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

Igor A. Chaves *, Robert E. Melchers

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

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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.

1. 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].

$$c(t) = A \cdot t^{B} \tag{1}$$

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

* Corresponding author. Tel.: +61 (02) 4921 2006; fax: +61 (02) 4921 6991.
E-mail address: igor.chaves@newcastle.edu.au (I.A. Chaves).

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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.

2. 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 [10–12]. 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).

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

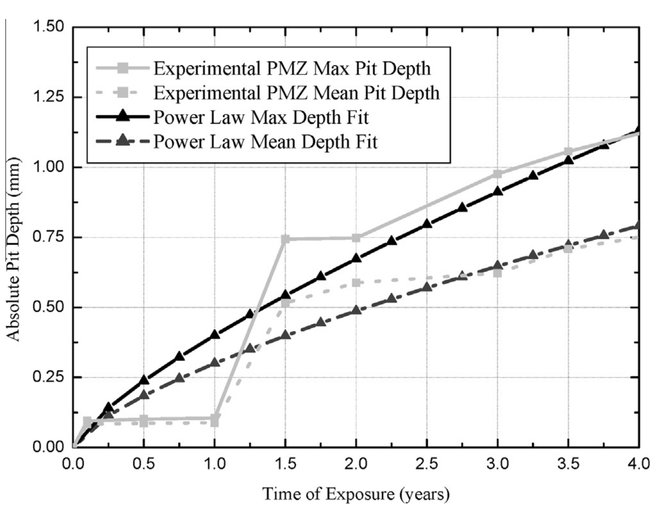

Fig. 1. Comparison between absolute maximum and mean pit depth reported field trial measurements for parent metal [15] and the fitted power laws to the same data, showing the wide discrepancy between actual data trends and the power law.

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].

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