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Extreme value analysis for assessing structural reliability of welded offshore steel structures

Igor A Chaves, and Robert E Melchers

Centre for Infrastructure Performance and Reliability, The University of Newcastle, Australia

Abstract:

Natural deterioration of mild steel exposed to marine environment compromises the long-term integrity, serviceability and safety of new and existing infrastructure and increases the risk of structural failure. Welded structures are known to be prone to even higher risks as a result of adverse effects of pitting corrosion in weld-heated areas. A bi-modal model has been shown recently to be a better description for the long-term development of the maximum depth of pits. Also, the statistics of pit depth have been shown to be better represented, for long term exposures, by the Frechet extreme value distribution. Both new developments present challenges for structural reliability analysis. Herein a linearization is used to represent long-term development of pit depth. It is shown that data for maximum pit depths can be separated into those with Gumbel statistics and those for which a Frechet distribution is more appropriate. An example is given for the reliability analysis of a welded pipeline subjected to localized corrosion. The effect of random variable uncertainty is assessed using a sensitivity study. Results show the considerable influence on the probability of failure of pit diameter and the parameters describing the pitting corrosion model.

Keywords: Modelling; Reliability; Pitting Corrosion; Steel; Pipeline; Weld.

Corresponding Author: Igor A Chaves igor.chaves@newcastle.edu.au +61 (02) 4921 7844

Introduction

Corrosion is a significant potential threat to new and existing infrastructure. It may cause loss of material and thereby affect the ultimate load capacity of the structure and potentially, its safety. It also may change its elastic and dynamic properties, thereby affecting serviceability and possibly fatigue strength. Further, corrosion may cause perforation such as through pitting or the formation of crevices, thereby affecting containment capacity. Regardless of the failure mode, both for rational economic decision-making and for structural engineering assessments there has been an increasingly need to estimate the likely progression with time of deterioration of infrastructure. This has associated risks for structural safety and structural performance and, for asset management these need to be estimated. Structural reliability theory provides a sound framework for this [1,2].

Corrosion also has major economic significance, since for many highly developed industrial societies there is intense economic activity close to or on the seaboard. In the USA alone costs related to all forms of corrosion have been estimated at around 4% of GNP per annum [3,4]. It follows that even relatively small improvements in understanding deterioration of safety and of serviceability may provide the means for life extension or improved asset management. This means that corrosion mechanisms, particularly for long term exposure, are relevant. In this paper attention is focussed on the long-term corrosion of welded structural steels in marine exposure conditions. This environment is recognized to be particularly aggressive. Moreover, the heat affect of the welding process in such structures is thought to cause increased localized pitting corrosion [5]. Structures of interest include harbour and coastal and offshore structures, ships and pipelines.

The progression of maximum pit depth with time traditionally has been modelled by either a linear function (pit depth corrosion rate) or, as a more refined approximation, a power law function [6].

$$c(t) = A \cdot t^B \quad (1)$$

where A and B are constants and c is the amount of corrosion as a function of the period of exposure t . Applications include pitting in underground structures [7] and pitting in containers for nuclear wastes or in nuclear systems [8]. However, for the pitting of steels in marine environment recent studies have shown that the power law, while adequate for data from short term exposures, is not a particularly good fit to data obtained under longer term exposures, such as years or decades. It has been shown that a better fit to the data can be obtained using a model that has a bi-modal form [9]. It also has been shown [9] that the uncertainty in maximum pit depth, conventionally represented by the Gumbel extreme value distribution, is, for long-term exposures with deeper pits, better represented by a Frechet distribution [9]. The aim of the present paper is to show how these developments can be incorporated in structural reliability analysis. This is illustrated with data and trends for pitting of weld zones and the use of the Frechet distribution to represent pit depth uncertainty in long-term exposures. An example is given. The parameters considered include those related to corrosion, to pipeline dimension, to liquid flows and their respective related uncertainty, all treated as probabilistic (or random) variables. For serviceability the critical parameter is considered to be the loss of liquid through pit holes and for this pitting in the welding heat affected zone is critical in the analysis [5]. To assess the effect of the level of variability of the random variables on the failure probability a sensitivity study is also given for a typical example problem.

Progression of corrosion and extreme value analysis

Models systematize data and provide relationships for the effect of various influences, preferably consistent with fundamental principles. For infrastructure applications the progression of corrosion (or pitting) with time the models must be able to deal both with short and long term exposures [10]. For dealing with uncertainty such as maximum pit depth, application of the theory of extreme value statistics is a now traditional approach in the corrosion literature [10,11,12]. It, and the extension known as generalized extreme value (GEV) theory, is a standard approach for modelling pitting uncertainty in the classic extreme value literature [13]. In many applications, however, scarcity of data has led to the combination of data from different sources and for different exposure periods, these typically being tied together through the empirical pit depth growth law (Eq. 1).

The power law function (Eq. 1) is still commonly used for extrapolation to periods well beyond the available time period of the data [6]. Recent field trials, however [14,15], have shown that such a growth law does not fit observations for mild steel exposed to marine immersion conditions (Fig. 1).

Figure 1. Comparison between absolute maximum and mean pit depth reported field trial measurements for parent metal [15] and the fitted power laws to the same data, showing the wide discrepancy between actual data trends and the power law.

Apart from lack of suitable long-term data, one of the difficulties has been insufficient understanding of the fundamentals involved, resulting in assumptions being made for possible parameters which are included in the correlation studies but that have not actually been measured. One such parameter, the variability of maximum pit depths and its changing behaviour with time in long term exposures, is vital for effective prediction and often is poorly or incorrectly assumed or modelled. Moreover, most of the statistical techniques which come under the heading of 'extreme value' methods are predicated, in first instance, on the assumption of an underlying 'large sample

size' of possible measurements, in principle all arising from a single population of measurements [13,16]. Recent research on modelling pitting corrosion with extreme value theory [10,17] shows that the assumption of a single population for all pit depths is not appropriate for long-term exposures.

The distinction between, for example, stable and metastable pitting and so-called 'broad' pitting is well known in the pitting corrosion literature [14] but such heterogeneity does not appear to have been considered and therefore not exploited for the statistical analysis of extreme pit depths. This fundamental heterogeneity means that there are several sub-populations of pits. However, in the theory of conventional extreme value statistical analysis it is assumed that the data are from a single homogeneous population. In the classical applications of extreme value analysis to maximum pit depth [11,13,16], the data has been assumed homogeneous, usually without justification.

Following conventional practice, the scatter in the long term reported data is then represented by a Gumbel extreme value distribution, typically using a Gumbel plot. Fig. 2 shows data extracted from a study of pitting in weld zones [15,18].

(a) (b)

Figure 2. Gumbel probability plots showing maximum pit depth data for 3 year (a) and 33 year (b) exposure for three different weld zones, together with fitted lines corresponding to Gumbel distribution applied to the complete data sets [15]. Note that the fitted lines do not fit very well for deeper pit depths.

As described previously [15,18] extreme pit depths were obtained for each exposure period, including the 33 year samples, by physically measuring the depth of pits. By convention this is relative to a reference surface, and if there is general corrosion as well, making an allowance to obtain absolute rather than relative pit depths. This is a well-established procedure and has been used in all previous pitting studies [e.g. 6-11]. Typically, also, the surfaces of interest are subdivided into equal areas and the depth of the deepest pit in each area measured. The set of maximum pit depths so obtained may then be analysed using extreme value statistics. This approach was used also to obtain the data on which the present work is based.

In Fig. 2 for each weld zone at any given exposure time the statistics of the pit depths measured in each zone were obtained by first ranking, in decreasing magnitude the maximum observed pit depths and then assigning each a rank order of occurrence probability (i.e. rank order statistics). Conventionally, pit depth is plotted along the horizontal axis. The associated rank order data are plotted along the vertical axis, typically on Gumbel Probability paper [13], with the probability represented by the standardized variable W . This is defined [13] as $W = (y - u)\alpha$, further defined through $F_y(y) = F_w[(y - u)\alpha]$ with $F_w(w) = \exp(-e^{-w})$ and $f_y(y) = \alpha f_w[(y - u)\alpha]$. In this formulation it is assumed that the data do indeed follow a Gumbel distribution and that the data set can therefore be represented by a single straight line drawn through each entire data set. In Fig. 2(a) such a line is that shown as YY for heat affected weld zone data set. Similar lines are shown for the parent metal and weld zone data sets. The parameters u and α , respectively, are the "mode" and "slope" of the straight line (e.g. YY) fitted to the data set on the Gumbel plot. These two parameters are related to the mean μ_y and standard deviation σ_y through $\mu_y = u + 1.1396/\alpha$ and $\sigma_y = 0.40825 \pi / \alpha$. Measurement of "slope" α of the Gumbel line gives the variability associated with each data set and hence, uncertainty related to long-term pitting.

However, closer observation of Fig. 2(a) suggests that for each weld zone data set, a single straight line (such as YY) does not fit all the data in each complete data set particularly well, as would be expected if the data set was indeed truly Gumbel distributed. This suggests that the Gumbel extreme value function may not be appropriate for describing the variability associated with all the data in a set, and in particular with the data for long term maximum pit depth. In the past deviation of data from a straight line (i.e. the Gumbel line such as YY) usually was dismissed as the result of random variability and inherent error in deriving trends from a limited number of observations [2].

While the Gumbel distribution has been widely accepted and has a long history of application, there are sound reasons why it is not always appropriate for the complete data set. As noted briefly above, one of these is that pitting behaviour changes with increased exposure time, implying that the population of all pits is not homogeneous [9,10,19]. As a result it was proposed earlier that an appropriate extreme value probability model for longer term exposures (i.e. the deeper pits) is the Frechet distribution [9]. Frechet is the asymptotic extreme value distribution for an underlying random variable that is represented by the Cauchy distribution. The Cauchy distribution, in turn, is the distribution that results when one random variable with an exponential tail (e.g. a Normal distribution) is divided by another such random variable. This situation could arise, for example if there is a different mechanism for control of the processes involved in corrosion. This observation of a change in extreme value behaviour is consistent with the bimodal model for pit depth progression with time [14]. Conversely, it is known in the corrosion literature that very shallow pitting for short-term exposures tends to follow an Exponential distribution [9,19]. In Fig. 2(a) this is marked, for example, for the heat affected zone.

In Fig. 2(b) in each case the data set can be subdivided into three sub-sets, one for very shallow pits, best represented as noted above by the Exponential distribution, one for intermediate pits and one for deeper pits. As shown, they are divided at points A and B respectively, each estimated simply from observation of the departure from linearity of the subset of the intermediate depth pits, with a Gumbel line drawn through that subset (Fig. 2). This discrimination makes it possible to attempt to find a better fit for the distribution of the deeper pits. Fig. 3 shows that each of the data sets for pit depths greater than B in each case is better represented by Frechet distributions. This is shown for each data set by the straight lines plotted through data to the right of B on Fig. 3 (the Frechet plots). As noted, the reason for the change in the trends of each data set is related to the bimodal nature of the model [14]. Different mechanisms for pitting corrosion control are involved [9] and these represent different statistical populations.

(a)

(b)

Figure 3. Frechet probability plots showing maximum pit depth data for 3 year (a) and 33 year (b) exposure for three different weld zones, together with fitted lines corresponding to parts of the data representing deeper corrosion pits [15]. In each case the subset of deepest pit data can be fitted by a Frechet distribution.

Until recently [9,10,19] the possibility that pit depths could constitute two (or more) statistical populations was not recognized and thus not considered in the statistical analysis of maximum pit depths. It is particularly relevant for longer term exposures. Because the actual development of maximum pit depth with time is relatively complex particularly for shorter exposure periods (Fig. 1) and because long-term pitting is of most interest in infrastructure applications, the approach taken herein is to consider only long term pitting progression and to model the empirical results using a linear function. Evidence that long-term pitting follows a linear trend is available in the empirical corrosion literature [20]. As illustrated in Fig. 4, the long-term progression of pitting corrosion may be approximated using the linear function:

$$R(t) = R_0 + r_I \cdot t \quad (2)$$

where R_0 = ‘y-intercept’ at the point of intersection and r_I = slope gradient. This extends the model for pit depth beyond the immediately available data and is consistent with other data that shows linearity in the long-term corrosion and pitting corrosion trends [9].

The uncertainty associated with each of the values of R_0 and r_I are important for reliability analysis. In the present case data for 3 year and 33 year exposures were used to estimate the uncertainty and the associated statistics for parameters R_0 and r_I . The statistics for parameter R_0 was estimated directly from the variability in the data set at 3.5 years of exposure, based on the assumption that the latter is approximately the point in time at which the pitting mechanics has stabilized. The variability in the slope r_I (which is always greater than 0) was estimated by using a succession of values of R_0 as a lower cut-off and for each applying the data at 33 years of exposure to obtain sample estimates of r_I . These were then used to estimate the variability in r_I . This approach was used in the example below.

Figure 4. Trends of absolute maximum and mean pit depth readings and predicted power law depths for each weld zone [18] together with linear function approximations for the long-term rate of pit development.

Example Application

Consider a low carbon steel pipeline, grade SAE 1025 [21], transporting crude oil. To estimate the probability of failure it is necessary to define the failure event being considered. This requires the mathematical definition of the ‘failure’ or ‘limit state’ function. In the present case, let the failure function (Z) be defined as the difference between an allowable fluid loss (Q_P) and an estimated fluid loss through all pit holes formed on the surface of the pipe (Q_h):

$$P_f = P[Z(t) < 0] \therefore Z(t) = \delta Q_P - Q_h \quad (3)$$

where δ is a calibration factor and (δQ_P) is the acceptable limit of the fluid that is considered to be allowed to be lost through leakage. Z satisfies the usual requirements of the ‘failure function’, i.e. $Z(t) > 0$ indicates a safe region, $Z(t) = 0$ indicates a failure surface and $Z(t) < 0$ indicates a failure region. Any or all of the parameters in Eq. (3) may be random variables.

As well-known, several techniques exist to estimate the probability of failure when random variables are involved [2,22]. Here the first-order second moment reliability method is applied. It requires an iterative solution when the random variables are not all normally distributed and the ‘failure function’ is not linear. The relevant algorithms are readily available in the literature [2].

When one or more pits perforate the pipe wall, a fraction of the fluid that is carried along the pipe will be lost. Let it be assumed that the fluid (e.g. hydrocarbons) is incompressible and the flow is steady. These assumptions are not too unrealistic in most cases of practical pipeline flows. Based on this assumption, the Continuity Equation is implemented [23]. Describing the transport of a conserved quantity of mass or energy which is conserved under appropriate conditions, a variety of physical phenomena may be modelled. The total discharge through an orifice may be given as a product of its charge of storage, density, speed and area. The total loss of fluid through all the pit perforations (holes) is then given by:

$$Q_h = n_l \cdot C_d \cdot A_h \cdot v_h \quad (4)$$

where Q_h = total discharge through all pit holes, n_l = cumulative number of pipeline leaks, C_d = pipe coefficient of discharge, A_h = cross-sectional area of a pit hole and v_h = mean velocity of fluid at the pit hole. In practice, of course, a single leak may be all that can be tolerated, in which case $n_l = 1$.

In any practical scenario it is not possible to predict the number of the exact location where pitting and also where perforation might occur. One possible approach is to use an exponential leak-growth relationship model to estimate the cumulative number of pipeline leaks as a function of time. For carbon steel pipelines the mathematical model chosen for this relationship is as follows [24,25]:

$$n_l = e^{[-1]} \cdot e^{\left[\frac{R \cdot t}{(b_o + C_A)} \right]} \quad (5)$$

where R = pitting rate, t = exposure period, b_o = nominal wall thickness and C_A = design corrosion allowance.

If the expression for R (Eq. 2) is now substituted into Eq. (5), the expression for the total number of leaks becomes:

$$n_l = e^{[-1]} \cdot e^{\left[\frac{(R_0 + r_1 \cdot t) \cdot t}{(b_o + C_A)} \right]} \quad (6)$$

This equation can be used to estimate the cumulative number of leaks (n_l) for any given service life (t) if the other parameters of the equation are known.

A_h is given by $A_h = (\pi d_h^2)/4$ where d_h is the diameter of a pit hole. From Bernoulli's theorem [23], v_h can be written as:

$$v_h = \left(\frac{2g}{\gamma} \cdot P_p + \frac{16Q_p^2}{\pi^2 \cdot d_p^4} \right)^{1/2} \quad (7)$$

where g = gravitational acceleration, γ = unit weight of fluid, P_p = pressure inside pipe, v_p = mean velocity of fluid inside pipe, Q_p = discharge through pipe and d_p = diameter of pipe.

Substituting for n_l , A_h and v_h in Eq. (3), results:

$$Q_h = e^{[-1]} \cdot e^{\left[\frac{(R_0 + r_1 \cdot t) \cdot t}{(b_o + C_A)} \right]} \cdot C_d \cdot \frac{\pi d_h^2}{4} \cdot \left(\frac{2g}{\gamma} \cdot P_p + \frac{16Q_p^2}{\pi^2 \cdot d_p^4} \right)^{1/2} \quad (8)$$

Random Variables

Assume that in the long-term all mitigation and corrosion controls are nonexistent or have ceased to be effective. Let the failure event be defined as wall perforation and leakage of pipe content from the pipe. Normally in industry the tolerance levels for leakage are very low. For the purpose of the present example let the tolerance level be represented by a calibration factor δ with value $10e^{-5}$.

When multiplied by the flow in the pipe Q_p , the quantity δQ_p represent the practical ‘zero’ tolerance level of the transported fluid that is allowed to be lost through leakage.

For the present example, consider mild and low carbon steel pipelines exposed to a marine environment. Only the case of pitting corrosion is considered. The random variables involved and their probability distributions and statistics are listed in Table 1. These are arbitrary, but not unrealistic values. Evidently, not all random variables have the same degree of uncertainty. For example, the pipe radius and pipe wall thickness have little inherent associated uncertainty. What there is, in part, is the result of geometrical imperfection which results, unintentionally, from the process of manufacture.

In Table 1 the following notation applies: Q_p = discharge through pipe, b_0 = nominal wall thickness, C_A = design corrosion allowance, C_d = coefficient of discharge of pipe, d_h = diameter of pit hole, γ = unit weight of transported liquid, P_p = pressure of liquid inside pipe, d_p = diameter of pipe, R_0 = calibration parameter for pitting rate for heat affected zone (HAZ), weld zone (WZ) and parent metal zone (PMZ), r_I = multiplier parameter for pitting rate for each zone.

Table 1. Basic design random variables (HAZ = heat affected zone, WZ = weld zone, PMZ = parent metal zone).

Symbol	Unit	Type	Mean	COV	Symbol	Unit	Type	Mean	COV
Q_p	mm ³ /s	Normal	9.7e ⁸	0.10	R_0 (WZ)	--	Gumbel	0.273	0.710
b_0	mm	Normal	9.52	0.06		--	Frechet	0.516	0.852
C_A	mm	Lognormal	1.50	0.05	R_0 (PMZ)	--	Gumbel	0.306	0.401
C_d	--	Lognormal	0.60	0.10		--	Frechet	0.411	0.372
d_h	mm	Normal	0.35	0.12	r_I (HAZ)	--	Gumbel	0.099	0.316
γ	N/mm ³	Lognormal	8.2e ⁻⁶	0.05		--	Frechet	0.111	0.190
P_p	N/mm ²	Lognormal	5.52	0.19	r_I (WZ)	--	Gumbel	0.089	0.288
d_p	mm	Normal	914	0.02		--	Frechet	0.099	0.201
R_0 (HAZ)	--	Gumbel	0.742	0.567	r_I (PMZ)	--	Gumbel	0.081	0.360
	--	Frechet	1.114	0.870			Frechet	0.098	0.331

Results and discussion

The example above was analyzed using time-invariant structural reliability theory. The probability of failure was estimated for independent events and for different points in time using a standard computer program. It calculates the reliability index (and the probability of failure) together with the contributions of various basic variables to the variance of the failure function. Table 2 and 3 summarize the results. Table 2 is based on the assumption that the Gumbel extreme value distribution averaged over the complete data set for pit depths is appropriate to represent also the uncertainty in long-term pit depth data. This is the extreme value distribution shown, for example, as line YY in Fig. 2. Table 3 is based on the assumption that the Frechet extreme value distribution is appropriate for representation of the deepest pits – the ones that most likely govern the failure probability. In both cases failure is characterized by a level of containment loss exceeding an acceptable level, as discussed in the previous section. The last line in each table shows the probability of failure and how this changes with increased exposure time t . Comparison of the probabilities shown in Tables 2 and 3 shows the effect of choice of extreme value distribution for the deepest pits.

Table 2. Reliability and sensitivity as a function of service life, t (exposure period in years) for Gumbel distributed pitting corrosion parameters.

Symbol	Relative contribution (%) or (α^2)				
	$t=1$	$t=5$	$t=10$	$t=15$	$t=20$
Q_p	25.60	9.86	3.09	1.17	0.29
R_0	2.15	31.89	45.37	39.10	29.56
r_l	0.01	4.41	25.09	48.65	65.38
b_0	0.04	1.77	1.74	0.80	0.45
C_A	0.00	0.03	0.03	0.01	0.01
C_d	14.50	8.42	3.11	1.21	0.52
d_h	43.84	35.57	18.60	7.91	3.31
γ	0.91	0.53	0.20	0.08	0.03
P_p	12.92	7.50	2.77	1.07	0.46
d_p	0.00	0.00	0.00	0.00	0.00
P_f	0.00	0.87	62.38	96.37	99.39

Table 3. Reliability and sensitivity as a function of service life, t (exposure period in years) for Frechet distributed pitting corrosion parameters.

Symbol	Relative contribution (%) or (α^2)				
	$t=1$	$t=5$	$t=10$	$t=15$	$t=20$
Q_p	21.21	3.69	1.09	0.47	0.04
R_0	10.53	69.18	85.40	85.99	81.86
r_l	0.00	0.82	4.04	9.16	15.51
b_0	0.21	1.40	0.63	0.31	0.42
C_A	0.00	0.02	0.01	0.01	0.01
C_d	13.25	3.51	1.10	0.50	0.27
d_h	42.11	18.03	6.66	3.09	1.64
γ	0.83	0.22	0.07	0.03	0.02
P_p	11.81	3.12	0.98	0.44	0.24
d_p	0.00	0.00	0.00	0.00	0.00
P_f	0.00	11.61	74.45	95.36	98.70

The development with increased exposure time of the independent estimates of failure probability for both extreme value analyses are shown in Figure 5. It is seen that the Frechet assumption for longer term pitting corrosion results in higher failure probabilities. This is consistent with the expectation that longer-term anaerobic processes are involved [14,26] and that this is governed mainly by the parameter r_l . The calibration parameters R_0 and r_l (respectively the intercept and slope for the pitting rate with time) have associated with them the uncertainty related to the pitting rate, and this carries forward into the calculation of the probability of failure.

Figure 5 also shows that there is a considerable increase in the probability of failure after about 5 years exposure for the Heat Affected Zone, 6 years for the Weld Zone and about 8 years for the Parent Metal Zone. For maintenance strategies, this suggests that pipeline inspection should be increased at about this time. Such inspection may reveal whether the expected loss of wall thickness has actually occurred and this information may then be used in a Bayesian up-dating scheme to

refine the estimates of failure probability for longer periods of use. Details of such procedures are not central to the discussion here and are available in the literature.

(a) (b)

Figure 5. Estimated pipeline probability of failure for given example considering long term maximum pit depth distributed by Gumbel function (a) and Frechet function (b).

The results show that the probability of failure increases with increasing service life t , as would be expected. With increasing service life it can be expected that there will be an increase in the number of leaks or an increased likelihood of leak occurrence, thereby increasing the potential of more fluid loss and hence violation of the specified limit state failure condition. It is seen in Table 2 and 3 that the probability of failure increases very considerably after about 5 to 10 years of exposure.

The relative contributions (α^2) made by each of the random variables to the overall probability of failure (P_f), as a function of the service life (t), also are shown in Tables 2 and 3. In both cases the relative contribution of some variables (e.g. corrosion allowance, pipeline diameter, etc.) is very low and this continues to be the case over the total service life. This indicates that such random variables do not contribute much to the overall failure probability of the pipeline. The variable ‘Pit Hole Diameter’ (d_h) was found to have a significant influence on the overall reliability estimates. However, its contribution was found to decrease gradually with increased service life. The relative contributions of corrosion rate parameters (R_0 and r_I) increase significantly with increased exposure, with r_I having a much stronger contribution than R_0 in the long term. These observations are consistent with results for all three zones: heat affected, weld and parent metal zone. Both these observations confirm the expectation that pitting corrosion parameters play an important role in the reliability of pipelines with long term service lives. This means that, depending on the empirical trends for “ R_0 ” and “ r_I ”, there is a clear point in time at which the absolute pit depth increases significantly compared to earlier measurements. This is reflected in the sensitivity analysis, where “ R_0 ” and “ r_I ” are shown to have a much stronger influence than the other parameters. It is also the reason for the increase in failure probability between 5 to 10 years of exposure. However, the outstanding difference between the results is the difference in the probability of failure estimated using Gumbel compared with the Frechet distribution for the uncertainty related to the deepest pits (i.e. those most likely to cause pipe leakage and hence failure). This is most clearly illustrated by comparing Figs. 5(a) and 5(b). It applies to each of the weld zones as well as pitting of the parent metal.

The above example illustrates why good quality models for corrosion behaviour are required for structural engineering risk and reliability estimation. They are essential for the prediction of how the risk of failure can develop with time. Increasingly, maintenance of infrastructure is a critical and practical issue but the costs involved are high. Optimal scheduling of maintenance activities increasingly is seen as a sound approach, best achieved through methods based on probabilistic risk-based decision-making of which the theory of structural reliability is a crucial part [1].

Powerful methods now exist for estimating structural system failure probability. As the above example illustrates, there remains a need for realistic and accurate models for structural deterioration. For pitting corrosion the most appropriate model is the multi-phase model previously shown to be consistent with much pit depth data [12,14]. The data in Fig. 1 is consistent with this model. Obviously, better models will produce much more reliable estimates of pit depth and therefore better estimates of probability of failure. Nevertheless, more extensive field studies are required to elucidate information about uncertainty so that the probabilistic pit depth model can be

refined. This is also the case for the effect of environmental factors, such as the high influence of water velocity and level of nutrients [27] which were not considered in this work.

Although the above discussion is confined largely to pitting corrosion as an independent deterioration mechanism, in practice corrosion is not an independent issue for risk and remaining life assessments. Corrosion interacts with applied stresses, fatigue, mechanical damage and, most importantly, with protective systems such as cathodic protection, paint coatings and management practices. In practice these interactions cannot be ignored, even though the actual interactions are not in all cases fully understood. For the development of probabilistic models, at the present time the first priority must be to develop better mean-value models for the estimation of reliable long term predictions. This requires a sound approach to modelling the physical, chemical, biological and environmental factors involved as well as understanding of the corrosion processes involved, using both corrosion science principles and empirical observations. Evidently, these interactions for particular applications also provide a rich field for further research in which probabilistic models will be important. This is considered to be an exciting and demanding challenge.

Conclusions

1. The development of maximum pit depth with time may be modelled as a linear function asymptotic and calibrated against the observed pit depth data trend. This approach contrasts with other models predominantly fitted only to short-term pit depth observations;
2. The parameters R_0 and r_I used to model the development of maximum long-term pit depth as a function of time have considerable uncertainty. By example this is shown to have a strong effect on the estimated structural reliability and the estimated probability of failure;
3. Some parameters in the modelling of reliability make minimal contribution to the overall probability of failure while others contribute significant only initially, and have diminishing contributions with time;
4. The analysis for the example given herein shows that pipeline failure probability as defined herein increases with increased service life significantly only after about 5-10 years of service.

Acknowledgments

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