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Probability distribution of pitting corrosion depth and rate in underground pipelines: A Monte Carlo study

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ABSTRACT

The probability distributions of external-corrosion pit depth and pit growth rate were investigated in underground pipelines using Monte Carlo simulations. The study combines a predictive pit growth model developed by the authors with the observed distributions of the model variables in a range of soils. Depending on the pipeline age, any of the three maximal extreme value distributions, i.e. Weibull, Fréchet or Gumbel, can arise as the best fit to the pitting depth and rate data. The Fréchet distribution best fits the corrosion data for long exposure periods. This can be explained by considering the long-term stabilization of the diffusion-controlled pit growth. The findings of the study provide reliability analysts with accurate information regarding the stochastic characteristics of the pitting damage in underground pipelines.

1. Introduction

Aging underground oil and gas pipelines can suffer from several localized forms of corrosion, primarily pitting, which results from pipe coating disbondment and inadequate cathodic protection [1]. The severity of the threat posed by external pitting corrosion in a pipeline depends upon the distribution of pit depths and the rate of pit growth. The distribution of pipeline pit depths at a given time can be measured by in-line inspection (ILI) or can be estimated from direct observation of a sufficiently high number of excavations. The corrosion rate can be estimated by comparing successive in-line inspections [2–4] or it can be assessed from direct corrosion rate measurements [1]. The advantages and disadvantages of each of these approaches have been discussed elsewhere [1–5].

A knowledge of the corrosion rate (v) probability distribution is critical for developing reliability and risk-based models for inspection and maintenance planning of corroded pipelines [4–8]. Let us assume that the probability distribution of pit depths ($f(x)$) in a given pipeline has been measured at a given time (t) and that the probability distribution of the pitting rate ($g(v)$) is known. If only the threat of leakage through the pipeline wall is considered, then the pipeline reliability (R) at a later time ($t+\delta$, $\delta > 0$) can be predicted using the following equation [4,8]:

$$R(t+\delta) = 1 - \int_{pwt}^{\infty}\int_{0}^{\infty} g(v)f(x - v\delta)\,dv\,dx \qquad (1)$$

where *pwt* is the pipe wall thickness.

In physical terms, Eq. (1) states that the reliability of a pipeline decreases with increased prediction time and with a greater mean and variance of the pitting corrosion rate distribution. Additionally, it is well known that the uncertainty in pipeline reliability predictions increases with increased pit depth measurement tolerance and pitting rate uncertainty [6,7]. However, in spite of the impact that the pitting rate has on pipeline reliability, the amount of information reported in the literature regarding the probabilistic distribution of corrosion rates in buried pipelines is rather scarce. The existing empirical models for the average value of corrosion rate in underground pipelines as a function of the local soil characteristics cannot fully predict the statistical properties of corrosion rate based on the observed soil properties. To the best of the authors' knowledge, there are only a few models available for predicting external corrosion rate distributions in underground pipelines [3–5].

Recently, Kiefner and Kolovitch [5] developed a Monte Carlo method for determining the corrosion rate distribution in buried pipelines that uses the probability distributions of corrosion depth and initiation time. In order to estimate corrosion growth rate distribution, random values were drawn from the (measured) depth and (assumed) starting time distributions and entered into a Monte Carlo algorithm based on a linear growth model. The results were very sensitive to the distribution of corrosion starting times, which was proposed to be inferred from pipeline operating records. Application of the method to real pit depth data measured by in-line inspection produced average corrosion rates (6–11 mpy) that were lower than the default rate given in Appendix D of NACE RP0505–2002 (16 mpy) [9].

Alamilla and Sosa [4] developed a stochastic model for corrosion damage evolution. In this model, the probability distributions

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of corrosion depth and corrosion rate at a given time are estimated analytically from the empirical probability density function of corrosion damage depth, the number of detected corrosion features and the distribution of the time of corrosion nucleation. The average corrosion rate of each detected corrosion metal loss was approximated by a linear relationship between the defect depth and lifetime. It was assumed that the corrosion starting times arise from a homogeneous Poisson process. Additionally, the authors claim that the intervening environmental factors in the corrosion process are considered explicitly in their model. The common limitations of the two predictive approaches outlined above are the assumption of a linear pit growth with respect to time, the need for inferring the distribution of corrosion initiation time and the lack of an explicit consideration of soil and pipe characteristics in determining pit growth.

In this work, the statistical characteristics of the local soil and pipe variables are used to predict the time evolution of the probability distribution of pit depth and pit growth rate in underground pipelines. The investigation is based on a field study recently reported by the authors, from which a non-linear, multivariate predictive model for maximum pit depth in underground pipelines was proposed [10]. The time derivation of this depth model led to a predictive formula for the time evolution of the average corrosion rate as a function of the local environmental factors. In order to estimate the time dependence of pitting corrosion depth and rate distributions, Monte Carlo simulations were conducted based on the proposed pitting model. The probability functions fitted to the empirical distributions of the soil and pipe characteristics were used as the inputs for the Monte Carlo simulations. The type, mean and variance of the distribution that best fit the corrosion depth and rate data produced by this procedure were obtained for pipelines in contact with clay, clay loam and sandy clay loam soils. A real pipeline reliability assessment is used as a case study to illustrate an application of the results and how they can improve the accuracy of reliability estimates.

2. Model foundations

2.1. Field data collection

In a field study recently reported by the authors [10], maximum pit depth and local soil and pipe data were collected over a three-year period from 250 excavated pipeline sites located across southern Mexico. In the field, pits were identified as corrosion-caused metal losses with a diameter equal to or less than two times the pipe wall thickness [10]. The studied pipelines had been in service for up to 50 years. The measured soil variables included resistivity, pH, water content, redox potential, bulk density and dissolved chloride, bicarbonate and sulphate ion concentrations. The pipe-to-soil potential, pipe coating type and pipeline age were also included within each dataset. Based on the relative proportions of sand, silt and clay, the soil samples were grouped into four textural classes: clay (C), clay loam (CL), sandy clay loam (SCL) and a generic class containing all collected samples (All).

The probability distributions of the empirical soil and pipe variables were investigated for use as inputs to the Monte Carlo simulations. The probability density function that best-fits the experimental data associated with each variable in each soil class was determined using EasyFit 3.2 [11]. The results of the fitting analysis are presented in Table 1. For each variable considered in this table, the parameters of the distributions fitting the observed data were determined using the MLE (maximum likelihood estimates) method, whereas the best model was selected based on the value of the Kolmogorov–Smirnov (K–S) test statistic. The random values put into the Monte Carlo simulations were drawn from these distributions. The influence of the pipeline coating type on pitting corrosion was modelled numerically using a scoring model previously reported by the authors [10]. This model, presented in Table 2, is based on practical criteria given in [12] and [13]. Higher scores were assigned to coatings that provide lower protection. The proposed scores quantify the general body of practical experience reported in the literature on the susceptibility of pipeline coatings to failure [1,3,10,12,13]. The probability of occurrence of each score used in the Monte Carlo simulations is also given in Table 2. It was assigned according to the frequency at which the corresponding coating was observed during the field study reported in [10].

2.2. Maximum pit depth model

Pit growth in low-carbon steel is commonly modelled with a power law function that relates the average value of the maximum pit depth (d_m) to the exposure time [10,14]:

$$d_m(t) = k(t - t_0)^{\alpha} \tag{2}$$

where the subscript "m" is used for predictions made for maximum pit depth (deeper pits), t_0 is the corrosion starting time, and k and α are the pitting proportionality and exponent factors, respectively. In most pitting corrosion studies, k and α are assumed to be constant, with α ranging from 0.3 to 1.0 [15].

Table 1
Statistical fitting of the observed corrosion data.

Variable, symbol (units)	Probability density function[a]			
	Clay (110)[b]	Clay loam (61)	Sandy clay loam (79)	All (250)
Max. pit depth, d_m (mm)	GEV (2.25, 3.90)[c]	GEV (1.88, 2.97)	GEV (1.25, 0.99)	GEV (1.84, 2.92)
Resistivity, *re* (Ω–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)[d]	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)[e]	Uniform (2.14, 348)[f]	Uniform (19, 301)	Uniform (20, 339)	Uniform (2.14, 348)

[a] Expressed in *Type*(*mean*, *variance*) format.
[b] Soil class (number of field observations).
[c] Generalized extreme value.
[d] Relative to a $Cu/CuSo_4$ (sat.) reference electrode.
[e] Relative to the standard hydrogen electrode.
[f] The range of the variable is given instead of the two first moments.