth, and t_{lcr} indicates the time for long crack growth. The following subsections discuss modeling approaches for the four damage growth stages, the time of occurrence for each of the three transition stages, and the associated uncertainty analyses.

2.1.1. Time for pit nucleation and growth

Pit nucleation (Stage 1) signifies the commencement of localized corrosion, characterized by the formation of minor defects or discontinuities on the metal surface. These defects evolve into microscopic pits under the influence of corrosive forces. The time for pit initiation (t_{pn}) in pitting corrosion is influenced by various physical and chemical factors, particularly the characteristics of passive films, environmental factors, and temperature [55,56]. Several models have been proposed to predict pit initiation time [55,57–60], but each model has some limitations. For example, Nguyen and Foley's approach [55] does not account for the early initiation phase near the open circuit potential (OCP), while Lin et al.'s Point Defect Model [57] overlooks initiation close to OCP, focusing instead on passive film breakdown at applied potentials. Sridhar et al. [58] conservatively use pit reactivation potential (E_{rp}), neglecting scenarios where OCP exceeds E_{rp} . In particular, none of these previous efforts have considered underground steel pipe corrosion. Therefore, using one of these methods to estimate the RSL of a buried steel pipe requires conducting expensive experiments to calibrate the respective models. These experiments include repassivation potential test or potentiodynamic polarization test [58]; such experimental data for buried pipeline steel are unavailable in the literature.

Due to these challenges, phenomenological approximations have been pursued, where the pit initiation time has been simply described as a deterministic or probabilistic quantity. Velázquez et al.'s model [39] treated pit initiation time (t_{pn}) as a deterministic parameter in the pit growth model for buried pipeline steel. This approach is extended in this work, and the pit nucleation time is treated as a random variable. The randomness in pit nucleation time captures the uncertainty in the nucleation process. Velázquez et al. [39] reported the mean pit initiation time of 2.88 years for buried steel pipelines. Here, the mean value of pit initiation time (t_{pn}) is taken to be 2.88 years and a suitable coefficient of variation is assumed for the sake of illustrating the methodology. In practical applications, the coefficient of variation needs to be determined by conducting laboratory experiments.

Once pits are initiated, under favorable conditions, they enter the pit growth stage (Stage 2) to reach the *critical depth* (P_{cr}) at which microstructural short cracks could be initiated (Stage 3). The duration of pit growth (t_{pg}) is the duration from pit initiation till pit-to-crack transition. In order to compute t_{pg} , a time-dependent pit depth evolution model and an estimate of the critical pit depth are needed. The generally accepted mathematical model for pit growth was initially proposed by Romanoff [43] as $P = \gamma(t)^{\lambda}$. Here, γ and λ are model parameters, t is time, and P denotes the pit size. This model could be calibrated for different soil characteristics using experimental pit growth data for the particular soil environment. Caley et al. [40] included pit initiation (Stage 1) time (t_{pn}) as an additional parameter in this model, which is calibrated along with the other parameters based on experimental data. Their model is given by: $P = \gamma(t - t_{pn})^{\lambda}$.

Rearranging this equation to determine the time (t_{pg}) required for pit initiation and growth, we obtain:

$$t_{pg} = t_{pn} + \left(\frac{P}{\lambda}\right)^{(1/\gamma)} \quad (2)$$

Caleyo et al. [40] also developed regression models to predict proportionality and exponent parameters (λ and γ) for different soil compositions and pipe properties. Their model is given as:

$$\lambda = \lambda_0 + \lambda_1 RP + \lambda_2 PH + \lambda_3 RE + \lambda_4 CC + \lambda_5 BC + \lambda_6 SC, \quad (3a)$$

$$\gamma = \gamma_0 + \gamma_1 PP + \gamma_2 WC + \gamma_3 BD + \gamma_4 CT. \quad (3b)$$

In this model, the influence of the following important environmental factors on soil corrosion was considered: resistivity (RE), sulphate concentration (SC), bicarbonate concentration (BC), chloride concentration (CC), water content (WC), pH (PH), pipe/soil potential (PP), bulk density (BD), redox potential (RP), and coating type (CT). Each of these factors influences the complex soil corrosion processes in buried steel structures. This regression model is used in [40] to simulate pit nucleation and growth in different soil conditions. Refs. [39,40] give further details of this model. Caleyo et al. [40] calibrated the regression model parameters (λ_i for $i = 1, 2, \dots, 6$ and γ_j for $j = 1, 2, \dots, 4$) in Eq. (3). Here we consider the uncertainty in RP , PH , PP , RE , WC , BD , CC , BC , and SC , and treat them as random variables. Based on the scoring model proposed by Velázquez et al. [39], CT is treated as a deterministic parameter. To estimate the total time needed for pit nucleation and pit growth till the pit reaches the critical pit depth P_{cr} , we set $t = t_{pg}$, $P = P_{cr}$ in Eq. (2). We discuss next the model used to estimate the critical pit depth.

2.1.2. Transition from pit to short crack

After nucleation, the pit grows (Stage 2) to reach the critical depth (P_{cr}) at which a microstructural short crack could be initiated. This is referred to as the transition from pit to short crack (Stage 3). Pit to short crack transition can be mathematically modeled by considering pits as notches [61], long cracks [22,62], or short cracks [63]. Treating pits as notches, as suggested by Smith and Miller [61], may overestimate their impact on fatigue strength or critical pit depth. The calculated fatigue notch factors and pit depths based on this model do not match with experimental data, often leading to overestimation.

Moreover, the observation of non-propagating cracks from pits contradicts the assumption of blunt notches, where initiation and propagation happen at the same threshold stress level. Treating pits as long cracks suffers from the same limitations as those of conventional linear elastic fracture mechanics (LEFM) [22,62]. These models provide overly conservative predictions for critical pit depth or fatigue strength compared to experimental test data. Under small-scale yielding and negligible microstructural influence, the threshold stress intensity factor range should ideally be independent of crack length (or pit size in this context). However, observed changes in threshold stress intensity factor range values due to variations in pit depth indicate a fundamental mismatch with LEFM assumptions.

El-Hadad et al. [63] observed that considering corrosion pits as short cracks and incorporating intrinsic defect size (ρ_0) enables accurate estimation of the transition pit depth or fatigue strength. Their method addressed several limitations of previous approaches (overestimation of fatigue strength or critical pit depth, disagreement with experimental data [61], mismatch with LEFM assumptions, and contradiction with observed non-propagating cracks [22,62]). In this work, we adopt the empirical relationship proposed by El-Hadad et al. [63] to estimate the transition pit depth. This relationship is given by:

$$\Delta K_{th} = Y \Delta \sigma \sqrt{\pi P_{cr} + \rho_0}. \quad (4)$$

Upon rearrangement, the equation becomes:

$$P_{cr} = \frac{1}{\pi} \left(\left(\frac{\Delta K_{th}}{Y \Delta \sigma} \right)^2 - \rho_0 \right). \quad (5)$$

This equation expresses the critical pit depth, P_{cr} , as a function of several factors: the applied cyclic stress range ($\Delta \sigma$), the threshold stress intensity factor range (ΔK_{th}), which indicates the threshold below which a crack should not grow under LEFM conditions; the intrinsic defect size $\rho_0 = \frac{1}{\pi} \left(\frac{\Delta K_{th}}{Y \Delta \sigma} \right)^2$; and the geometric factor (Y), is a dimensionless constant that accounts for the influence of the geometry of a crack or defect on the stress intensity factor (SIF). It adjusts the theoretical SIF for the specific shape, size, and orientation of the defect to the loading, as well as the structural configuration of the material. For example, the shape of the defect (whether sharp or blunt) influences the stress intensity factor at the crack tip, with sharper cracks leading to higher stress intensities. The position of the crack (whether external or internal) also affects the stress distribution, with external cracks typically experiencing higher stress. The size of the domain (whether finite or infinite) further impacts the stress distribution, as cracks in finite domains are influenced by boundary effects. Additionally, different loading modes (Mode I, II, or III) modify the stress distribution and crack propagation behavior.

In this article, ΔK_{th} is considered as a random variable, acknowledging the inherent variability in material properties, manufacturing processes, and environmental conditions. The applied cyclic stress range, $\Delta \sigma$, is also treated as a random variable to account for the variability in loading conditions [64]. The geometric factor, Y , is analytically calculated assuming semi-circular pits and does not have variability; therefore, it is considered to be a deterministic parameter with $Y = 0.67$ chosen for semi-circular pits [64]. The critical pit depth, denoted by P_{cr} , is thus a dependent random variable. This means that the variability in both ΔK_{th} and $\Delta \sigma$ contributes to the uncertainty in P_{cr} . Given the probability distributions of ΔK_{th} and $\Delta \sigma$, the distribution of critical pit depth P_{cr} could be estimated and used in Eq. (3) to probabilistically estimate the total time for pit nucleation and growth.

2.1.3. Short crack growth

Microstructurally short crack growth (Stage 4) refers to the propagation of small cracks that are much shorter than typical crack lengths observed in traditional fatigue testing. These short cracks are often of the order of micro or millimeter length scale and are typically initiated from defects (in this context, pits), such as inclusions, pores, or other microstructural features within the material. The principle of microstructurally short crack growth recognizes that the behavior of these small cracks differs significantly from longer cracks due to various factors such as local stress concentrations, material heterogeneity, and interactions with microstructural features. Recent studies [64,65] have shown that the microstructure influences the rate of crack growth and crack arrest phenomenon in this early stage of crack development. As cracks grow to longer lengths (multiple grains), the influence of microstructure tends to diminish. The transition from short crack to long crack growth marks Stage 5, and microstructural factors no longer influence long crack growth in Stage 6. The short and long crack growth are illustrated schematically in Fig. 2. The relationship between crack growth rate and crack length is better understood in the long crack regime (Stage 6, Section 2.1.5). Nevertheless, the discontinuous growth of short cracks [66–68] has been successfully modeled by considering perturbations arising from the resistance posed by microstructural variables.

The growth rate of microstructurally short cracks is expressed as [64,69,70]:

$$\frac{da_s}{dN} = C_{s(i)} (d_{(i)} - a_s), \quad (6a)$$

$$C_{s(i)} = A_{(i)} \Delta \sigma^{a_{(i)}}; \text{ for } i = 1, 2, \dots, n. \quad (6b)$$

Here, $\left(\frac{da_s}{dN}\right)$ represents the growth rate of microstructurally short cracks, $d_{(i)}$ denotes the distance between adjacent microstructural barriers influencing crack propagation, and a_s is the surface length of a short crack. The material constant $C_{s(i)}$ is a factor dependent on the

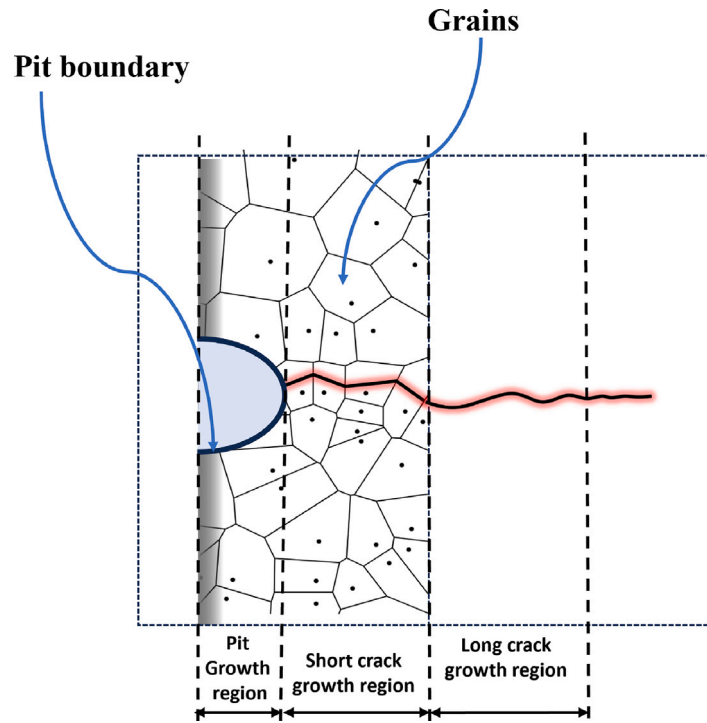


Fig. 2. Schematic representation of regions of pit and crack growth.

applied cyclic stress range ($\Delta\sigma$) and environment and material constants such as $A_{(i)}$ and $\alpha_{(i)}$, reflecting the specific conditions of each segment. Eqs. (6) apply to individual grains within the material, with i signifying the grain number and n representing the average number of grains defining the length of the dominant barrier beyond which the influence of microstructure is negligible.

Combining Eqs. (6a) and (6b) for a fixed number of cycles, f , yields:

$$\frac{da_s}{dt} = f [A_{(i)} \Delta\sigma^{\alpha_{(i)}}] (d_{(i)} - a_s); \text{ for } i = 1, 2, \dots, n. \quad (7)$$

To determine the time required for the short crack to grow across each segment, the growth rate expression is integrated over the range of crack lengths. The time required for crack growth in each length segment for a fixed number of cycles can be obtained through integration as:

$$t_{scg} = \sum_{i=1}^n \frac{2}{f [A_{(i)} \Delta\sigma^{\alpha_{(i)}}]} \log \left(\frac{d_{(i)} - a_{0(i)}}{d_{(i)} - a_{f(i)}} \right), \quad (8)$$

where $a_{0(i)}$ and $a_{f(i)}$ represent the initial and final crack lengths for the i th segment, respectively. For clarity and simplicity, we designate $a_{0(i)}$ as a_0 , representing the surface roughness value for a polished surface [64,65]. Similarly, $a_{f(i)}$ is denoted as a_{tr} for the final segment, representing the transition length from short to long crack.

In this study, a_0 is treated as a random variable, reflecting the variability in surface roughness values [64,65], while a_{tr} is an analyst-selected threshold and therefore regarded as deterministic, with its value determined by the analysis conducted in [64] (discussed in Section 2.1.4). $\Delta\sigma$ is considered as a random variable, capturing fluctuations in the applied load experienced by microstructurally short cracks within the material. Eq. (8) provides a model for estimating the time needed for short crack growth in each grain (length segment).

2.1.4. Transition from short crack to long crack growth

The transition from short crack growth to long crack growth occurs when the short crack surpasses the microstructural barriers. This condition needs to be incorporated in Eq. (6) through the parameter a_{tr} . The magnitude of the transition crack length a_{tr} depends on the material's microstructure, and a_{tr} varies even within the same material

due to inherent texture differences [64]. Fatoba et al. [64] analyzed crack growth rate versus crack length data in an ambient and corrosive environment. In regions showing deceleration in crack growth rates, the value of $d_{(i)}$ was determined through linear regression analysis. The results highlighted the variability in $d_{(i)}$ due to the material's grain size diversity. This diversity suggests that the transition crack length (a_{tr}) and the distances between successive barriers ($d_{(i)}$) depend on the distribution and actual sizes of grains throughout the microstructure. The estimated a_{tr} values in [64] ranged from 54 to 146 μm , with a mean value of 105 μm . In the current analysis, a_{tr} is considered as a deterministic parameter with $a_{tr} = 100 \mu\text{m}$. The distance between successive barriers closely aligns with the size of the largest grains within the material. Consequently, a value of $d_{(i)} = 25 \mu\text{m}$ was chosen as grain size for the material and employed for the analysis of crack growth. The number of grains $n = a_{tr}/d = 4$ for short crack growth. Note that these assumptions are made only to demonstrate the probabilistic RSL prediction methodology. These values or the treatment of variables could be easily changed, if needed, in real-world applications.

2.1.5. Stable long crack growth

The term *stable long crack growth* implies the gradual progression of a crack within a material subjected to load. It is meant to distinguish the phenomenon from abrupt failure associated with unstable crack growth, discussed in Section 2.1.6. This gradual crack growth is commonly considered in fatigue/fracture analysis. Engineers and researchers have employed diverse methodologies and analytical tools to study corrosion with stable long-crack growth characteristics and behavior in various materials [50,51,71,72]. Paris' law is the most widely used model in this regime. It is given by:

$$\frac{da_l}{dN} = C_l (\Delta K)^{m_l}, \quad (9)$$

where $\frac{da_l}{dN}$ is the crack growth rate, C_l is the material constant for long crack growth, $\Delta K (= \beta \Delta\sigma \sqrt{\pi a_l})$ is the stress intensity range, m_l is the growth exponent for long cracks, and $\Delta\sigma$ is the applied cyclic stress range. The material constant C_l is treated as a random variable, acknowledging its inherent variability in material properties [73]. The geometric factor (β) is similar to the geometric factor Y defined in

Section 2.1.2. It captures the influence of the notch size, specifically in this context, the pit size, the dimensions of the specimen, and the loading. In the case of long-edge cracks, where the pit depth is relatively small and adheres to the Saint-Venant principle, its impact on the stress distribution at the remote crack tip diminishes; thus, the stress concentration factor could be neglected for long cracks [74]. For large specimens (relative crack length $\frac{a}{W} \rightarrow 0$, where W is the characteristic width of the specimen) and relatively small-sized specimens (when $\frac{a}{W} \rightarrow 1$), the geometric factor assumes values of 1.0 and 1.12, respectively. Here, β is treated as a deterministic parameter, and $\beta = 1.12$ is used in our numerical example.

In this analysis, we have considered an external location, a semi-circular pit (shape) in Stage III, and Mode-I fatigue in a finite domain (loading and domain type) in Stage VI. The geometric factors Y in Stage III and β in Stage VI are chosen based on these considerations. For different cases of these factors influencing fatigue behavior, different values of the geometric factor could be chosen. Taking into account the load frequency f as a deterministic parameter as in [50,51,75], the crack growth rate is expressed as:

$$\frac{da_I}{dt} = f C_I (\Delta K)^{m_I}. \quad (10)$$

The long crack growth duration ($t_{l_{cg}}$) is the time from the transition from a short crack to a long crack (a_{tr}) till the crack grows to the critical length (a_{th}) and enables sustained long crack growth. This duration is given by:

$$t_{l_{cg}} = \frac{2}{(2 - m_I) f C_I (\beta \Delta \sigma \sqrt{\pi})^{m_I}} \left(a_{th}^{(1 - (\frac{m_I}{2}))} - a_{tr}^{(1 - (\frac{m_I}{2}))} \right). \quad (11)$$

Eq. (11) estimates the time required for long crack propagation, considering deterministic parameters, such as load frequency (f) and geometric factor (β), growth exponent for long cracks (m_I), transition from short crack to a long crack (a_{tr}), and critical crack length (a_{th}) (which is addressed in Section 2.1.6) while the material constant for long crack growth (C_I) is taken as a random variable to capture material variability.

2.1.6. Unstable fracture

In buried steel pipelines, unstable fracture (Stage 7) is considered by defining the crack size as a threshold for potential structural failure. This crack size signifies an unacceptable damage growth that demands immediate attention or repair to prevent further compromise to the pipeline's structural integrity. Vilkys et al. [76] proposed a method for establishing this crack (defect) size and determining the failure pressure of pipelines with defects. Their analysis showed that immediate attention or repair is needed when the depth of a defect reaches approximately 0.5 times the wall thickness of the pipe. This chosen value denotes the threshold beyond which structural integrity is compromised, prompting the need for intervention and repair to ensure the continued secure operation of the buried steel pipeline. In the current work, the critical crack length for buried steel pipelines based on a criterion established by Vilkys et al. [76] is considered as a deterministic (upper) bound on damage growth.

2.2. Uncertainty and sensitivity analyses

2.2.1. Uncertainty propagation

This section details the uncertainty propagation methodology for estimating the probability distribution of external pitting corrosion fatigue life in underground steel pipelines. The analysis is performed for different soil types (clay, clay loam, sandy clay loam) and surface coatings (bare-pipe, asphalt enamel, wrap-tape, coal-tar, and fusion bonded epoxy (FBE)). The uncertainty in the corrosive environment, material properties, and loading needs to be propagated through multiple computational models corresponding to different damage evolution

stages. The uncertainty is modeled by considering various inputs and parameters in computational models as random variables. These are summarized in Table 1.

The uncertainty propagation analysis thus incorporates 14 random variables. We also consider the statistical correlations among ten environmental parameters in the pit nucleation and growth stages due to known interactions and supporting data [40]. Material and loading parameters in the crack growth models (ΔK_{th} , $\Delta \sigma$, a_{cr} , and C_I) are treated as independent random variables due to the lack of data quantifying their interdependence. If correlation/interaction information for all 14 random variables is available, then it can be easily incorporated into the proposed framework. The correlation matrix is given by:

$$C_{comb} = \begin{bmatrix} [C]_{10 \times 10} & [0]_{10 \times 4} \\ [0]_{4 \times 10} & [I]_{4 \times 4} \end{bmatrix}_{14 \times 14} \quad (12)$$

Here, $[0]_{10 \times 4}$ represents a zero matrix of dimensions 10×4 , $[0]_{4 \times 10}$ signifies a zero matrix of dimensions 4×10 . Additionally, $[I]_{4 \times 4}$ denotes an identity matrix of size 4×4 . The correlation matrix ($[C]_{10 \times 10}$) is assumed to be known and is adopted from [39]. The uncertainty propagation procedure requires obtaining samples of the 14-dimensional random vector whose elements are correlated as specified by the correlation matrix C_{comb} . The procedure for obtaining these samples using the inverse CDF method is detailed in Algorithm 1 [77]. These samples are propagated through the models discussed in Section 2.1 to obtain samples of RSL. These samples of RSL represent the probability distribution of RSL.

Algorithm 1 Procedure for obtaining correlated samples

- 1: **Inputs:** #samples N , M random variable marginals: $\mathcal{W} = \{\mathcal{W}_1, \mathcal{W}_2, \dots, \mathcal{W}_M\}$, correlation matrix $C_{comb} \in \mathbb{R}^{M \times M}$.
- 2: **Cholesky decomposition of correlation matrix** C_{comb} : $C_{comb} = LL^T$; where L is a lower triangular matrix.
- 3: **Repeat for each sample:**
 - Step 1: Generate independent standard normal samples ($\mathcal{Z}$): Generate a matrix $\mathcal{Z}$ consisting of M independent standard normal variables with N samples: $\mathcal{Z}_{(i,j)} \sim \mathcal{N}(\mu = 0, \sigma = 1)$, where $i = 1, 2, \dots, M$ and $j = 1, 2, \dots, N$.
 - Step 2: Obtain correlated standard normal samples (X'): $X' = L\mathcal{Z}$.
 - Step 3: Compute CDF for correlated standard samples (X'): $Y_{X'} = F_X(X')$, where $F_X(x) = P(X \leq x)$, represents the probability that X will take a value less than or equal to x .
 - Step 4: Obtain correlated random samples (X): $X = F_X^{-1}(Y_{X'})$.

2.2.2. Global sensitivity analysis

We conduct global sensitivity analysis (GSA) to assess the influence of the environmental, material, and loading parameters on RSL and critical pit depth. GSA is probabilistic and quantifies the effect of uncertainty in the model inputs on the uncertainty in the model output. In this work, Sobol' indices are computed to quantify the contribution of each random input parameter to the output variance [78]. Consider a model of the form:

$$Y = f(X), \quad (13)$$

where $X = X_1, X_2, \dots, X_M \in \mathbb{R}^M$ represents the vector of M input variables. The model output Y is evaluated for each given input. GSA can then be used to assess the influence of each input variable on the output. This is typically done by decomposing the output variance and quantifying the contribution of each input variable to the total variance using techniques such as Sobol' indices.

The first-order Sobol' index (S_i) quantifies the contribution of each individual input variable to the output variance, considering only the main effect of that variable. For the model in Eq. (13), it is defined as:

$$S_i = \frac{\text{Cov}[f_i(X_i), Y]}{\text{Var}[Y]} \quad (14)$$

Table 1
Random and deterministic variables used in the numerical example.

Stage	Parameter, Symbol (Units)	Parameter Type	Random Distribution Type (Mean, CV)	Deterministic Value
I & II. Pit Nucleation and Growth	t_{pn} , RP , PH , PP , RE , WC , BD , CC , BC , SC , & CT	Random & Deterministic	Refer to Tables A.3–A.5	Refer to Tables A.3–A.5
III. Transition for Pit to Short Crack	(1) Threshold stress intensity factor range, ΔK_{th} (MPa $\sqrt{m}$) [64]	Random	Lognormal (6.47, 0.1/0.2)	–
	(2) Applied fatigue stress limit range, $\Delta\sigma$ (MPa)	Random	Lognormal (200, 0.1/0.2)	–
	(3) Geometrical factor for short crack, Y [64]	Deterministic	–	0.67 (semicircular pit)
IV. Short Crack Growth	(1) Initial short crack size a_0 (μm) [64,69,70]	Random	Lognormal (0.25, 0.1/0.2)	–
	(2) Frequency, f (Hz) [75]	Deterministic	–	12
	(3) Short crack growth exponent, α_i , $i = 1, \dots, 4$	Deterministic	–	(3.315, 3.315, 8.092, 0.640)
	(4) Distance d_i , $i = 1, \dots, 4$ between adjacent microstructural barriers (μm)	Deterministic	–	(25, 50, 75, 100)
	(5) Material constant for short crack growth, A_i , $i = 1, \dots, 4$	Deterministic	–	(1.18×10^{-12} , 1.18×10^{-12} , 1.16×10^{-25} , 2.23×10^{-6})
V. Transition from Short to Long Crack	(1) Short crack to long crack transition size, a_{tr} (μm) [64]	Deterministic	–	100
VI. Stable Long Crack Growth	(1) Material constant for long crack growth C_1 (MPa $\sqrt{m}$) [73]	Random	Lognormal (1.577×10^{-9} , 0.1/0.2)	–
	(2) Long crack growth exponent, m_1 [73]	Deterministic	–	2.12
	(3) Geometric factor for long crack, (β) [74]	Deterministic	–	1.12
VII. Unstable Fracture	(1) Specified final crack length, a_{th} (mm) [76]	Deterministic	–	5

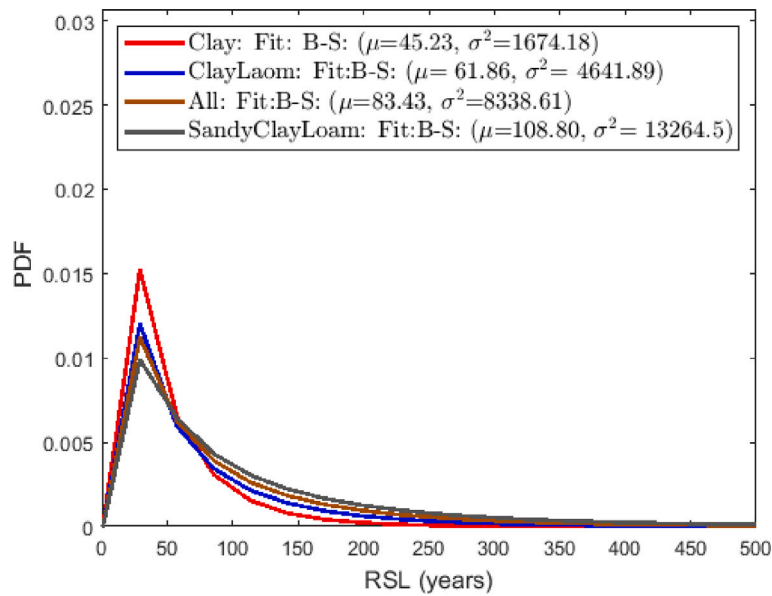


Fig. 3. RSL for steel pipelines buried in different soil environments.

The total effects index (S_i^T) for variable X_i is given by:

$$S_i^T = 1 - \frac{\text{Cov}[f_i(\mathbf{X}_{\sim i}), Y]}{\text{Var}[Y]} \quad (15)$$

where $\mathbf{X}_{\sim i}$ denotes a vector of inputs excluding X_i . The index, S_i^T , accounts for the total variance attributed to X_i , encompassing all orders of interaction.

Sobol' indices for independent inputs could be computed using a simple Monte Carlo sampling-based approach. When dealing with correlated random variables, the calculation of Sobol' indices becomes more complicated, particularly for higher-order interactions and total effects [79]. Several methods have been developed to address this issue [80–83]. Here, we compute Sobol' indices (both first order and total effects) using Kucherenko's method [84]. It uses quasi-random

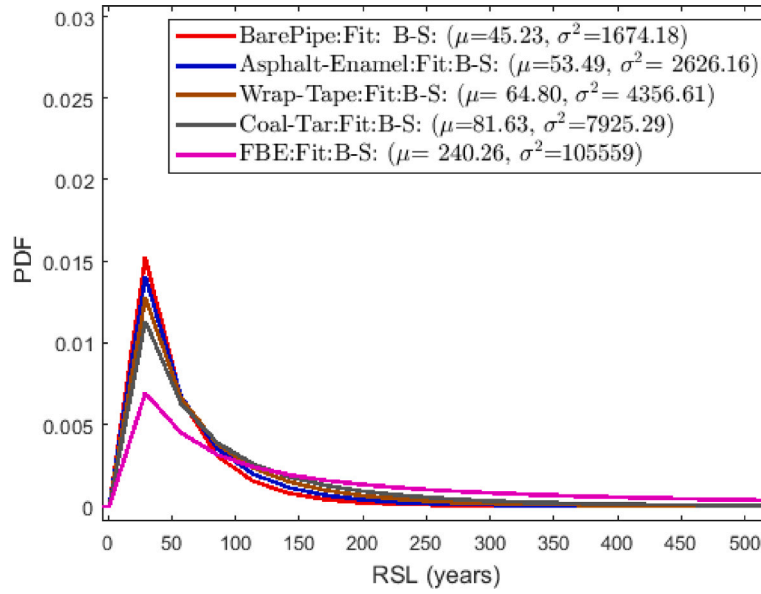


Fig. 4. RSL for steel pipelines buried in clay soil for different coating types.

sequences, such as Sobol' sequences, for integration over the input space to provide uniform coverage and robust estimates. This makes it computationally feasible and effective for high-dimensional sensitivity analysis. Kucherenko's efficient Monte Carlo estimators for the first order and total effects Sobol' indices avoid the computationally expensive double-loop procedure. The estimator of the first-order effect (S_i) is formulated based on N Monte Carlo samples as:

$$S_i = \frac{\frac{1}{N} \sum_{j=1}^N \left(f(\mathbf{x}_{i,j}, \mathbf{x}_{w,j}) f(\mathbf{x}_{i,j}, \bar{\mathbf{x}}'_{w,j}) \right) - \left(\frac{1}{N} \sum_{j=1}^N f(\mathbf{x}_{i,j}, \mathbf{x}_{w,j}) \right)^2}{\text{Var}[Y]} \quad (16)$$

Similarly, an efficient estimator for the total effect index (S_i^T) is derived as:

$$S_i^T = \frac{\frac{1}{N} \sum_{j=1}^N f(\mathbf{x}_{i,j}, \mathbf{x}_{w,j}) \left(f(\mathbf{x}_{i,j}, \bar{\mathbf{x}}'_{w,j}) - f(\mathbf{x}'_{i,j}, \mathbf{x}'_{w,j}) \right)}{\text{Var}[Y]} \quad (17)$$

These estimators require $N \times (2M + 1)$ function evaluations, where M is the number of variables. The samples $\mathbf{x} = (\mathbf{x}_i, \mathbf{x}_w)$ and $\mathbf{x}' = (\mathbf{x}'_i, \mathbf{x}'_w)$ are i.i.d. (independent and identically distributed) samples of $\mathbf{X}$. In $(\mathbf{x}_{i,j}, \bar{\mathbf{x}}'_{w,j})$, the overbar indicates that the marked sample $\bar{\mathbf{x}}'_w$ is conditioned on $\mathbf{x}_i$. Detailed procedures and implementation for both these methods can be found in [85]. We utilize MATLAB-based UQLab [86] software for computing these global sensitivity indices.

3. Numerical example

We consider a buried steel pipe segment with a wall thickness of 10 mm to illustrate the proposed methodology. This pipeline is in a soil-corrosive environment and is susceptible to pitting corrosion on its outer surface. Additionally, the pipeline is subjected to random cyclic loading, characterized by a mean stress range of 200 MPa and a coefficient of variation (COV) of 0.2. This loading occurs at a mean frequency of approximately 12 Hz. To predict the remaining service life (RSL) of this pipeline, the values of the deterministic model inputs/parameters and the probability distributions of the random model inputs/parameters, as given in Table 1, are used at each stage of the damage evolution.

For the pit nucleation and growth stage, the variability in soil environment parameters (RE , SC , BC , CC , WC , PH , PP , BD , and RP) as well as the calibrated model coefficients (λ_i and γ_i) are needed.

The values reported in the study conducted by Caley et al. [40] and Velázquez et al. [39] are used in this work. The mean values of the model coefficients are given in Table A.2, and the probability distribution types and parameters are given in Table A.3. Table A.2 shows regression coefficients corresponding to several soil types and the associated pit nucleation time (t_{pn}). We have treated pit nucleation time as a lognormal random variable. The mean value for this distribution is the pit nucleation time specified in Table A.2 [39] and we assume that the COV is 0.1. The influence of pipeline coating type (CT) on pitting corrosion [39] is considered using scores for each coating type [38–40] in each soil category (Table A.4). Higher scores are given to coatings that offer lower protection [38,39,87–90]. The correlation matrix for the relevant variables is presented in Table A.5 [39]. Table 1 provides a summary of the random and deterministic variables used in the numerical example. This information is used in the uncertainty propagation analysis discussed in Section 2.2.1.

The following analyses are conducted in the numerical example, using the damage evolution models, input/parameter uncertainty defined in Table 1, and the uncertainty propagation method described in Section 2.2.1:

1. Probabilistic estimation of RSL

- Bare pipes exposed to various types of soils (clay, clay loam, clay loam, and the combination of the three soil types (referred to as 'all types')).
- Comparison of different pipe coatings (bare pipe, asphalt-enamel, wrap-tape, coal-tar, and fusion-bonded epoxy (FBE)) interacting with clay soil.

2. Global sensitivity analysis to identify factors that significantly influence the RSL and critical pit depth.

For the probabilistic estimation of RSL and sensitivity analyses, the sampling strategy outlined in Algorithm 1 is employed. Specifically, 10^6 samples of the correlated random variables (described in Table 1) are generated. All the samples are used for uncertainty propagation to obtain the probability distribution of RSL. However, for the global sensitivity analysis, only 10^4 samples are needed to compute the Sobol' indices using Kucherenko's method. Fewer samples are adequate in Kucherenko's method since it uses sparse sampling techniques rather than exhaustive outcome exploration [84]. Numerical tests with different sample sizes (not reported here) confirmed that 10^4 samples are sufficient to obtain accurate estimates of Sobol' indices.

4. Results and discussion

The results of probabilistic RSL prediction, and local as well as global sensitivity analyses are discussed in this section.

4.1. Probabilistic estimation of remaining service life

Probability distributions of RSL for the bare steel pipe in different soil types are shown in Fig. 3. MATLAB Distribution Fitter App [91] was used to fit probability distributions to the samples of RSL. In this case, the Birnbaum-Saunders (B-S) distributions were the best-fitting distribution type. The B-S distribution is commonly used in fatigue life prediction [92]. The mean RSL values for different soil types were determined as follows: clay (45.23 years), clay loam (61.86 years), sandy clay loam (108.80 years), and 'all types' (83.43 years).

From the mean RSL values, it is evident that the susceptibility of the steel pipe to corrosion varies significantly across different soils. Sandy clay loam emerges as the least corrosive, with a mean RSL of 108.80 years, indicating that pipelines in this soil type have the longest lifespan. Conversely, clay, with a mean RSL of 45.23 years, is identified as the most corrosive soil environment. Clay loam and 'all types' (a combination of clay, sandy clay loam, and clay loam) fall between these extremes. These findings agree with previous research [39,40], which ranked the soils by corrosiveness (from highest to least corrosive) as follows: clay, clay loam, and sandy clay loam.

The influence of different coating types (bare pipe, asphalt enamel, wrap tape, coal tar, and FBE) is investigated next for a pipe buried in clay. Leveraging the same set of samples from the previous example, RSL samples are obtained for different coating materials with different CT scores in Eq. (3). The results are shown in Fig. 4. B-S distributions were fitted to the RSL samples. The mean RSL values obtained for the various coating types in clay are as follows: bare-pipe (45.23 years), asphalt-enamel (53.49 years), wrap-tape (64.80 years), coal-tar (81.63 years), and FBE (240.26 years). These results help rank the various coating types from the least to the best protection. This ranking provides valuable insights into the effectiveness of various coatings in safeguarding steel pipelines against corrosion, with FBE presenting the most reliable protective option. This assessment agrees with previous research findings [89,90].

4.2. Global sensitivity analysis

Global sensitivity analysis is conducted using the procedure outlined in Section 2.2.2. Through this analysis, changes in RSL (using model Eq. (1)) are observed, providing valuable insights into the sensitivity of the model output to different input variables, including uncorrelated parameters (ΔK_{th} , $\Delta\sigma$, a_0 , and C_l) and correlated environmental variables (RP , PH , PP , RE , WC , BD , CC , BC , SC , and CT). Additionally, GSA is performed on the Stage 2 sub-model to analyze the sensitivity of the critical pit depth (estimated using Eq. (5)) to different ΔK_{th} , $\Delta\sigma$ values. This transition point from pit to small crack marks a crucial juncture in the overall corrosion-fatigue damage evolution process.

Fig. 5 depicts the GSA results. GSA reveals that soil pH is the most influential factor. Other variables such as WC , BD , and BC also play significant roles, particularly when interacting with other variables. For a comprehensive prediction of total fatigue life, it is thus essential to consider the correlation between these variables. These variables can be classified into three groups: environmental, material, and loading factors. Among the environmental factors, soil pH is the most important factor, followed by pipe/soil potential, chloride concentration, water content, coating type, bicarbonate concentration, bulk density, redox potential, sulphate concentration, and resistivity. Among material and loading parameters, the stress range ($\Delta\sigma$) is the most important factor, followed by ΔK_{th} , C_l , and a_{cr} .

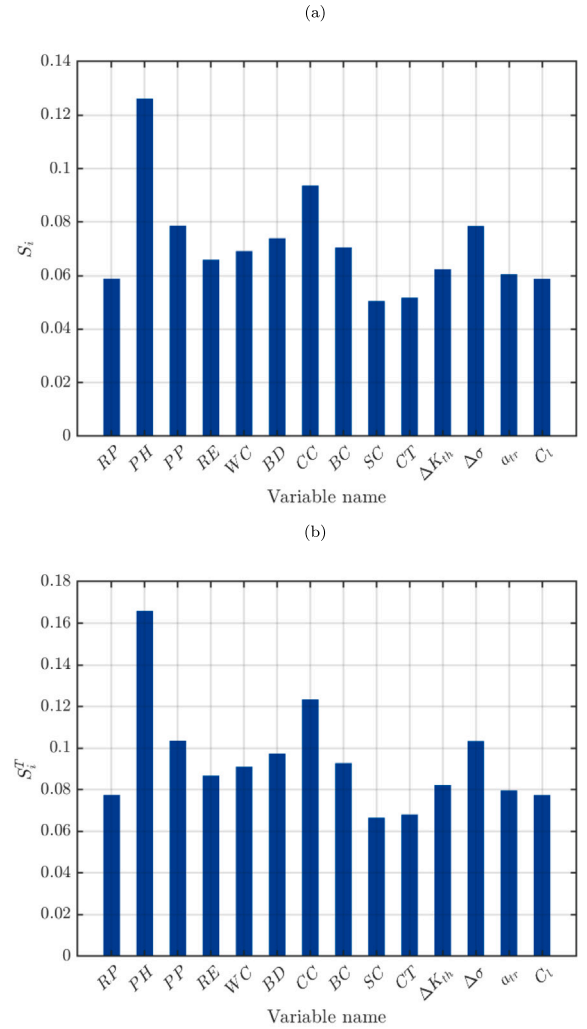


Fig. 5. Global Sensitivity Analysis on RSL: (a) First order indices (S_i), and (b) Total effects (S_i^T) indices. Environmental variables analyzed include redox potential (RP), pH (PH), pipe/soil potential (PP), resistivity (RE), water content (WC), bulk density (BD), chloride concentration (CC), bicarbonate concentration (BC), sulphate concentration (SC), and coating type (CT). Additionally, material variables include threshold stress intensity factor range (ΔK_{th}), applied fatigue stress limit range ($\Delta\sigma$), initial short crack size (a_0), and material constant for long crack growth (C_l).

Global sensitivity analysis for identifying the most influential factors for RSL of buried steel pipelines has not been previously reported in the literature. Local sensitivity analysis of the pit depth estimation model was reported in [39]. This analysis gave the following order of importance: pH (PH), pipe-to-soil potential (PP), pipe coating type (CT), bulk density (BD), water content (WC), and dissolved chloride concentration (CC). Note that chlorides are well-documented as critical in promoting internal pitting corrosion. However, in external corrosion, soil properties and electrochemical factors, such as pH and pipe-to-soil potential, dominate the corrosion dynamics. This is consistent with studies on external pipeline corrosion [39], where environmental factors at the pipe surface outweigh the impact of dissolved chloride concentrations. In this study, as well as in [39], pH and pipe-to-soil potential are found to be the most influential factors. However, the importance order of other parameters differs because (a) RSL is the quantity of interest in this study, whereas the pit depth was the quantity of interest in [39], and (b) a global sensitivity analysis is conducted in this work, which also considers the variability in different factors.

Fig. 6 shows the global sensitivity analysis results for the pit-to-crack transition: (a) first-order Sobol' indices (S_i), and (b) total effects

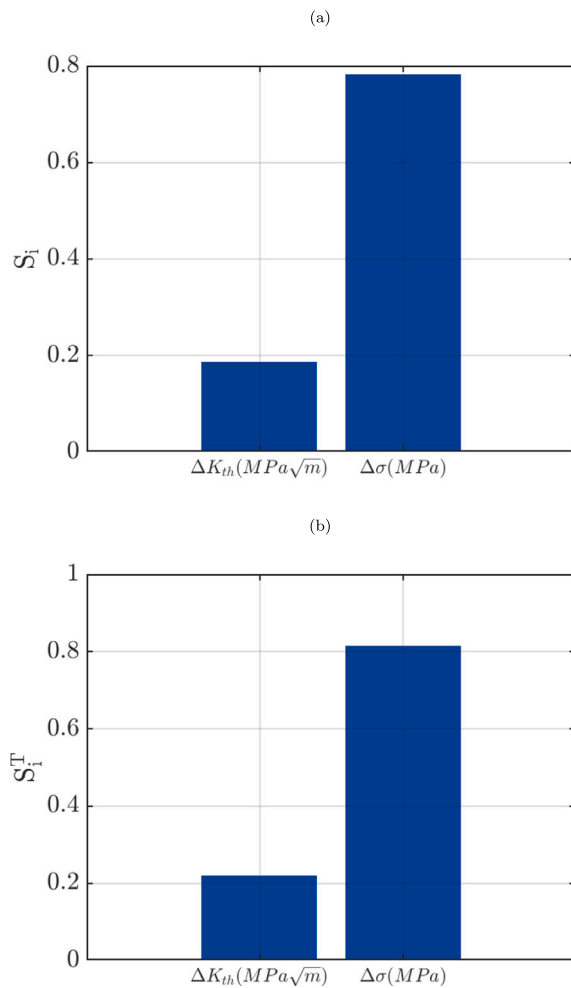


Fig. 6. Global Sensitivity Analysis of pit-to-crack transition model: (a) First order indices (S_i^T), and (b) Total effects (S_i^T) indices. Note that the variables considered in this analysis are the threshold stress intensity factor (ΔK_{th}) and the applied cyclic stress range ($\Delta\sigma$).

indices (S_i^T). Both sets of indices are calculated using the Kucherenko method. GSA for the pit-to-fracture transition model reveals that the applied cyclic stress range ($\Delta\sigma$) exerts a significantly greater influence on the variability of critical pit depth compared to the threshold stress intensity factor (ΔK_{th}).

5. Conclusion

In this study, a comprehensive probabilistic modeling framework was developed to predict the lifetime of external corrosion fatigue of buried steel pipes. State-of-the-art computational models were used at different stages of damage evolution. The variability in environmental, material, and loading parameters was considered to arrive at a probabilistic estimate of RSL. The framework is able to account for a wide range of factors, including soil conditions, coating types, material/loading parameters, and correlations between these factors. The probabilistic RSL estimation yielded valuable insights into buried steel pipes' corrosion fatigue life and the influence of soil types and coating materials. In particular, sandy clay loam was identified as the least corrosive soil type, while clay soil turned out to be the most corrosive. These conclusions agree with established research findings (see [89,90]). In addition, FBE emerged as the most effective coating material for preventing corrosion, followed by wrap-tape, coal-tar, and

asphalt-enamel coatings, with bare pipe showing the highest vulnerability. This study investigated the effects of soil properties, coatings, and cyclic loading on external pipeline corrosion. Future work will focus on integrating additional factors, such as temperature and cathodic protection, to enhance the model's predictive capability.

We also conducted GSA to identify the important factors influencing the RSL as well as critical pit depth. The stress range ($\Delta\sigma$) has a greater impact on critical pit depth than the threshold stress intensity factor ΔK_{th} . Further, it was found that soil pH, pipe/soil potential, chloride concentration, and the applied stress range have the highest influence on RSL and that soil pH is the most important factor. Other factors such as water content, bulk density, and bicarbonate concentration also play significant roles, particularly in interactions, thus justifying the consideration of correlations between these factors in probabilistic RSL estimation.

While the proposed probabilistic RSL prediction method considers all the relevant stages of damage initiation and growth, it assumes a single pit with a semi-circular shape. Future work needs to consider more sophisticated cellular automata-, phase-field-, and peridynamics-based approaches [65,93–96] for modeling pit growth. These models closely mimic real-world physics and can account for the effect of interactions between multiple pits. Utilizing state-of-the-art statistical methods with these advanced models will enable more robust and reliable predictions of the external corrosion fatigue life.

CRedit authorship contribution statement

J. Ramesh Babu: Writing – original draft, Visualization, Validation, Software, Investigation, Formal analysis, Data curation. **Pranav M. Karve:** Writing – review & editing, Supervision, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Sankaran Mahadevan:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Model inputs and parameters

See [Tables A.2–A.5](#).

Data availability

Data will be made available on request.

Table A.2

Regression coefficients for the pit growth model [40].

Parameter (Variable, Symbol)	Soil category			
	Clay	Clay Loam	Sandy Clay Loam	All
λ_0	5.51×10^{-1}	9.84×10^{-1}	5.99×10^{-1}	6.08×10^{-1}
γ_0	8.85×10^{-1}	2.82×10^{-1}	9.65×10^{-1}	8.96×10^{-1}
t_{pm} (years)	3.05	3.06	2.57	2.88
λ_1 (redox potential, RP)	-8.98×10^{-5}	-1.06×10^{-4}	-1.82×10^{-4}	-1.80×10^{-4}
λ_2 (pH, PH)	-5.90×10^{-2}	-1.15×10^{-1}	-6.42×10^{-2}	-6.54×10^{-2}
λ_3 (resistivity, RE)	-2.15×10^{-4}	-2.99×10^{-4}	-2.12×10^{-4}	-2.60×10^{-4}
λ_4 (chloride, CC)	8.38×10^{-4}	1.80×10^{-3}	8.62×10^{-4}	8.74×10^{-4}
λ_5 (bicarbonate, BC)	-1.28×10^{-3}	-4.88×10^{-4}	-6.78×10^{-4}	-6.39×10^{-4}
λ_6 (sulphate, SC)	-5.33×10^{-5}	-2.09×10^{-4}	-1.13×10^{-4}	-1.22×10^{-4}
γ_1 (pipe/soil potential, PP)	4.93×10^{-1}	4.61×10^{-1}	5.12×10^{-1}	5.19×10^{-1}
γ_2 (water content, WC)	3.72×10^{-3}	1.69×10^{-2}	4.50×10^{-4}	4.65×10^{-4}
γ_3 (bulk density, BD)	-1.01×10^{-1}	-9.87×10^{-2}	-1.58×10^{-1}	-9.90×10^{-2}
γ_4 (coating type, CT)	4.67×10^{-1}	5.67×10^{-1}	4.34×10^{-1}	4.31×10^{-1}

Table A.3

Probability distributions of environmental parameters [40].

Variable, symbol (units)	PDF ^a			
	Clay (110) ^b	Clay loam (61)	Sandy clay loam (79)	All (250)
Resistivity, RE (X-m)	Weibull(62, 4275)	Weibull(28, 566)	Lognormal(49,2363)	Lognormal(50,2931)
Sulphate, SC (ppm)	Gamma(131,12566)	Lognormal(208,65549)	Weibull(144,9836)	Lognormal(154,25328)
Bicarbonate, BC (ppm)	Lognormal(19, 639)	Lognormal(23, 548)	Lognormal(14,36)	Lognormal(19,436)
Chloride, CC (ppm)	Lognormal(53,4709)	Lognormal(45,2946)	Lognormal(22,559)	Lognormal(41,3135)
Water content, WC (%)	Normal (24, 47)	Weibull (25, 27)	Normal (22, 33)	Normal (24, 38)
pH, PH	Gumbel (5.94, 0.97)	Gumbel (6.36, 0.77)	Normal (6.23, 0.637)	Gumbel (6.13, 0.84)
Pipe/soil potential, PP (V) ^c	Normal (-0.86, 0.04)	Normal(-0.81, 0.04)	Normal(-0.92, 0.023)	Normal(-0.86, 0.04)
Bulk density, BD (g/ml)	Normal (1.22, 0.003)	Gumbel(1.32,0.0005)	Gumbel(1.39,0.002)	Normal (1.30, 0.007)
Redox potential, RP (mV) ^d	Uniform (2.14, 348) ^e	Uniform (19, 301)	Uniform (20, 339)	Uniform (2.14, 348)

^a Marginals ($\mathcal{W}$) are expressed in Type (mean, variance) format.^b Soil class (number of field observations).^c Relative to a Cu/CuSO₄ (sat.) reference electrode.^d Relative to the standard hydrogen electrode.^e The range of the variable is given instead of the two first moments.**Table A.4**

Evaluation scores for pipeline coating types [40].

Coating Type (CT)	Score
Bare pipe	1.0
Asphalt enamel	0.9
Wrap-tape ^a	0.8
Coal-tar	0.7
FBE ^b	0.3

^a Single and double-wrapped polyolefin tape.^b Fusion bonded epoxy.**Table A.5**Correlation matrix, C , for random variables — All data [39].

Variable ^a	RP	PH	PP	RE	WC	BD	CC	BC	SC	CT
RP	1	-0.268	-0.248	0.339	-0.291	0.05	-0.267	-0.124	-0.133	0.145
PH	-0.268	1	0.048	-0.32	0.165	0.206	-0.051	0.44	0.129	-0.227
PP	-0.248	0.048	1	-0.351	0.274	-0.124	0.302	0.038	0.158	-0.226
RE	0.339	-0.32	-0.351	1	-0.532	-0.092	-0.13	-0.199	-0.188	0.180
WC	-0.291	0.165	0.274	-0.532	1	-0.155	0.196	0.117	0.193	-0.149
BD	0.05	0.206	-0.124	-0.092	-0.155	1	-0.229	0.166	0.159	0.179
CC	-0.267	-0.051	0.302	-0.13	0.196	-0.229	1	0.102	0.204	-0.052
BC	-0.124	0.44	0.038	-0.199	0.117	0.166	0.102	1	0.268	0.029
SC	-0.133	0.129	0.158	-0.188	0.193	0.159	0.204	0.268	1	0.082
CT	0.145	-0.227	-0.226	0.180	-0.149	0.179	-0.052	0.029	0.082	1

^a Note: Each row and column represents a variable, and the corresponding cell entries denote the correlation coefficients between the variables. Positive values indicate positive correlation, negative values indicate negative correlation, and the magnitude reflects the strength of the correlation. The main diagonal consists of 1's, representing perfect correlation with itself.

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