STATISTICAL MODELLING FOR PITTING CORROSION OF CAST IRON PIPELINES

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ABSTRACT: External corrosion is the main reason of the deterioration of cast iron water main in the Australia Water Industry. Prediction of the life time and the maximum pit depth which causes failure can help to reduce the cost of water system maintenance. Due to the complexities of the mechanism of pitting as well as existence of numerous uncertainties, none of the conventional electrochemical approaches is capable of accurate prediction of pipe lifetime. This study, therefore, aims at investigating the maximum pit depth based on the probabilistic theory in order to assist with the prediction of the lifetime of pipelines. A probabilistic model based on the extreme value theory is suggested for this study. Real field data of pitting corrosion of a series of old underground pipelines have been gathered from some sites in Australia. Although Gumbel distribution has been widely employed for extrapolation of maximum pit depth of pipelines, analysis of these real data indicates that the variability of maximum pit depth in long-term exposure fits the Frechet extreme value distribution. Moreover, results of this study show that for cases whose ages have been 30-50 years the maximum pit depth tends to follow one Frechet distribution, while two subsequent Frechet curves have been observed in the probabilistic distributions of data of cases which are older than 50-60 years.

Keywords: Cast iron water mains, maximum pit depth, extreme value theory, Frechet extreme value distribution.

1. INTRODUCTION

Ferrous pipes have been used for urban water supply systems in Australia for more than 100 years and many are still in service. The majority are embedded in soil (Nicholas and Moore 2009). In consequence, the pipes are vulnerable to corrosion, particularly pitting corrosion. Since the process of corrosion is slow but progressive, corrosion of pipelines can, eventually, cause pipeline failure. Numerous studies have been conducted related to finding appropriate predictive models for estimating the lifetime of pipelines in order to (i) reduce the cost of maintenances and (ii) reduce the occurrence of unexpected failure events (Rajani and Makar 2000; Bjornoy and Marley 2001; Katano et al. 2003; Rajani and Tesfamariam 2007; Peterson and Melchers 2012; Peterson et al. 2013).

It is generally accepted that pitting corrosion is intrinsically an unpredictable process (i) in time, (ii) where pitting is likely to initiate and (iii) the rate of propagation of pits. This issue has motivated engineers to develop models for predicting pitting corrosion. Both empirical and mechanical models can be used for analyzing pitting corrosion. Empirical models involve statistical methods to obtain trend curves for use in uncertainty analysis. Mechanical methods require modelling the complex physical and electrochemical processes and using these to interpret field and laboratory observations.

Generally, modelling the effects of pitting corrosion based on mechanical models is complex. For modelling the pitting process using electrochemical/mechanical methods, the physical or electrochemical processes must be translated in to mathematical equations. These may need several levels of approximation and/or abstraction. Although simplification of the complex mechanism of corrosion is one of the main drawbacks of these types of models, they can provide useful information about the effect of pitting corrosion (Sharland et al. 1989; Engelhardt and Macdonald 1998; Rajabipour and Melchers 2013). For example, a series of finite element methods have been performed in order to evaluate the stress cracks which were resulted from pitting corrosion. The results show that the crack initiate on the pit wall close to the pit mouth and localized- plastic strain occurs in this area (Horner et al. 2011).

However, in some cases this simplification leads to not very realistic prediction. Sharland and Tasker (1988) developed a mechanical model for predicting the solution chemistry and electrochemistry within the pits as a function of numerous physical and chemical parameters of systems. Due to the existence of numerous parameters, some possible chemical reactions may need to be neglected. Overall, however, these types of modelling approaches are complex and not suitable for practical applications or for practical design or maintenance applications.

Due to the complexities of the mechanism of pitting as well as existence of numerous uncertainties, conventional electrochemical approaches are not very suited to accurate prediction of the lifetime of pipes and in particular the occurrence and the associated probability of a given pit depth occurring. To deal with this issue it is more appropriate to employ statistical models. These are known from previous experience to be able to provide reasonably accurate prediction of pitting corrosion provided data is available from previous experience.

Since in pitting corrosion of structures, usually the deepest pits are considered to cause failure, in probabilistic and reliability models the maximum pit depth is of most interest. Therefore, the extreme value distributions and in particular the Gumbel distribution, which is one of the extreme value distributions, are relevant. Aziz (1956) was one of the first to use the Gumbel distribution for maximum pit depths. It has been used extensively since then by many authors (e.g.; Finley 1967; Scarf 1994; Shibata 1994; Melchers 2008; Valor et al. 2010). However, more recently it has been shown that the deepest pits in the corrosion of steel in seawater are more consistent with the Frechet extreme value distribution (Melchers 2008, Chaves and Melchers 2011).

The use of extreme value distributions assumes that the maximum depths of pit are independent of each other. Independency of pit depths is the result of the homogeneity assumption. Homogeneity of pits is related to the macro-scales. However, at the micro-scale level metal surfaces are essentially nonhomogeneous. Pits tend to nucleate in high energy locations such as inclusions and grain boundaries. Usually this nonhomogeneity of metal structure does not change significantly from one small area to another, and in addition it is often the case that a large part of the surface of a structure is exposed to the same external environment, including pH, temperature, and level of dissolved oxygen. Thus although at the micro-scale the metal may be nonhomogeneous, at the macro-scale the surface can be considered homogenous (Melchers 2005a; Melchers 2005b). This enables the use of extreme value distributions.

A Gumbel plot is one in which the probability of exceedence of a given pit depth as plotted against maximum pit depth. The probability axis is distorted such that of the data were truly Gumbel distributed the plot would be a linear function (Galambos 1987). The idea is similar to a Normal distribution plot in which data truly Normal distributed plot as a straight line. A similar situation holds, for example, for Frechet plots. In each case the slope of the line is a measure of the uncertainty, or standard deviation, applicable to the data set that is plotted (Galambos 1987). One significant benefit of using linear plots such as Gumbel plot is for linear extrapolation. By employing linear extrapolation the probabilities of the corrosion incidents in different environments and different pit depths can be estimated. Therefore, by estimating maximum pit depths for a particular situation or exposure condition, the probability of exceedence of a pit deeper than covered by the data set can be predicted and on this basis the expected lifetime of a structure can be predicted (Melchers 2005b).

In the study described herein pit depth field data from a series of older cast iron water pipes from Australian sites are investigated for pit depth statistics. In each case the corrosion pit depth is analyzed using extreme value probability theory. The actual prediction of the expected lifetime of the pipes is not considered herein as this depends on factors additional to maximum pit depth.

2. FIELD EXPOSURES AND PIT DEPTH MEASURMENTS

A series of field observations have been conducted by the University of Newcastle. Hunter Water Australia has conducted the exhumation and subsequent abrasive blasting of pipes sections to provide suitable conditions for gathering data related to corrosion and soil environments for this project.

Abrasive blasting is used to remove the graphitized zone and clean the surfaces in order to measure the pit depths. Pit depth profiles have been determined by using laser scanning techniques. The external surface of a selected part of each pipe, which is almost one meter in length, was scanned by a handheld Creaform Laser Scanner to generate a 3D image of the pipe. To distinguish the locations of pits on the surface, the surface was signed by some points as has been depicted in Figure 1. Then the pipe surface was scanned over the surface (see Figure 2). It is not always possible to use laser scan technique. Thus, in some cases pit depths were measured by using a pit depth gauge.

The laser scanning device can generate 2D and 3D maps of the surface. Figure 3 and 4 show examples of 2D and 3D maps of corrosion losses. Corrosion depths can be recorded based on axial and circumferential positions in tables with 2 x 2 mm grid spacing, and then are imported in Microsoft Excel for further analysis.

Consistent with the usual approach in the extreme value literature (Galambos 1987) in this study the maximum pit depths in each pipe were obtained by dividing the pipe surface into equal, smaller, sub-areas and selecting the (one) maximum pit from each sub-area. This method is accurate enough for engineering analysis, because maximum pit depths have been achieved from areas with similar surface topography, grain structures and imperfection. All of them also have been exposed to the same environment with similar physical, chemical and microbiological properties.

Figure 1. External surface of pipe WS5 with scanning coordinate points shown.

Figure 2. Laser scanning in progress.

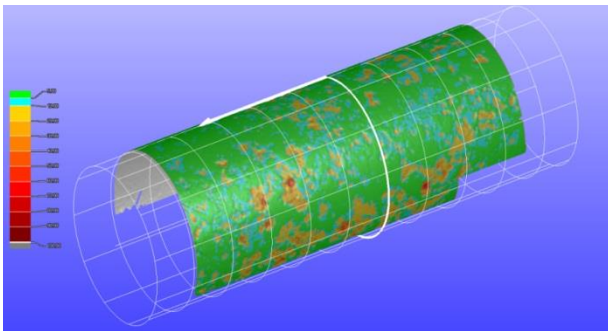

Figure 3. 3D view of a pipe scan, showing contour plot of corrosion losses

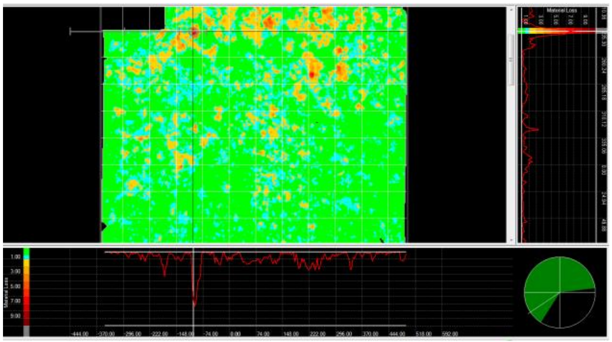

Figure 4. A typical 2D corrosion loss map.

3. RESULTS

To verify whether the Gumbel distribution is an appropriate model for the statistical distribution of maximum pit depth, the approach is to plot maximum pit depths on Gumbel Probability Paper. To do this the data for maximum observed pit depth are ranked and their relative frequencies computed. These are plotted on the vertical axis against the corresponding maximum pit depth on the horizontal axis. For a Gumbel plot the vertical axis is shown as the standardized variable w ($w=(y-u)\ \alpha$). w is defined through the cumulative distribution function *(CDF)* $F_Y(y)$ and probability density function *(PDF)* $F_Y(y)$ by:

$$F_Y(y)=[(y-u)\ \alpha];\ \ F_W=exp(-e^{-w}) \qquad (1)$$

$$f_Y(u)=\alpha f_W[(y-u)\ \alpha] \qquad (2)$$

where u and a are the mode and slope of the Gumbel distribution, respectively. As noted, if the data are truly Gumbel distributed, they will plot as a straight line on a Gumbel plot (Galambos 1987).

Two sets of data are considered here. The first is for pit depths obtained for a 51 year old cast iron pipe. The Gumbel plot for this data set is shown in Fig. 5(a). It can be seen that the complete set of data does not fit a straight line as would be expected for a Gumbel distribution. Following on from earlier work (Melchers 2008), it is possible that the deepest pits follow a different distribution, namely the Frechet extreme value distribution. As is well-known, the Frechet distribution is related to the Gumbel through a logarithmic mapping of the random variable. Fig. 5(b) shows the Frechet Plot for the complete set of maximum pit depths in the data set. It is evident that deepest pits closely follow a linear trend for long term exposure on the Frechet plot. This indicates that the Frechet extreme value distribution is the most appropriate distribution for the deeper pits. Note, however, that shallow maximum pit depths still are best described by the Gumbel distribution.

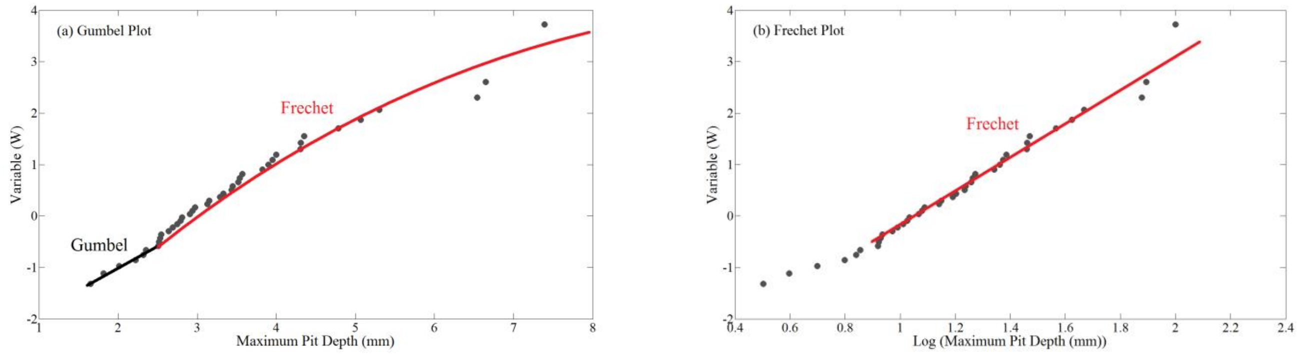

Figure 5. Maximum pit depth distributions for 51 year data in (a) Gumbel plot and (b) Frechet plot.

The second set of data considered here is from another site, where the pipe scanned is 90 years old. Fig. 6(a) shows the pit depths and associated probabilities on a Gumbel plot. In this case it would have been possible to use one straight line through all of the data but closer inspection reveals that there are subtleties in the trend that could be described by a Gumbel line for the least deep maximum depth pits, one Frechet trend for mid-deep pits and another for the deepest pits. To verify whether such an interpretation of the data is reasonable, Fig. 6(b) shows the Frechet plot for these data. This shows apparently two regions of data with a linear trend. It indicates that there appear to be two, successive, Frechet distributions.

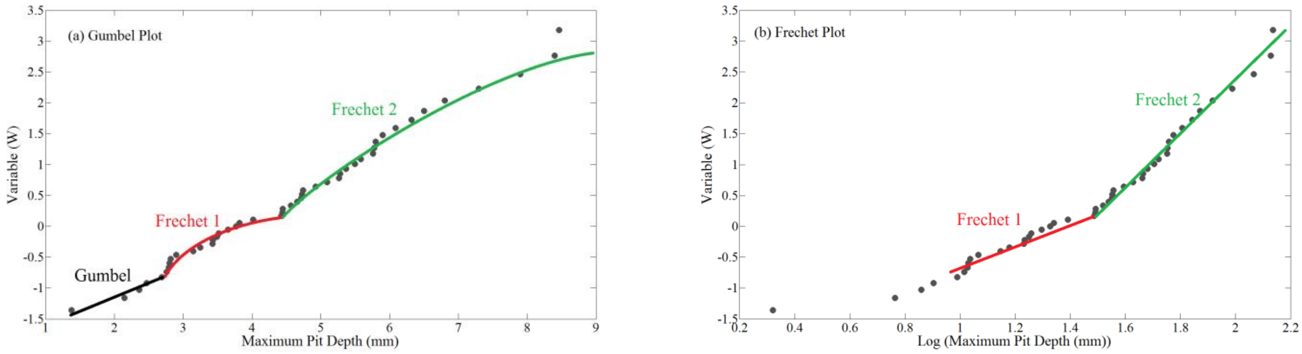

Figure 6. Maximum pit depth data for a 90 year old pipe plotted on (a) a Gumbel plot and (b) the corresponding Frechet plot, showing the clear presence of two parts of the data set that can be identified as Frechet distributed.

4. DISCUSSION

The results shown in Fig. 5 are consistent with what has been identified previously, namely that in some circumstances the extreme maximum pit depths tend to follow a Frechet extreme value distribution (Melchers 2008). The results in Fig. 6, however, are somewhat surprising in that the trend of the maximum pit distribution for these data is not exactly what was expected. The interesting point is that the data in this case suggests the existence of two successive Frechet probability distributions. It follows that the overall extreme value distribution is a mix of Gumbel and two different Frechet component distributions.

In both cases, the present findings are consistent with the notion that pitting corrosion is a self- perpetuating process. At first, a population of pits commences to grow. As the pits grow in size and depth, the original cathodic regions tend to reduce in size and to break-up and the anodic regions tend to spread. In longer exposure, isolated pits which are close to each other may join together and create pit clusters. In fact, pits continue to grow both in depth and in surface area. Eventually, they join together to make clusters (Jeffrey and Melchers 2007).This tends to leave plateaus of corroded regions and these create conditions are suitable for nucleation and growth of a newer generation of pits. Although the newer pits tend on the whole to be less deep than (relatively, from the surface of) the depression formed by earlier coalesced pits, the total depth from the original surface is greater. This suggests that the first Frechet trend represents these newest pits while the second Frechet represents the remainder of the earlier pits coalesced into plateaus.

Examination of the surfaces of the corroded pipes tends to support this interpretation of the development of pit depth and size. Figs. 7 and 8 show the 2D corrosion maps of the surfaces of the 51 year-old and 90 year-old pipes, respectively. Comparison between these two figures indicates that the deep pits are closer to each other in the 90 year-old pipe compared with those on the 51 year-old pipe. Fig. 8 also shows what appears to be the coalescence of small pits into larger localized pits.

The present observations suggest that after 50-60 years a new population of pits, of course of initially small size, can initiate on the plateau of the pit clusters and then grow sufficiently to become the extreme sized pits. As is well-known, Pits appear to form preferentially at locations with higher surface energy and this suggests that the new pits will tend to nucleate inwards from earlier, older pits or plateaus formed by earlier pitting.

The interesting point from a practical perspective is that the present observations indicate that the conventional Gumbel extreme value distribution is not capable of accurate prediction of the depth of the deepest pit likely to occur for long term exposure times. The results given above are in general agreement with the findings for corrosion pit depth for steels and for welds exposed to seawater (Melchers 2008; Chaves 2011). The result of the present study extend these earlier findings to much longer exposure periods and highlight again that the Frechet distribution is more consistent with the extreme long- term pit depth data. This means that the Frechet extreme value distribution, based on the extreme depth pits, is more appropriate to be used for extrapolation and prediction of the probability of exceedence of deeper pits. Investigations are in progress to ascertain whether these conclusions are valid also for other pipes exposed for long periods in the ground.

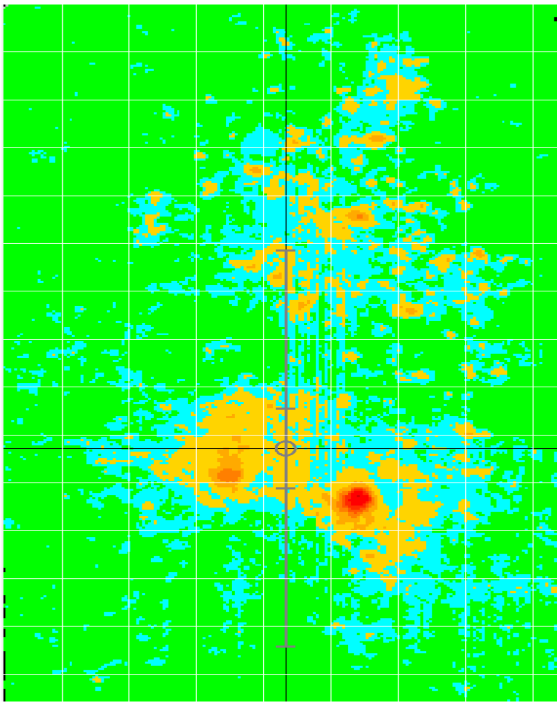

Figure 7. The 2D corrosion loss map of the 51 year pipe.

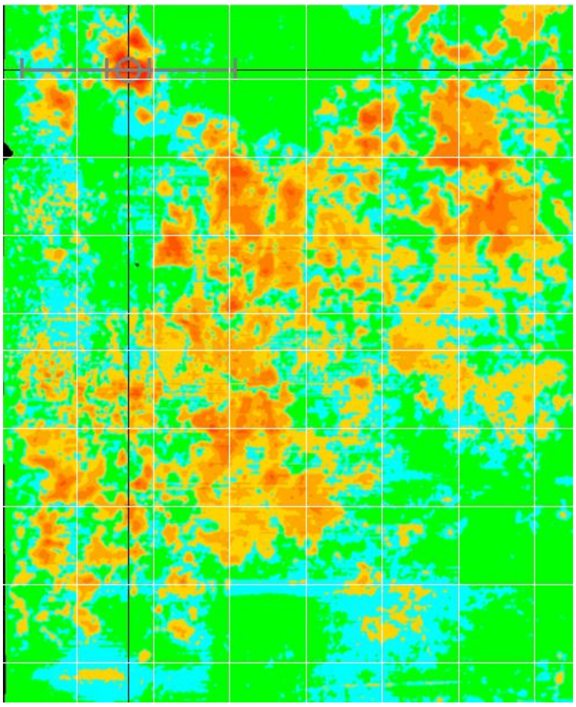

Figure 8. The 2D corrosion loss map of the 90 year pipe.

5. CONCLUSION

Since pitting corrosion is one of the main reasons of water main distribution failure in Australia, this study has been conducted to attempt to find an appropriate predictive model for estimating the maximum pit depths of pipelines. This has been done using pitting corrosion data for older, actual in-ground cast iron water pipelines gathered from sites in Australia.

The analysis of the pit depth data indicates that for long term exposure of cast iron underground pipelines the Frechet extreme value distribution is the best candidate distribution. Furthermore, two successive Frechet distributions appear to be appropriate to describe the extreme deepest pits in one of the cases examined. Whether this is true more generally is under active investigation.

6. ACKNOWLEDGEMENTS

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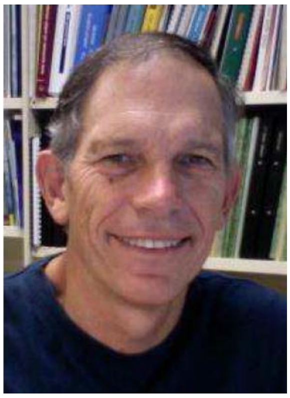

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