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Characterization of external corrosion pits in ductile iron pipes

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Abstract:

Varying lengths of ductile iron (DI) pipes were exhumed by several North American water utilities. The exhumed pipes were cut into short sections, sandblasted and tagged. Pipe sections were scanned for external corrosion using a specially developed laser scanner. Scanned corrosion data were processed using specially developed software to obtain information on corrosion depth, area and volume along the pipe. A general definition of corrosion pit was proposed and statistical analyses were subsequently performed on these three geometrical attributes of the pit populations.

Keywords: Ductile iron pipe, corrosion pits, corrosion pit geometry, probability distribution

Introduction

Virtually all the models in the literature that endeavor to propose a relationship between soil characteristics and corrosion rate of buried metallic pipes are empirical, and can generally be divided into two classes, namely, practical and empirical/probabilistic. The most widely known practical approach is the 10-point scoring method proposed by AWWA (Appendix A of ANSI/AWWA C105/A21.5-99), which classifies a soil as corrosive/noncorrosive based on the weighted aggregation of 5 soil properties. The 25-point scoring method of Spickelmire (2002) is similar to the AWWA 10-point method except that other additional factors are included.

Several researchers have used statistical/probabilistic tools to characterize the properties of corrosion pits. Aziz (1956) used extreme value statistics (EVS) to propose the Gumbel distribution for the analysis of corrosion pit-depth maxima. Hay (1984) also found that the Gumbel distribution fitted corrosion pit-depth maxima well in buried cast iron pipes. Sheikh *et al*. (1989) proposed a truncated exponential distribution as the underlying distribution for pit depth. Laycock *et al.* (1990) used the generalized extreme value statistics to analyze corrosion pit-depth maxima. Katano *et al.* (1995) and Katano *et al.* (2003) found that the log-normal distribution best fitted their pit data; Melchers (2003, 2004a, 2004b), fitted multi-phase power models (as a function of time) to corrosion data. Melchers (2005a,b,c) questioned the use of extreme value distribution such as Gumbel to represent the distribution of corrosion pit-depth maxima and reasoned that corrosion pits form two populations, one of metastable pits (those pits that initiate but stop growing immediately or a short while after initiation) and stable pits (those pits that continue to grow). Several researchers, including Ferguson *et al.* (1993), Kalantzis (1997), Restrepo *et al.* (2009), Caleyo *et al.* (2009), among others, investigated the impact of various soil properties on the corrosion pit properties of buried pipes.

The National Research Council of Canada (NRC), with funding from the Water Research Foundation (WaterRF), undertook a research project to investigate the long term performance of ductile iron (DI) water mains. One of the objectives of this research was to gain a thorough understanding of geometry of external corrosion pits and the factors (e.g., soil properties, appurtenances, service connections, etc.) that influence this geometry. It was hoped that this understanding would lead to the ultimate objective of achieving a better ability to assess the remaining life of ductile iron pipes for a given set of circumstances. Four North American water utilities exhumed each about 91.4 m (300 ft) of DI pipe, which were cut into sections, sandblasted and tagged. Soil samples were also obtained at discrete locations along the exhumed pipe. A laser scanner that was specially developed at the NRC to scan the pipe for external corrosion using and special software was developed to process the scanning data and obtain information on pit-depth, pit-area and pit-volume. This paper focuses only on the general definition of corrosion pit and the statistical analysis that follows. He full research report can be found at Rajani *et al.* (2011).

Data collection, cleansing and preparation

Four water utilities exhumed approximately 91.4 m (300 ft) of ductile iron pipe slated for replacement (Table 1), which were cut into sections (approx. 1 meter long), sandblasted and scanned, using a specially developed laser scanner (Figure 1). Using software specially developed for this purpose, a six-step process was used to record the data and remove these undesired effects: (a) read in raw data and apply a raw data filter; (b) rearrange the data into a grid; (c) establish the "correct" pipe surface; (d) apply 2-D grid-level filter; (e) apply 3-D grid-

Table 1. Details of exhumed pipes

City (Water utility)	Pipe diameter	Depth	Length	Installation year
Kansas City (Water One)	300 mm (12")	1.07 m (3.5')	91.4 m (300')	1989
St. Louis (American Water)	300 mm (12")	1.22 m (4')	42.7 m (140')	1970
Louisville (Louisville Water Co.)	200 mm (8")	1.07 m (3.5')	91.4 m (300')	1972
Calgary (Calgary Water Dept.)	250 mm (10")	3.05 m (10')	91.4 m (300')	1969

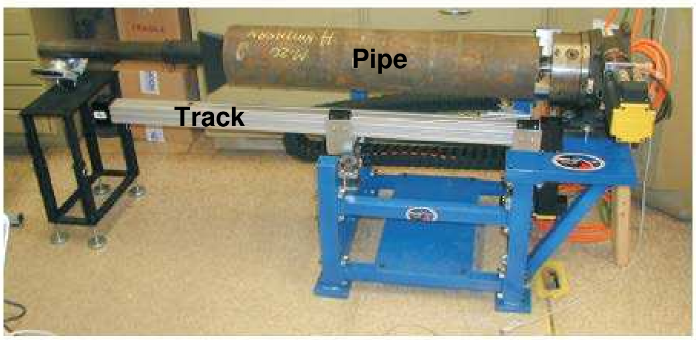

Figure 1. Pipe scanner (left: pipe mounted ready for scanning; right: laser point range finder mounted on track).

level filter; and (g) remove unusable data for statistical analysis. Details on the various filters applied to the data can be found in Rajani *et al.* (2011). Statistical analyses were conducted on geometrical properties of corrosion pits including pit-depth maxima, pit-area and pit-volume that were generated from the cleansed scanned data. Two different approaches were investigated as to the definition of the corrosion pit populations to which statistical analysis should be applied, namely individual pit populations and pipe ring populations. In this paper we focus only on individual pit populations and specifically on pit-depth maxima.

Definition and analysis of individual pit population

Corrosion pits are naturally small upon initiation and some will grow over time while others will become passivated (Aziz, 1957, used the term "stifled" and Melchers, 2005c referred to them as metastable (passivated) and stable pits). If two pits in close proximity continue to grow they will eventually combine (coalesce) to form one larger pit. This larger pit can continue to grow and may combine with yet more adjacent pits to become an even larger pit. This corrosion pit morphology presents a challenge as to what constitutes a single pit and its associated geometric properties. We used the notion of threshold depth to define a single pit.

Figure 2 illustrates two adjacent corrosion pits that partially coalesced into one. If “Threshold 1” is taken as a reference then we have one corrosion pit with length X1 and maximum depth = (wall thickness - Y2). If “Threshold 2” is taken as a reference then we have two corrosion pits with lengths X2 and X3 and depths = (wall thickness - Y2) and = (wall thickness - Y3), respectively. It is thus clear that a population of pits generated with threshold *x* is different from a population of pits generated with threshold *y*, and one population is not a subset of the other.

For each of the four cities, three pit populations were generated, with three different threshold depth values as described in Table 2. Note that higher threshold depths result in a lower number of corrosion pits in the population. This is expected because, for example, all pits with depth smaller than 2 mm are not considered when the threshold depth is 2 mm. However, note also that the number of through-holes can increase as the threshold depth increases. This can be explained with the help of Figure 2. Suppose that Y2 and Y3 were zero, i.e., there would be two through-holes in these locations. If the reference threshold depth is “Threshold 2” then there are two pits, each with depth exceeding wall thickness, i.e., two through-holes. However, if the reference threshold depth is “Threshold 1”, then there is only one pit with maximum pit depth exceeding wall thickness. In this case a through-hole is counted only once, even though there could be multiple perforations within the pit.

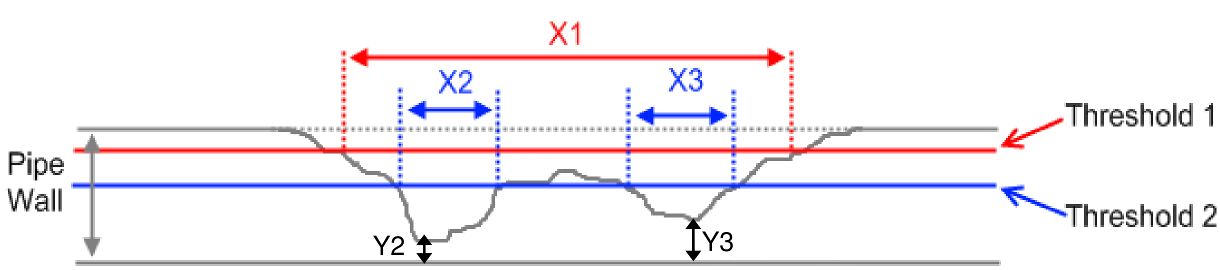

Figure 2. Corrosion pits and threshold depth

Table 2 Pit populations generated with various threshold depth values

	Threshold depth	# pits	# through holes	Depth (mm)		Area (mm^2)		Volume (mm^3)	
				Min.	Max.	Min.	Max.	Min.	Max.
Calgary	1 mm	10,346	24	1.0	8.44	2	33,208	2	81,996
	2 mm	3,451	27	2.0	8.44	2	15,438	4	58,246
	4 mm	1,059	42	4.0	8.44	2	6,455	9	39,812
Kansas City	1 mm	29,380	12	1.0	10.89	2	35,791	2	78,970
	2 mm	2,732	12	2.0	10.89	2	14,868	4	47,613
	4 mm	219	12	4.0	10.89	2	3,296	9	21,760
Louisville	1 mm	13,454	15	1.0	8.89	2	39,017	2	91,732
	2 mm	2,074	17	2.0	8.89	2	21,830	4	65,014
	4 mm	309	18	4.0	8.89	2	4,199	9	27,416
St. Louis	1 mm	17,904	11	1.0	10.51	2	66,107	2	161,202
	2 mm	2,195	12	2.0	10.51	2	35,178	4	109,139
	4 mm	207	12	4.0	10.51	2	4,754	9	34,358

Three different probability distributions as well as their right-truncated variants were examined as candidates to describe the populations of pit-depth maxima, where pipe wall-thickness is the upper bound of the truncated probability distribution. The distributions explored included Weibull (2-parameter), Gumbel (or double-exponential) and the exponential distribution. Probability distribution parameters were discerned using the maximum likelihood method. Pearson's chi-square test was used to ascertain "goodness of fit" between model and data (in all cases there were sufficient data to warrant chi-square test). Through-holes were excluded in the exploration of probability distributions for pit-depth maxima because they comprise an ever-increasing category of pits with constant depth, which would bias the distribution.

Figure 3 illustrates the fitting of the truncated Weibull distribution to pit maxima derived with 1, 2 and 4 mm pit depth threshold. Chi-square test results are provided as P-values. It can be seen that the truncated Weibull distribution fits the pit-depth maxima data very well. As explained earlier, through-holes were excluded from the analysis of pit-depth maxima.

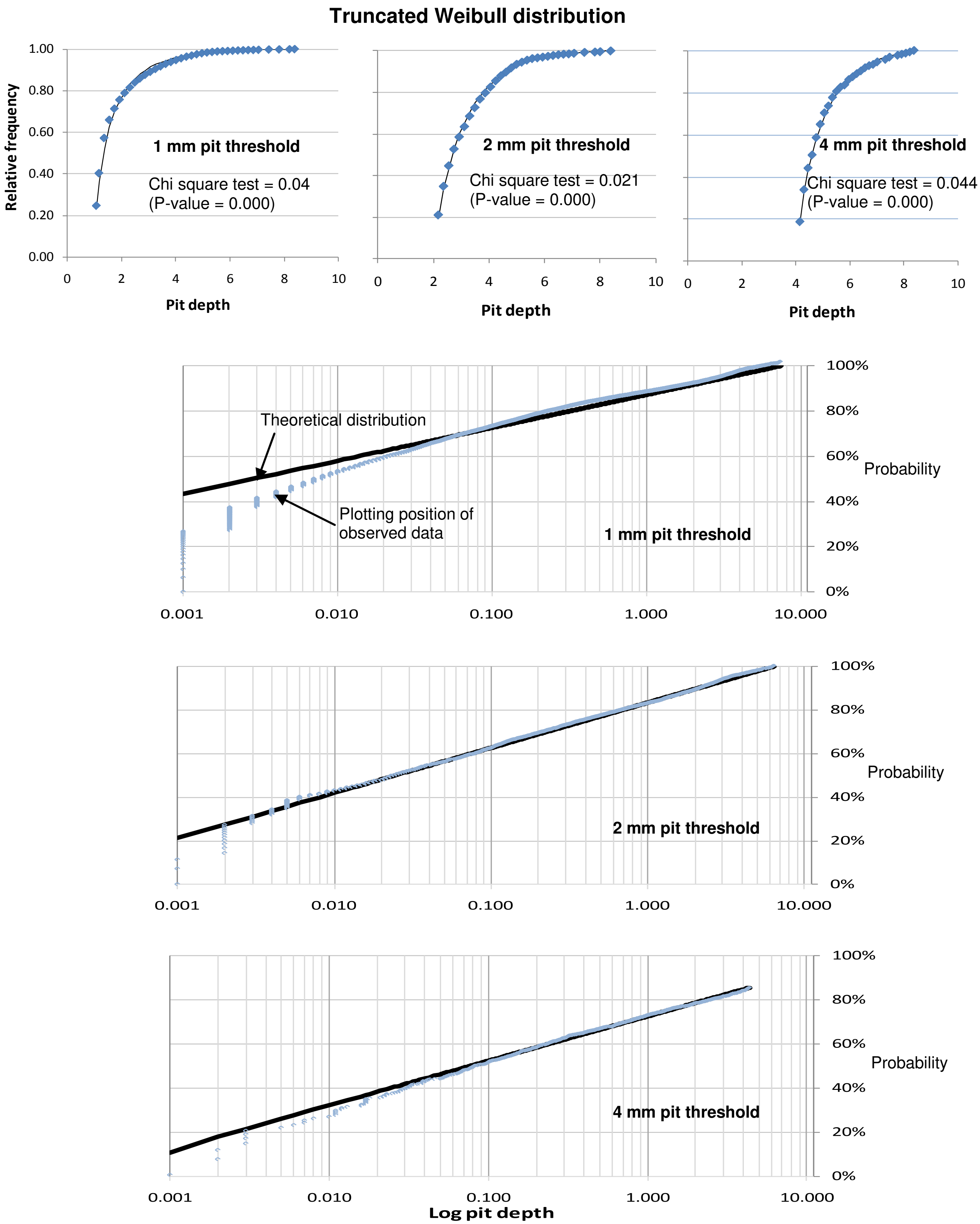

Figure 3. Statistical properties of pit-depth maxima (Calgary) with 1, 2 and 4 mm threshold depth

The bottom of Figure 3 illustrates the plotting position of the data, linearized using the assumed right-truncated Weibull probability distribution. Note that due to the limitations of log scale, the data were shifted so that pit-depth is taken relative to the respective threshold values. Note also that the straight line was not visually fitted to the data but rather obtained using the distribution parameters that were discerned using the maximum likelihood method. Data that are perfectly distributed according to the assumed model will appear as a straight line on such a linearized plot. Data related to 1 mm threshold appear to be fairly linear for the most part, except at the lower tail of the distribution. This deviation from straight line of the lower tail is all but eliminated for 2 mm and 4 mm thresholds, which suggests that the deviation could be attributed to the various data filtering methods that were applied during data preparation which may have created some distortion in the very small values of pit depth. Similar results (not shown here) were obtained for the pit data of pipes exhumed in Kansas City, Louisville and St. Louis.

The right-truncated Weibull probability distribution was found to fit best the observed frequencies in all four data sets, i.e., Calgary, Kansas City, Louisville and St. Louis, and therefore was deemed to be the most likely underlying probability distribution of pit-depth maxima, regardless of the threshold depth value used. In some cases, the non-truncated and right-truncated exponential distribution also fit the data fairly well, but never as well as the right-truncated Weibull distribution. This finding is in contrast to observations made by Aziz (1957), and as noted earlier also by Sheikh *et al*. (1989), who assumed the truncated exponential distribution and Sheikh *et al*. (1990), who assumed the normal distribution of the square root of pit depth at the early stage of corrosion and lognormal in the more advanced stages of corrosion.

Concluding comments

The right-truncated Weibull probability distribution was found to fit best the observed frequencies in all four data sets, i.e., Calgary, Kansas City, Louisville and St. Louis, and therefore was deemed to be the most likely underlying probability distribution of pit-depth maxima, regardless of the threshold depth value t_o used. In some cases, the non-truncated and right-truncated exponential distribution also fit the data fairly well, but never as well as the right-truncated Weibull distribution. This finding differs from observations made by Aziz (1957), who assumed exponential distribution at an early stage of corrosion and a bi-modal distribution at a later stage as well as from observations by Sheikh *et al*. (1989), who assumed the truncated exponential distribution and Sheikh *et al*. (1990), who assumed the normal distribution of the square root of pit depth at the early stage of corrosion and lognormal in the more advanced stages of corrosion.

This investigation of pit populations was conducted to expand on existing knowledge and to compare findings with those of other researchers rather than for any practical purpose. It is much more practical to create sampling schemes and inference methods based on ring population rather than pit population. Practical sampling scheme would typically involve examination of a number of small pipe samples that represents the entire pipe. As the area of a single pit can vary significantly, sample sizes would have to be quite large to contain entire large pits. Furthermore, when a pipe is virtually divided into rings, the location of each ring can be easily related to the location of a soil sample. Moreover, ring-based analysis lends itself better to develop inference techniques that are based on return period computations (Rajani *et al*., 2011) because a ring is always geometrically well defined.

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