Probabilistic modeling of cast iron water distribution pipe corrosion

Sophie Duchesne, Naoufel Chahid, Nabila Bouzida and Babacar Toumbou

ABSTRACT

Due to the random nature of the corrosion process, stochastic approaches are more appropriate to mathematically represent the corrosion depths on metallic objects. Based on data from 202 pipes, a model was developed to compute the probability of finding maximal corrosion depth in a given interval of values for 150-mm cast iron water distribution pipes. Only the age of pipes was taken into account as an explanatory variable to compute this probability, since the soil characteristics were not available in the close surroundings of the inspected pipes. The model combines two functions: (1) a Weibull distribution function to represent the distribution of pipe ages at the time when the maximal corrosion depth reaches 100% of the pipe wall thickness; and (2) a generalized extreme value (GEV) distribution function, with the location parameter varying as a function of pipe age, to represent the distribution of maximal corrosion pit depths on pipes that did not reach a maximal corrosion pit equal to 100% of their wall thickness. The developed model offers a good representation of the distribution of observed maximal corrosion depths for Quebec City's 150-mm cast iron water pipes.

Key words | censored data, GEV distribution function, maximum likelihood, pipe age, soil characteristics, stochastic model

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INTRODUCTION

In North America, most of the small diameter water distribution pipes that were installed up until the 1990s are made of ductile or gray cast iron. According to a survey conducted in 1993 over 21 Canadian cities and comprising 11% of the country's population, approximately 50% of all water distribution pipes are gray cast iron in Canada (Rajani & McDonald 1995, cited in Sadiq *et al.* 2004). Kirmeyer *et al.* (1994, cited in Yamini & Lence 2010) also state that 48% of water distribution pipes in the United States are gray cast iron. Duchesne *et al.* (2011) report that in Quebec City (Canada), 89% of water pipes of known material are made out of ductile or gray cast iron. Corrosion is the primary cause of breaks and leaks in cast iron water distribution pipes (O'Day 1989; Agbenowosi 2000; Rajani *et al.* 2000; Sadiq *et al.* 2004; Liu *et al.* 2010). Corrosion defects in water pipes can be detected using various inspection tools (Dingus *et al.* 2002; Duchesne *et al.* 2011). However, predictive models are required to estimate the future evolution over time in these defects' severity or to identify the pipes that are the most at risk of being highly corroded. Some mathematical models that relate the corrosion pit depth on buried metallic objects to the duration since their first exposure to soil have been developed over the years. Some of these models take the soil characteristics into account, since correlations have been found between corrosion pit depths on buried metal and soil resistivity (Logan & Koenig 1939, cited in Doyle *et al.* 2003; Cole & Marney 2012), soil type (Katano *et al.* 2003), soil chloride content (Katano *et al.* 2003; Velazquez *et al.* 2009), pH and soil bulk density (Velazquez *et al.* 2009). However, according to Cole & Marney (2012), the weakness of these correlations suggests that there are many other factors affecting the variations in soil corrosion rate and that the interactions between all these factors cannot be easily incorporated into the existing modeling approaches.

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Two distinct mathematical approaches exist to model the initiation and evolution of corrosion, namely deterministic and stochastic approaches. Both types of model can take into account the physical and chemical properties of pipes and surrounding soil, as well as the age of pipes. Deterministic models can be entirely empirical or can be based on a mathematical description of the physical laws governing the corrosion process. One of the most cited among these models, the Rossum model (1969), combines electrochemical theory with the observation of corrosion over many years on short lengths of various types of bare metal buried in different types of soil. Papavinasam *et al.* (2010) developed a regression equation to relate the internal corrosion rate of oil and gas pipelines to construction variables (e.g. pipe characteristics) and operational variables (e.g. pressure in the pipes). Velazquez *et al.* (2009) proposed a regression equation to compute the maximal pit depth on buried oil and gas pipelines as a function of pipe age and of soil characteristics (redox potential, pH, chloride content, etc.). Only a few models were developed specifically for water distribution pipes. In Rajani *et al.* (2000), the observation of external corrosion pit depths on 71 excavated water pipes led to a regression equation between the maximum corrosion pit depth observed on a pipe and the pipe age. Doyle *et al.* (2003) established, from the observation of external corrosion pit depths on more than 50 excavated water pipes, a regression equation estimating the maximal corrosion rate on a cast iron water pipe as a function of the surrounding soil pH and resistivity.

However, due to the many factors involved in the corrosion process and also to the lack of knowledge about all these factors and their combined effect on corrosion rates, the corrosion process is often considered and modeled as stochastic (Alamilla & Sosa 2008). Randomness is even observed under highly controlled laboratory conditions, such as in Shibata & Takeyama (1976), Provan & Rodriguez III (1989), Tsukaue *et al.* (1994), Scarf & Laycock (1996), Vajo *et al.* (2003), Darmawan & Stewart (2007), Stewart & Al-Harthy (2008), Valor *et al.* (2010) and Jarrah *et al.* (2011). Localized corrosion shows a large dispersion in parameters such as corrosion rate, maximum pit depth, etc., which is due to the influence of metal surface heterogeneities on pit development and to the variation over time in the corrosive environment (Valor *et al.* 2007). As opposed to laboratory samples, buried infrastructure such as water mains pipes are exposed to corrosive conditions over many years and the factors that govern the corrosion process on these pipes are continuously changing over time, and are highly variable from one pipe to the other. As suggested by Valor *et al.* (2007), stochastic models are thus better suited to describe corrosion than deterministic models. Gumbel, who gave his name to the famous distribution function for extreme values, described potential applications of the extreme value statistics in the area of corrosion (Gumbel 1954, cited in Shibata 1991). Aziz (1956) was the first to model the distribution of corrosion pit depths using the Gumbel distribution, on aluminum alloys in tap water. Since then, many authors have used extreme value statistics to model corrosion pit depths in buried oil and gas pipes (Isogai *et al.* 2004; Alamilla *et al.* 2009; Caleyo *et al.* 2009a, b; Li *et al.* 2009). To our knowledge, this type of model has never been applied to modeling the evolution of corrosion pit depths on water distribution pipes. Yamini & Lence (2010) actually take into account the distribution functions of input parameters to compute the probability of failure of water cast iron pipes caused by internal corrosion, but their corrosion model remains deterministic.

This paper proposes a stochastic corrosion model to compute the distribution functions of corrosion depths on cast iron water distribution pipes, using input data that are commonly available to distribution network managers. This model is meant to describe the general aging behavior of cast iron water distribution pipes and to plan the required investment for pipe rehabilitation and/or replacement. The following section presents the data that were available to develop the model. The model equations, calibration method and results are presented and discussed afterwards.

AVAILABLE DATA

The difficulty with developing corrosion models for water distribution pipes, as opposed to oil and gas pipes, is that water pipes are rarely inspected and that the inspection tools used in water pipes usually provide less precise information than those used in oil and gas pipes. From 2003 to 2010, the City of Quebec (Canada) inspected 308 cast iron water distribution pipes, 150 mm in diameter, with a

Remote Field Eddy Current (RFEC) tool, as described in Duchesne *et al.* (2011). This *in-situ* inspection technology provides the location and magnitude of corrosion defects on the inspected pipes. The capacity of the RFEC tool to detect corrosion defects was evaluated in Duchesne *et al.* (2011) by comparing its results with those obtained from the analysis of computed tomography (CT) scan images of inspected pipes. The conclusion of this work was that the RFEC probe provides reliable information on the main corrosion defects in water distribution pipes.

Since the installation date was highly uncertain for the oldest inspected pipes, only the 202 pipes installed in 1960 or after were considered for the analysis presented here. The location of these pipes is illustrated in Figure 1 (in black) while Figure 2 gives the corresponding age distribution. Soil analysis results were also available for 615 samples, whose location is illustrated in dark gray in Figure 1. The soil type, AWWA soil corrosiveness score (ANSI/AWWA C105/A21.5 99 standard) and soil moisture were available for all these 615 points. However, soil resistivity, soil redox potential and soil pH were known for only about 450 (even though these characteristics were certainly measured since they are used to compute the AWWA soil corrosiveness score, they were not available in the

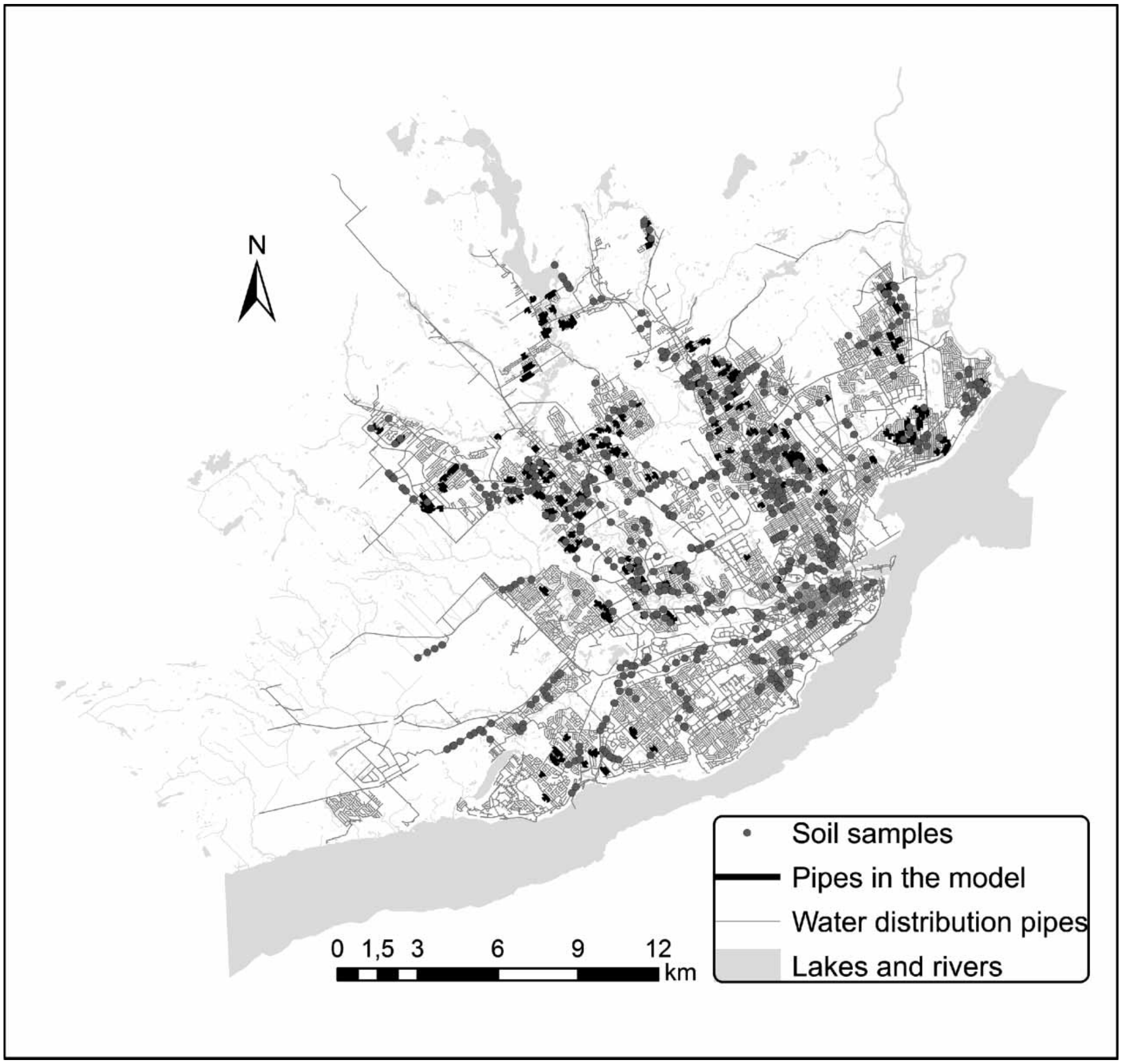

Figure 1 | Location of the soil samples and the pipes used to develop the model.

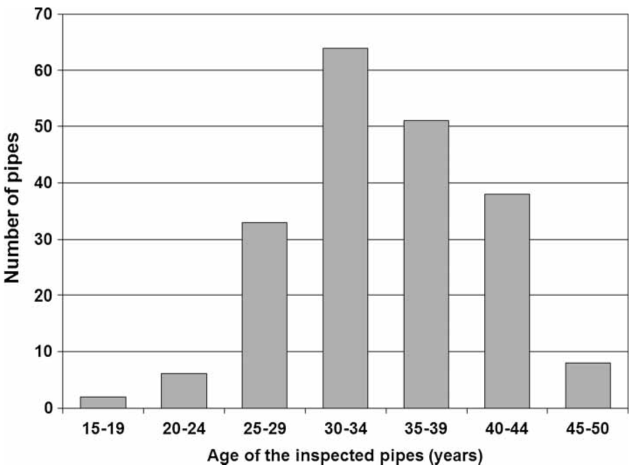

Figure 2 | Age distribution for the 202 inspected pipes used to develop the model.

database provided by the city). As can be seen in Figure 1, the soil samples were rarely collected close to the water distribution pipes (in light gray in Figure 1) and even less near the pipes for which the magnitude of corrosion defects is known (in black in Figure 1).

Consequently, for each inspected pipe, the soil type was assumed to be the one of the nearest soil samples (if situated within 500 m). The soil resistivity, soil redox potential, soil pH and AWWA soil corrosiveness score in the neighborhood of the inspected pipes were estimated from the available soil sample data using the following inverse distance weighting estimator:

$$X_0 = \frac{\sum_{i=1}^{n} (1/d_i) X_i}{\sum_{i=1}^{n} (1/d_i)} \tag{1}$$

where: X_0 = estimated value (soil resistivity, redox potential, pH or AWWA corrosiveness score) in the neighborhood of the inspected pipe; n = number of soil samples located inside a 500-m radius from the inspected pipe; d_i = distance between soil sample i and the inspected pipe centroid; and X_i = measured value of the soil characteristics (soil resistivity, redox potential, pH or AWWA corrosiveness score) for soil sample i. Table 1 summarizes the information that could be retrieved using this method. It should be noted that this interpolation method can only give approximate values, since the spatial variability of soil characteristics in urban areas is high and since pipes are usually buried in backfill material that is not necessarily taken *in situ*.

Table 1 | Number of pipes for which the soil characteristics could be retrieved

	Number of pipes
Inspected with the RFEC tool	202
Inspected with nearest soil type and estimated soil corrosiveness score	148
Inspected with estimated resistivity	137
Inspected with estimated redox potential and pH	125

MODEL

General model

The model developed here represents the statistical distribution function of the deepest corrosion defect on a 150-mm cast iron water distribution pipe. As stated by McNeil (1988, cited in Scarf & Laycock 1996), it is advisable to concentrate on the deepest defect, since it is the one that usually leads to failure. The information retained to construct the model is thus the depth, in terms of percentage of pipe wall thickness, of the deepest corrosion defect in each inspected pipe. Since, the RFEC inspection tool does not distinguish between external and internal corrosion defects, the deepest corrosion defect identified on a pipe could be either external or internal. For pipes on which one or more repairs were detected, a 100% maximum corrosion depth was assigned.

In order to identify the explanatory variables to be retained in the model, linear correlation coefficients were computed between the maximum corrosion depth on each pipe and (a) pipe age at inspection, (b) soil resistivity, (c) AWWA soil corrosiveness score, (d) soil redox potential and (e) soil pH. At the 0.01 significance level, only the correlation between the maximum corrosion depth and pipe age proved to be significant. Figure 3 gives an overview of the relation between maximum corrosion depth, pipe age and soil resistivity for pipes located in different types of soil. The results of these very simple analyses do not mean that the soil characteristics do not impact on the corrosion process, rather when information on soil type is not available in the surroundings of the pipes (as in many water distribution organizations) then this incomplete information cannot

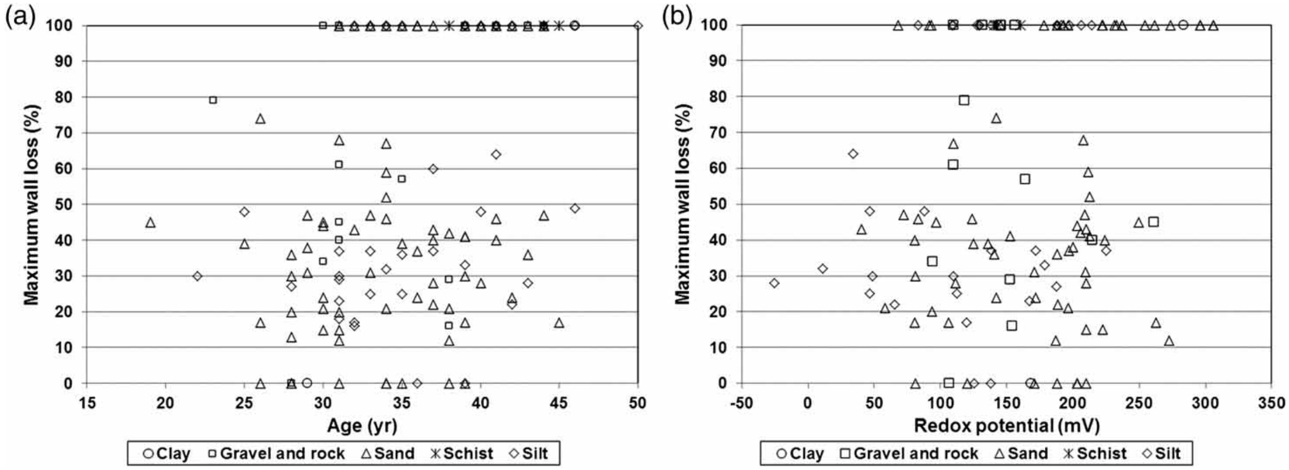

Figure 3 | Relation between maximum wall loss and (a) pipe age and (b) soil redox potential for different soil types.

be constructively used to model the severity of corrosion on water distribution pipes.

Consequently, only the age of pipes was retained as an explanatory variable in the model. In this context, the model gives the probability, for a pipe of age t years, to present a corrosion defect superior or equal to z% of its pipe wall thickness (with z being the depth of the deepest corrosion defect on the pipe, that can vary from 0 to 100). Due to the nature of the available data, the model is a combination of two distributions. The first distribution, $F_1(t)$, gives the probability, for a given 150-mm cast iron water distribution pipe, that the time to reach a 100% corrosion depth is inferior to a given time t. This distribution can be used to estimate the probability that a pipe of age t will show a 100% corrosion depth. For pipes that do not reach a 100% corrosion depth at age t, a second distribution, $F_2(z, t|z<100)$, computes the probability that its maximal corrosion depth is inferior to a given value z%. Consequently, the probability for a pipe of age t years to present a corrosion defect superior or equal to z% of its pipe wall thickness is given by:

$$P(\max\_\text{corrosion\_depth} > z) = (1 - F_2(z, t|z < 100))(1 - F_1(t)) + F_1(t) \quad (2)$$

where: t = pipe age; z = depth of the deepest corrosion defect on the pipe, that can vary from 0 to 100; $F_1(t)$ = probability that the time to get a maximal corrosion depth of 100% is inferior to t (which corresponds to the probability that a pipe of age t years will present a corrosion defect equal to z%); and $F_2(z, t|z<100)$ = probability that the maximal corrosion depth is inferior to z% for a pipe of age t years that did not reach a 100% maximal corrosion depth. The distribution functions $F_1(t)$ and $F_2(z,t)$ were first developed separately, taking all 202 inspected pipes into account for the development of $F_1(t)$ and taking into account only the 135 inspected pipes on which no repairs (i.e. no 100% pipe wall loss) was observed for the development of $F_2(z,t)$. Details of these developments are given in the following sections.

Model computing the probability of 100% pipe wall loss as a function of age

$F_1(t)$ represents the probability, for a given 150-mm cast iron water distribution pipe, that the time to reach a 100% corrosion depth is inferior to t. Various analyses, not presented here, showed that this probability is well represented by the Weibull distribution:

$$F_1(t) = 1 - e^{\lambda t^{\alpha}} \quad (3)$$

where α and λ are the parameters of the distribution, whose values will be determined from the observed data using the maximum likelihood method. For a pipe inspected at age t and presenting a 100% wall loss, the exact arrival time of this 100% wall loss is not known. The only available information is that the arrival time of the 100% wall loss is inferior to t; this information is thus termed left censored. In contrast, for a pipe inspected at age t and presenting a maximal wall loss inferior to 100%, the only available information is that the arrival time of the 100% wall loss is superior to t; this information is thus termed right censored. The corresponding likelihood function of $F_1(t)$ can be expressed as:

$$L_1(\lambda, \alpha) = \prod_{i \in cd100} F_1(t_i) \prod_{i \notin cd100} (1 - F_1(t_i)) = \prod_{i \notin cd100} \left(1 - e^{-\lambda t_i^{\alpha}}\right) \prod_{i \notin cd100} e^{-\lambda t_i^{\alpha}} \qquad (4)$$

where: t (years) = age of pipe i at inspection; and $cd100$ = the set of pipes presenting a 100% corrosion depth at inspection (i.e. those on which at least one reparation was detected). The values of the parameters that maximize Equation (4) are $\lambda = 1.20 \times 10^{-7}$ and $\alpha = 4.21$. This means that the probability of having a 100% corrosion depth on a pipe of age t years is equal to $1 - e^{-1.20 \times 10^{-7} t^{4.21}}$. This equation is illustrated in Figure 4. To obtain the points on this figure, the inspected pipes were divided into five age groups; the points represent the percentage of pipes with an observed 100% wall loss as a function of the median age in each group. One should note that the $F_1(t)$ model, illustrated in Figure 4, was developed based on observations from pipes of 19–50 years old. Even though the model satisfactorily reproduces the observations, the estimated values for pipes older than 50 years should be considered as extrapolations.

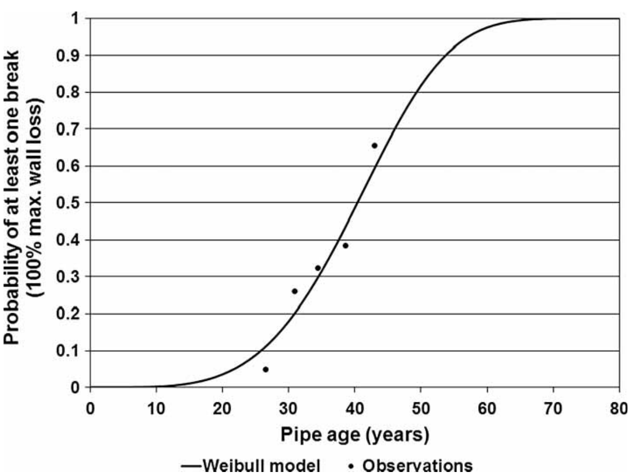

Figure 4 | Modeled and observed probability of having a 100% corrosion wall loss as a function of age.

Distribution of corrosion depths on pipes without repairs at inspection

The second step is to develop the $F_2(z,t)$ function that gives the probability of a wall loss inferior to z% for a pipe of age t on which no repairs (i.e. no 100% wall loss) were observed. As mentioned earlier, many authors have demonstrated that extreme value distributions are appropriate to model the maximal corrosion depths on metallic objects (see for examples Sheikh et al. 1990; Valor et al. 2007; Caleyo et al. 2009b; Velazquez et al. 2009). The generalized extreme value (GEV) distribution is the most general distribution to model maximal values. According to this distribution, the probability of the value of a random variable Z (here the maximal corrosion depth on a pipe) being inferior to a given value z is computed using:

$$F(z) = P(Z < z) = \begin{cases} \exp\left[-\left\{1 - \dfrac{k}{\sigma}(z - \mu)\right\}^{1/k}\right] & \text{if } k \neq 0 \\ \exp\left[-\exp\left\{-\dfrac{(z-\mu)}{\sigma}\right\}\right] & \text{if } k = 0 \end{cases} \qquad (5)$$

where: k = shape parameter; μ = location parameter; σ = scale parameter; and $[1 - k/\sigma(z - \mu)] > 0$. The introduction of explanatory variables in the GEV distribution is possible by varying the value of k, μ and/or σ as a function of values taken by these explanatory variables.

In order to identify the best way to include the time explanatory variable (i.e. pipe age at inspection) in the distribution of corrosion depths, the 135 pipes without repairs were divided into five groups of 27 pipes, according to their age. A GEV distribution was then fitted by the maximum likelihood method for each of these groups. Figure 5 shows an example of how well the GEV distribution fits the observed value for Group 4 (pipes from 34 to 38 years, median age = 36 years). The parameters obtained for each of the five groups are given in Table 2. These results show no clear relation between the k or σ values and pipe age. However, there is a strong linear correlation between μ and the median age of each group (the linear correlation coefficient between them is 0.91 and is significant at the 5% significance level). Consequently, and following other analyses whose results are not presented here, the μ parameter value in the $F_2(z,t)$ function was computed as a

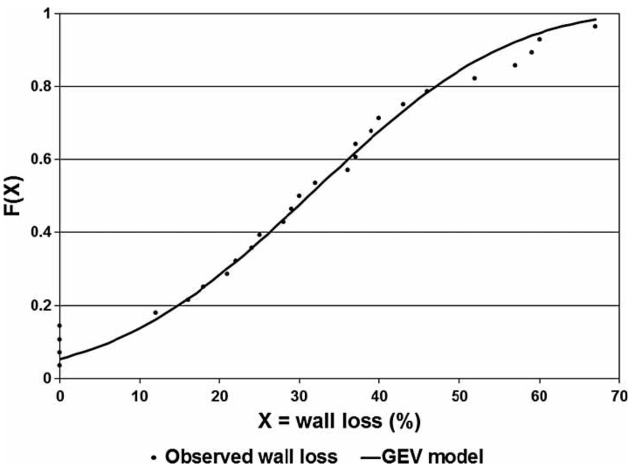

Figure 5 | Comparison between the GEV and empirical cumulative distribution functions for Group 4.

Table 2 | Calibration results of the GEV function for five groups of pipes

	k	σ	μ	Mean pipe age (years)	Median pipe age (years)
Group 1	−0.270565	14.4657	11.1586	25.7	26
Group 2	0.580613	19.1881	16.6707	29.6	30
Group 3	0.094189	15.7162	23.8287	32.1	32
Group 4	0.333115	18.9911	24.5698	36.1	36
Group 5	0.350486	17.2247	25.9790	40.9	40

linear function of pipe age, t. The $F_2(z,t)$ is thus given by:

$$F_2(z, t) = P(Z < z) = \exp\left[-\left\{1 - \frac{k}{\sigma}(z - (\mu_1 \times t + \mu_2))\right\}^{1/k}\right] \quad (6)$$

with $k \neq 0$ and $[1 - k/\sigma(z - (\mu_1 \times t + \mu_2))] > 0$.

For pipes on which no repairs were observed, the maximal corrosion depth at time t is known and thus the likelihood function can be expressed as (El Adlouni *et al.* 2007):

$$L_2(\mu_1, \mu_2, \sigma, k) = \prod_{i=1}^{n} f_2(z_i,t_i) = \prod_{i=1}^{n} \frac{1}{\sigma}\left[1 - \frac{k}{\sigma}(z_i - (\mu_1 \times t_i + \mu_2))\right]^{(1/k-1)} \times \exp\left[-\left(1 - \frac{k}{\sigma}(z_i - (\mu_1 \times t_i + \mu_2))\right)^{1/k}\right] \quad (7)$$

where: n = number of pipes taken into account (135); and z_i = maximal corrosion depth on pipe i (%) at time t_i. The parameter values that maximize Equation (7) are $k = 0.1515$, $\sigma = 17.5379$, $\mu_1 = 0.4383$ and $\mu_2 = 5.1804$.

Combination of both models

According to Equation (2), the combination of both models allows the calculation of the probability of having a corrosion defect superior or equal to z% of the pipe wall thickness, for any 150-mm cast iron water pipe in the Quebec City network. The results of the model are illustrated in Figure 6, for four different pipe ages. As expected, we can observe from this figure that younger pipes have a higher probability of being in a better state than older pipes. Also, there is still a significant probability that a 50-year-old pipe will have a wall loss equal to 100%; this probability is equal to 0.82 and can be directly computed with the $F_1(t)$ function. Indeed, the value of $F_2(z,t)$ is 1 for a 100% pipe loss for all ages, and thus the first term in Equation (2) is null for $z = 100\%$ (recall that the $F_2(z,t)$ function represents the probability of having a wall loss inferior to z% for a pipe on which no repairs were observed, thus the maximal corrosion depth is necessarily inferior to 100%).

The model illustrated in Figure 6 was constructed using data that have been observed in pipes of either gray or ductile iron. Pipes could not be divided into two groups as a

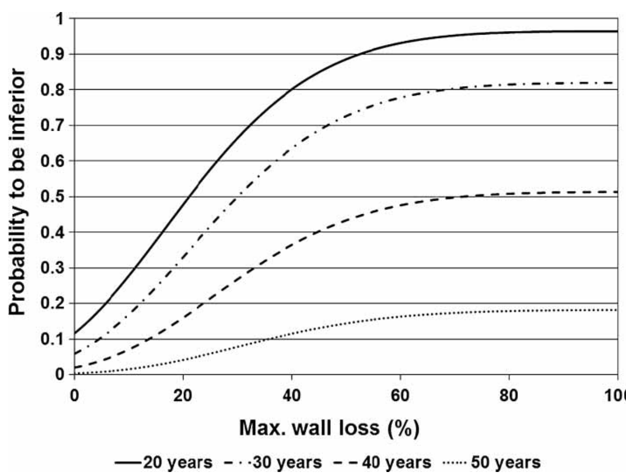

Figure 6 | Probability for the maximal corrosion depth to be inferior to various values as a function of pipe age.

function of their material, since the information on material was not precise enough in the database and the type of material cannot be detected with the RFEC tool. Variations in pipe material could probably lead to different corrosion rates; however, this could not be observed with the available data and, consequently, was not taken into account in the model. Also, for the development of the model, all pipes on which one or more repairs (clamps) were detected with the RFEC inspection tool were assigned a 100% maximum corrosion depth. It is thus assumed that the repaired failures were all caused by corrosion. For cast iron pipes, this could be true for the majority of pipe failures, although external factors can cause the failure of pipes that are already highly corroded. Due to this assumption, the model probably slightly overestimates the probability of pipes showing a corrosion defect deeper than a given value.

CONCLUSION

There is no standard equation commonly applied to predict the evolution of corrosion on metallic water distribution pipes. Due to the random nature of the corrosion process, stochastic approaches are more appropriate to mathematically represent the corrosion depths on metallic objects. The model presented in this paper computes the probability of a 150-mm cast iron water distribution pipe in the Quebec City network presenting a maximal corrosion depth that is included in a given interval of values. Owing to the available data, only the age of pipes was taken into account to compute this probability. Even though it is well recognized that the soil characteristics have a significant impact on the corrosion rate of buried pipes, these characteristics were not included in the model since information on soil in the close surroundings of the inspected pipes was not available. Consequently, no significant correlation could be observed between observed maximal corrosion depths and the soil characteristics. The availability of soil samples coming from the close surroundings of the inspected pipes could have allowed the integration of some soil characteristics in the model. However, it would be difficult to apply such a model to other pipe networks, since soil data are not commonly available to networks managers. Besides, taking the pipe ages as the only explanatory variable, the model developed offers a good representation of the distribution of observed maximal corrosion depths for Quebec City's 150-mm water cast iron pipes. The methodology developed in this paper could be used on any other water distribution network, and with other pipe diameters, provided that data concerning the maximal corrosion depths and the installation year are available to calibrate the model. Once calibrated, the model can be used to support the planning of rehabilitation and replacement works on water distribution pipes. Where data are available, and if necessary, any additional explanatory variable other than age could be added to the model equations.

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