Condition assessment to estimate failure rates in buried metallic pipelines

D. De Silva, M. Moglia, P. Davis and S. Burn

ABSTRACT

Pipe condition assessment provides useful information to assist rehabilitation and replacement decisions. Due to high cost or difficult pipe access, condition assessment must be limited to specific locations. To address this limitation, this paper presents a methodology in which values from discrete sampling positions are used to quantify systematic and random variation of pipe condition, and the statistical basis of applying the information to determine the failure probability in the network.

The methodology includes development of a sampling program on a network zoned according to the soil type, using extreme value statistics to describe the distribution of data from limited samples within each zone and where appropriate extrapolation of the distributions to larger areas of the network. Structural reliability methods, specifically Level II first-order-second moment reliability analysis, are then applied with distributions of pipe conditions as input in order to estimate pipe failure probability and failure rate predictions. A practical example of a mild steel pipeline subjected to external corrosion is used to illustrate the value of this technique in practice.

An overview of commercially available and emerging techniques suitable for condition assessment of pipes is presented. This includes direct assessment by electromagnetic, ultrasonic and acoustic techniques and indirect assessment through measurement of soil electrical and chemical properties.

Key words | condition assessment, extrapolation, limited data, probabilistic failure, reliability analysis, Weibull distribution

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INTRODUCTION

Faced with increasing economic pressures to satisfy the requirements of regulatory compliance (Ofwat 2005; VIC Regulator 2005), many water authorities are now looking beyond the traditional reactive maintenance of pipelines to proactive maintenance strategies to remain competitive (Englehardt *et al.* 2000; Sægrov *et al.* 1999). The ability to map the condition of pipelines and forecast future failures is a key prerequisite in the decision process leading up to rehabilitation projects (Burn *et al.* 2001). Numerous models that combine water distribution system performance, rehabilitation options, financial constraints and regulatory requirements have been proposed (Andreou 1987; Deb 1994; Deb *et al.* 1998), and predicting failure is an important element in all of them. Whilst most models are based on failure history (Jarrett *et al.* 2001; LeGat & Eisenbeis 2000), the availability of failure information is often limited in the whole system. Therefore, it is important to assess the condition of these pipelines, evaluate levels of deterioration and determine the probability of failure to allow selection of the most cost-effective maintenance or renewal strategy (Kleiner & Rajani 2001; Rajani & Kleiner 2001). Although continuous condition assessment is ideal, it is usually

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impractical to assess an entire pipeline length due to the high cost of assessment techniques and access limitations. Therefore, it is necessary to selectively assess the condition at several locations, and use the information to estimate the condition of the entire pipeline. This paper examines methods of using discrete sampling areas for condition assessment and proposes strategies for extrapolating this limited information to a full pipeline.

If the condition of a pipeline can be quantified, it can be combined with pipe loading conditions and material properties in an appropriate failure criterion. To this end, techniques to forecast future failure rates based on condition assessment are also presented. A structural reliability analysis is proposed to relate the probable distribution of damage levels in an individual pipe to the probability of failure in a complete pipeline. To illustrate how this approach can be used in practice, a buried mild steel pipeline subjected to external surface corrosion is analysed.

DETERIORATION MECHANISM IN METALLIC PIPES

The main cause of deterioration in buried metallic pipes is galvanic corrosion. Soils of varying physical and chemical composition create galvanic potential differences between different areas of the pipe. Under suitable soil electrolytic conditions, anodic and cathodic areas are created, which leads to galvanic corrosion (Figure 1). Buried iron pipes are also vulnerable to anaerobic corrosion by sulfur-reducing bacteria under specific ground conditions. Grey cast iron pipes are susceptible to a unique form of galvanic corrosion, in which selective leaching of iron leaves a relatively weak graphitic network in the pipe wall. This process is commonly referred to as graphitisation.

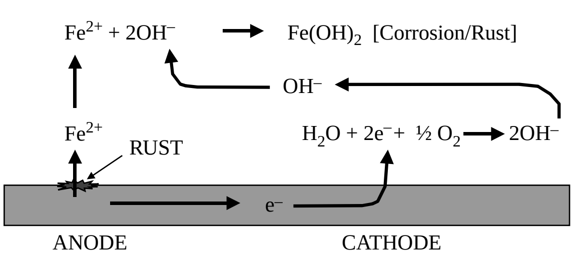

Figure 1 | Galvanic corrosion process in iron.

Whilst the pipe wall strength is reduced by these corrosion processes, failure is due to a combination of;

- Changes in the external stresses (soil load, soil shrink-swell movement)
- Effects of internal stress (water pressure, water-hammer, etc.)
- Deterioration of pipe wall strength.

Though condition assessment usually focuses on the pipe wall, water pressure, embedment support and external loading conditions are also important considerations (O'Day 1988) (Figure 2).

CONDITION ASSESSMENT OF PIPES

The techniques available for condition assessment fall into two categories - direct and indirect. The direct techniques are based on the physical properties of the pipe wall. Electromagnetic, ultrasonic and acoustic techniques are examples of direct techniques. These were first developed for pipelines in the oil and gas industry, and some have now been successfully adapted for water and wastewater pipelines. Indirect techniques provide pipe wall condition through measurement of a surrogate property, such as the electrochemical properties of the surrounding soil, or through other geochemical and geophysical techniques. While high-resolution direct techniques are potentially capable of identifying the exact position and dimensions of corrosion zones and other forms of wall deterioration, indirect techniques can provide, at best, only an average wall thickness.

Direct techniques

Eddy current methods are based on the induction of eddy currents in a pipe wall, by an alternating current in a primary coil placed on or inside the pipe (Mester & McIntire 1986; Sullivan et al. 1989). Whilst conventional eddy current inspection techniques use a single frequency (or a narrow frequency bandwidth), pulsed eddy current methods supply a wide bandwidth multi-frequency signal. The received signal resulting from a broadband transmission contains more information, and allows detection

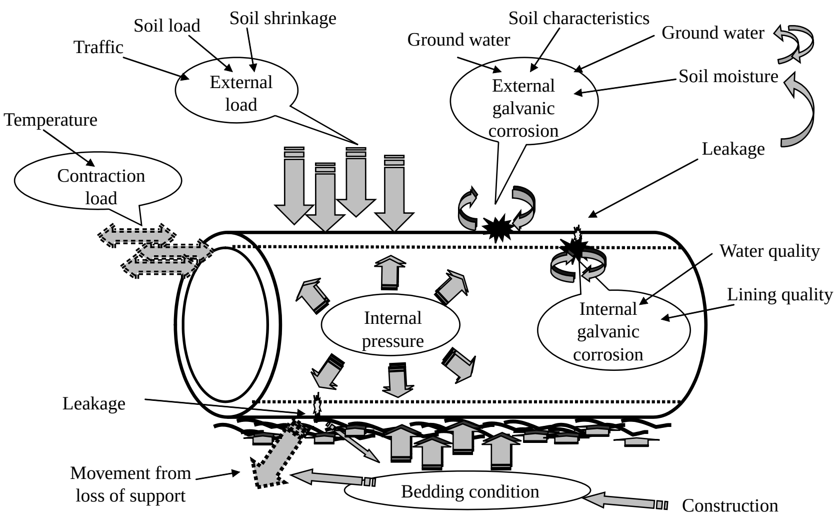

Figure 2 | Galvanic corrosion process and failure causes in iron-based water pipe (based on O'Day 1988).

and quantification of various wall thicknesses, as well as the effective conductivity of the complex through-wall components of the pipe. Remote Field Eddy Current (RFEC) method (Schmidt 1984; Atherton & Sullivan 1986) measures the electromagnetic field transmitted through the wall thickness as it passes through the outer surface of the pipe. A receiver coil placed in the remote field zone of the exciter picks up the field. Since the pipe wall attenuates the through-wall field, and the strength of the field is very sensitive to the thickness of the wall, the RFEC technique is claimed to detect wall thinning produced by corrosion (Makar & Chagnon 1999).

The sensitivity and resolution of the techniques depend on the configuration of the exciter and detector coils. Detector coils with small footprints improve the resolution, but reduce the scanning rate. The RFEC methods are claimed to detect changes in metal mass, graphitisation and wall thinning, while the direct field methods are reported to be more sensitive for detection of cracks and voids (Rajani *et al.* 2000). Pulsed eddy current methods employing highly sensitive magneto-resistive sensors are reported to detect defects of $1 \times 1 \times 5$ mm up to $3 \times 4 \times 20$ mm (Blitz 1997). An independent report states defects 2% or higher of the total pipe wall volume can be detected by RFEC (Dingus *et al.* 2002). At 10–20 m/min, inspection speeds with RFEC are significantly lower than conventional eddy current techniques, which can be used at 100 + m/min when applied to non-water piping (Birring 2001).

Magnetic flux leakage (MFL) techniques depend on the ferromagnetic nature of the object being inspected (Atherton *et al.* 1990; Laursen & Atherton 1992). It is widely applied in the oil and gas industry and provides excellent information on corrosion defects. However the requirement of MFL tools to have good contact with the pipe wall precludes applying the technique to cement-lined or other water pipelines that have internal coatings or sediment build up.

Ultrasonic inspection is a well established technique for non-destructive inspection of metal components (Birks *et al.* 1991). Although no commercial equipment is currently available for internal use in water pipelines, the ultrasonic thickness gauges commonly used in many industries can be used externally. Several companies produce ultrasonic pigs for internal inspection of oil or gas pipelines, but these are long, inflexible and expensive, and are not suitable for water pipes with bends and tees.

Acoustic methods are generally applied for detection of leaks and flaws (cracks) using a leak noise correlator supplemented by acoustic (listening) devices (Fuchs & Riehle 1991).

Acoustic emission methods are also employed to detect signals generated when the pipe is subjected to hydraulic pressure. Further analysis allows identification of the cause, but not quantification of wall thickness. A new tool based on acoustic principles -resonance thickness measurement (RTM) - is under development in Norway. It is claimed that the lower frequency range employed in an RTM system allows wall thickness assessment (Vangdal 2002).

Indirect techniques

Electrochemical properties of the soil are the only recognised criteria that have an influence on the deterioration of ferrous-based pipelines. Extensive studies were carried out in the 1940s and 1950s on the rate of corrosion in cast iron pipe in different soil types (Romanoff 1964; Rossum 1969). These studies have linked soil pH, soil resistivity (inverse of conductivity), soluble sulfates and chloride ion content, among others, to a "corrosivity index" of soil. Soil pH is more likely to have a direct chemical influence on iron pipes rather than promote the type of corrosion which is typically observed in practice.

More recently, an electrochemical property, described as Linear Polarisation Resistance (LPR), has been identified as a good indicator of the corrosion potential of cast iron pipes in some soil types (Nicholas *et al.* 2001). Preliminary data suggests LPR is related to the corrosion rate of ferrous pipe in a particular soil. Monitoring soil LPR may be a method of delineating sections of a pipe network into areas with similar degrees of deterioration.

AN OVERVIEW OF THE CONDITION ASSESSMENT PROCESS

Having briefly introduced some available techniques, the condition assessment process for buried pipelines needs to be addressed. To obtain the most useful condition assessment information in a cost-effective manner, the condition assessment process should involve four main stages:

- Planning the sampling strategy.
- Condition sampling of degradation data.
- Statistical analysis of degradation data.
- Failure analysis for estimation of failure rates.

Planning the sampling strategy

This stage should identify appropriate techniques and the areas of a pipe network that should be sampled. Clearly, the selection of sampling points is an important consideration for capturing meaningful data for a minimum cost. For any set of sampling points to be meaningful, the conditions that prevail within the sampling area must be "uniform". For buried pipelines, these conditions are:

- Pipe type.
- Pipe size.
- Pipe age.
- Soil type.

Geological/terrain maps such as those developed by Grant (1972) can provide a useful method of locating boundaries between different soil classifications. As a first approximation, these boundaries could be assumed to identify uniform soil types. GIS systems may also hold data on the particular pipe types, ages and dimensions that will be found within these uniform soil types. This information can be used to further segregate a pipe network into uniform sampling areas. If individual pipes can be segregated into groups with similar attributes, it may be possible to identify "hot spots" of potentially high failure rates. For example, a good sampling strategy may focus on those pipes that are contained within highly corrosive soils which also exhibit high shrink–swell indices.

Condition sampling of degradation data

In the second stage, data that quantifies the condition of the pipe wall is obtained at the individual sampling areas identified in stage 1. The result of the condition sampling should be a data set with degradation properties (see Table 1) from strategically chosen areas within the network.

Table 1 | Failure analysis input

Input	Structural reliability modelling
Statistical distributions for degradation	Yes
External loads (soil movements, soil load, traffic etc.)	Yes
Internal loads (e.g. operating pressure)	Yes
Failure data	For validation

For metallic pipes, the degradation process is more or less entirely due to pitting corrosion. The remaining strength of the pipe will depend on the geometry and size of corrosion pits. Pit sizes can be estimated with either indirect soil measurements or direct methods.

The three fundamental problems with indirect methods are:

- Actual pit depths are not measured.
- They provide only a snapshot of the pitting rate at one instant in time.
- Pit geometry is not measured.

The direct methods measure the actual pits, although mostly the depth and not the geometry.

Statistical analysis of degradation data

Having obtained condition data within each sampling area, its variation must be quantified. Typically, there is some type of systematic and/or random variation along the network; and therefore it is appropriate to use statistical methods. Statistical methods deal with:

- Random variation along the pipe length in pit density, pit size and pit geometry.
- Systematic variation between materials, soil types and pressure levels.

The output of the statistical analysis is often in the form of probability distributions for the appropriate degradation properties. However, it could also be some kind of qualitative rating, such as good, poor, very poor. The data set retrieved from the condition sampling typically only contains data valid for a limited area of the targeted asset. Therefore, whilst probability distributions can be applied to quantify uncertainty within actual sampling areas, techniques are also required to extrapolate this information to a greater area of pipe network. These will be explored under the heading 'Statistical analysis of limited sample data'.

Failure analysis for estimation of failure rates

If a condition probability distribution can be estimated for a pipeline, it can be used as input to a probabilistic failure model. By considering condition information together with pipe operating conditions, the probability of structural failure can be estimated, and future failure rates can be forecast. Structural reliability methods (Melchers 1999) are commonly used for this purpose and require the inputs given in Table 1.

Outputs from a structural reliability analysis that can be used to design rehabilitation plans are given in Table 2.

The condition assessment process stages are illustrated schematically in Figure 3 and the input requirements and output of the various stages can be seen. Note how additional information (i.e. pipe type, pipe size, pipe age and soil type) is initially collected to plan a condition sampling strategy. Information on pipe operating loads is also required for the final failure analysis stage of the condition assessment process.

STATISTICAL ANALYSIS OF LIMITED SAMPLE DATA

As outlined previously, the cost of using the current state-of-the art equipment is high and, when combined with the cost of surface civil works, it is impractical to sample an entire pipeline at regular intervals. Therefore, it is common to target a limited number of sampling positions and use that data as the basis for assessment on a larger scale. This section discusses the statistical basis for using information from a limited number of condition samples and extrapolating the information to a larger area. As a typical example, pitting corrosion in metallic pipelines is considered.

Applying a distribution for maximum pit depths

The interesting property of a pipe is the residual strength, which is defined by its weakest point. For metallic pipelines, the weakest point is more or less where the

Table 2 | Failure analysis output

Output	Structural reliability modelling
Asset failure rate	Yes
Asset hazard function	Yes
Failure rate per km	Yes

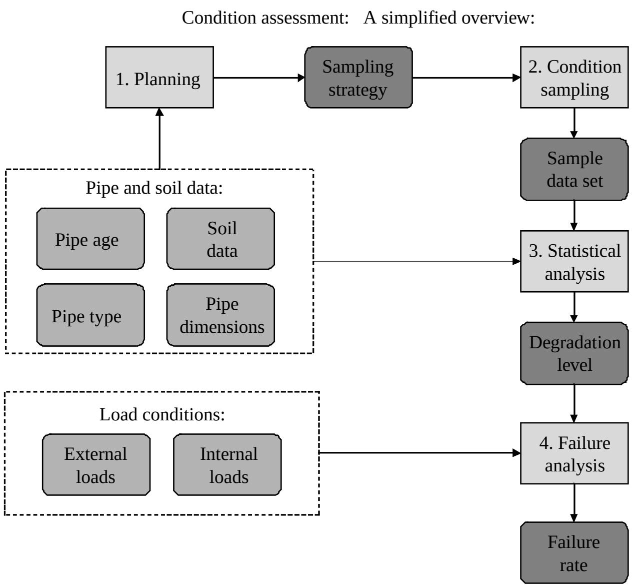

Figure 3 | Condition assessment process overview.

wall thickness is smallest, that is, where the corrosion is deepest. Therefore the primary interest is in the maximum corrosion pit depth.

In practice, the family of generalised extreme value (GEV) distributions (Laycock *et al.* 1990; Gumbel 1954) are well suited to describing variations in maximum corrosion pit depth. In most cases, the two-parameter Weibull distribution is fitted to maximum pit depth data obtained from each sample area:

$$F(x) = P(X \leq x) = 1 - e^{-(x/a)^c} \quad (1)$$

where X is the corrosion pit depth, and $F(x)$ is the probability that X is less than or equal to a particular value x. The terms a and c are referred to as the “scale parameter” and “shape parameter” for the Weibull distribution and are estimated using the maximum likelihood method (Crowder *et al.* 1991; http://www.weibull.com 2005). To do this, sampling measurements of pit depth should be grouped into a set of numbers x_i: $i = 1\ldots n$, with each value x_i corresponding to a measurement of maximum pit depth at a certain sample area i. The method maximises a likelihood function using the scale and shape parameters. In other words, the parameters a and c are chosen such that the actual sample result is the most probable outcome:

$$\textit{Likelihood function} = \prod_{i=1}^{n} f(x_i|a,c) \quad (2)$$

where $f(x|a,c)$ is the Weibull probability density function. Whilst there are alternatives to the maximum likelihood method, it is usually both relatively efficient and simple. The accuracy of the estimated parameters will depend on the number of samples that are available. Ideally, the number of sample points should be chosen so that the value of incremental information (eventually decreasing with additional samples) is equal to the additional cost of sampling.

To test the Weibull distribution assumption, there is a range of goodness-of-fit tests to apply, for example, the Anderson–Darling test, the Kolmogorov–Smirnov test or the graphical Weibull plot test (Evans *et al.* 1989; Crowder *et al.* 1991).

It should be noted that a common situation is to have more than one population (with separate distributions) within the collected samples; this is often referred to as mixed populations. If there is no basis for further separating the populations from each other, the theory of mixed populations Weibull distributions can be applied.

Extrapolation of pit depth data in space

Having fitted the results to an appropriate distribution, it remains to determine how these results can be extrapolated to a larger area of pipeline. It might not be immediately obvious that the probability distribution changes when viewing a larger area. The reason for the change is that extreme values (e.g. minimum or maximum values) are modelled for pipe condition assessment. As an illustrative example, assume for instance that the lowest price on a certain product is required. Queries can be made to different shops to get price quotes, which will be distributed with a mean and standard deviation. If the quotes obtained are x_1, x_2, $x_3 \ldots$, the interesting quantity is:

$$Z(m) = \min(X_i) \quad i = 1\ldots m \quad (3)$$

which is the minimum quote found after m queries. $Z(m)$ can be assumed to be distributed according to some extreme value distribution (such as Weibull). Intuitively, the probability of finding a good price increases with the number of queries made, which, in practice, means that the distribution for $Y(n)$ also changes with the number of queries, n, that are made. The problem therefore is to quantify how the distribution for $Y(n)$ changes with n.

In a similar sense, there are a number of corrosion pits in each segment of a pipeline. In condition sampling, a number of sample areas are chosen and a set of sample data retrieved from each, giving the maximum pit depth. An extreme value distribution for the maximum pit depth within the sample area is then estimated, which has an assumed number of pits equal to n (this is the same as making n queries in the pricing example above). To find the distribution for a larger pipe segment (which has a larger area and therefore a greater number of pits), it is necessary to find the related distribution based on the quota between the relevant areas.

Consider for example a sample area, A_s, and a target area for extrapolation, A_t. In practice, A_s would be the surface area of pipe that was examined at each sample site, and A_t could be the surface area of an individual pipe or pipeline. Each of the sampling areas is assumed to have a maximum pit depth, X_i (a stochastic variable), which is described by a two-parameter Weibull distribution as in Eq. (1). A_t is then idealised as consisting of individual segments (each with a surface area equal to A_s), which have independent and identically distributed stochastic variables, $\{X_i;\ i = 1\ldots n\}$, describing the maximum pit depth. The maximum pit depth Y within the target area A_t can be written as:

$$Y(k) = \max[X_i] \quad i = 1\ldots k \tag{4}$$

where k is the total number of segments within A_t ($k = A_t/A_s$) and X_i is the maximum pit depth within a certain segment. According to standard probability theory, the probability distribution function for the maximum pit depth within the target area can then described as:

$$F(y) = P(Y \le y) = \prod_{i=1\ldots k}(1 - e^{-(y/a)^c}) \tag{5}$$

This distribution is not a Weibull distribution but can be simulated on a computer, using a random number generator, to estimate the tables for its probability distribution, or to estimate statistical expectation and standard deviation, for a particular set of a and c parameters. The procedure to estimate mean and standard deviation would typically be:

1. generate a sample of k random Weibull numbers, and take the maximum value
2. repeat N times (typically 15–30) and calculate the sample mean, and the sample standard deviation

Hence, the probability distribution function for the sample area can be extrapolated to a larger target area based on their area ratio. It should be noted that the main underlying assumption in this transformation is that the number of pits in a particular segment is proportional to the area of that segment. In support of this assumption, it has been previously reported (Laycock *et al.* 1990) that the number of corrosion pits approaches a stationary level, which is proportional to the area of observation, after about 20–30 days. It should also be noted that a requirement for performing this transformation is that the results are only extrapolated over a uniform area (e.g. same pipe material, pipe age, soil type). Substantial estimation errors can be made if this recommendation is not followed.

Extrapolating maximum pit depths in time

Having defined an extrapolation between actual sampling and target areas, the extrapolation of pit growth in time must also be examined. To this end, three main assumptions are made, as follows.

Assumption 1 Pit growth function

It is assumed that the growth rate for any specific pit is deterministic (e.g. follows some given function) in time with a monotonously increasing (i.e. always increasing) function of time, $p(t)$, describing the pit depth (Aziz 1956).

Assumption 2: Order preservation

It is also assumed that the pit depth functions, $p(t)$, are described using a growth rate parameter, d, so that the following relation is true for individual corrosion pits:

$$d_1 \le d_2 \Rightarrow p_1(t) \le p_2(t); \quad t > T \tag{6}$$

where T is some initial time period.

Assumption 3: Initial pit creation stage

It can be approximated that no new pits are created after the initial period T (Laycock *et al.* 1990).

With these assumptions in place, the following general statements can be made:

- The maximum pit depth of a segment will remain the maximum pit depth unless new pits are created with significantly higher corrosion rates (and according to assumption 3, no new pits are created).
- This maximum pit will have a deterministic growth rate according to a pit depth growth rate function.

In this way, it can be assumed that what is actually sampled during condition assessment is the pit depth growth rates, d.

If pit growth is assumed to be constant in time (e.g. $p(t) = dt$), the growth rate can easily be estimated for a specific pit using only a single measurement and the known age of the pipe. However, during the early stages of corrosion, it is sometimes inappropriate to assume a linear degradation rate (generally producing a more conservative estimate with a linear approximation). Subsequent observations are required to obtain a more accurate pit depth growth function.

The function given below in Eq. (7) is usually assumed to describe the degradation process (note that in this case, assumption 2 above is only valid for $t > T = 1$):

$$p(t) = qt^d \tag{7}$$

The parameters q and d must be estimated using subsequent measurements on the maximum pit depth at a particular sampling site. If only one measurement is available, a linear model is assumed as a first approximation:

$$p(t) = dt \tag{8}$$

The pit depth growth rate, d, is a stochastic variable described by some probability distribution with mean or statistical expectation value $E(d)$ and a variance $V(d)$. As the pit depths, p, are observed, a distribution for the maximum growth rate parameter, $d_{\max}$ is estimated. The maximum pit depth can then be extrapolated over time as:

$$p_{\max}(t) = p(t, d_{\max}) \tag{9}$$

FORECASTING FAILURES BASED ON CONDITION ASSESSMENT

Failure mechanisms in buried metallic pipes can be idealised by the balance between the applied loads and the pipe resistance to those loads.

In-service loading can be split into contributions from internal pressure and external soil loading, including seasonal ground movement and traffic loads. The condition of a pipe is characterised by factors such as the extent of corrosion damage in ferrous pipes. It follows that failure will occur when the combination of pressure and soil loading exceed a critical property of the pipeline, such as its yield strength, or fracture toughness. As corrosion damage proceeds, the resistance of a pipe to applied loads will decrease.

Probabilistic failure models

Whilst deterministic failure models can be developed to predict remaining service lifetime (Rajani *et al.* 2000), a range of pipe conditions and loading types are encountered in practice. Consequently, these models must be modified to account for this uncertainty and determine the probability of failure (Ahammed & Melchers 1995).

In its simplest form, a criterion for pipe failure can be defined as:

$$z = s_f - s_a \tag{10}$$

where s_a is the maximum applied stress and s_f is the critical stress required for failure. Clearly, s_a will be a function of pipe loading and s_f will depend on pipe condition. For example, assuming that a pipe is subjected to internal pressure only, Eq. (9) is rewritten as:

$$z = s_f - \frac{pr}{b} \tag{11}$$

where p is internal pressure, r is the mean radius of the pipe and b is the pipe wall thickness. For the relatively simple case of a uniform, linear corrosion rate in metallic pipes, Equation (11) can be written in terms of the minimum remaining wall thickness at a time t:

$$z = s_f - \frac{pr}{(b_0 - d_{\max}t)} \tag{12}$$

where b_0 is the original pipe wall thickness, $d_{\max}$ is the maximum linear corrosion rate and t is the time elapsed since the pipe was installed. As time passes, the decreasing wall thickness results in an increasing applied stress until failure occurs. Clearly, a more realistic failure criterion would be based on fracture from defects in the pipe wall (Kiefner & Vieth 1990). However, in some cases, the resolution of condition monitoring output may not be sufficient to describe the geometry of such defects. Therefore, for the purposes of this study, a simpler failure criterion was adopted, based on net section yielding of the pipe wall. It should be noted that if sufficient information is available, then a fracture mechanics approach could be readily adopted (Kiefner & Vieth 1990). Whilst a "limit state" is defined when $s_a = s_f$ (or $z = 0$), it should be remembered that the maximum corrosion rate $d_{\max}$, is a stochastic variable. Therefore, it is appropriate to define the probability of failure at time t, which is given by:

$$P_f = P(z < 0) \tag{13}$$

In other words, this is the probability that the limit state variable z is less than zero. Whilst several methods are available to determine P_f (Melchers 1999; Thoft–Christensen & Baker 1982), Level II first-order-second-moment (FOSM) reliability techniques are well suited to this type of problem (Ahammed & Melchers 1995). In all probabilistic methods, the basic variables that govern failure are assumed to be stochastic, and the limit state (Equation (12)) is recast as:

$$Z = f(X_1, X_2 \ldots X_n) = f(\overline{X}) \tag{14}$$

where Z is the stochastic limit state variable and $\bar{X}$ is a random vector of the n stochastic basic variables that comprise the limit state function (i.e. s_f, p, $d_{\max}$ etc.). Whilst $d_{\max}$ was described by the Weibull distribution under the heading 'Applying a distribution for maximium pit depths', the key assumption in FOSM analysis is that all stochastic basic variables are independent and that their variation can be represented by normal distributions (Melchers 1999; Thoft–Christensen & Baker 1982). To this end, it is assumed that all non-normal stochastic variables can be transformed into equivalent approximate normal distributions. Whilst a number of techniques can be used for this purpose, the "normal tail" transformation is perhaps best suited to extreme value distributions (Ahammed & Melchers 1995). With this assumption in place, all the basic variables can then be converted to corresponding standard normal variables, and a "failure surface" is defined by setting the stochastic limit state function $z = f(\overline{X}) = 0$.

If all basic variables are normally (or approximately normally) distributed, then the limit state function can be modified to give the probability of failure defined as:

$$P_f = P(z < 0) = \Phi\left(-\frac{\mu_z}{\sigma_z}\right) \tag{15}$$

where μ_z and σ_z are the mean and standard deviation of the stochastic limit state variable Z and Φ is the standard normal distribution function (Melchers 1999). In practice, the FOSM analysis can be completed in three stages (Melchers 1999; Thoft–Christensen & Baker 1982):

- Convert all stochastic basic variables in the limit state function (Equation (12)) to equivalent standard normal variables.
- Linearise the limit state function (Equation (12)).
- Use the normal distribution laws for linear functions (Melchers 1999) to determine μ_z and σ_z and hence calculate P_f from Equation (15).

Although the main components of Level II FOSM reliability analysis are outlined above, there are several algorithms for calculating P_f and the reader is referred to the literature for a more rigorous treatment (Melchers 1999; Thoft–Christensen & Baker 1982).

A case study – buried mild steel pipe subjected to external surface corrosion

To illustrate the value of Level II FOSM analysis in practice, consider the case study of a buried mild steel cement-lined (MSCL) pipeline subjected to external surface corrosion. Figure 4 schematically illustrates the layout of the pipeline.

What is needed is to assess the condition of the mild steel sections of the pipeline and estimate the variation in statistically expected failure rate over time. As shown in Figure 4, four sections of buried MSCL pipes were identified (each section of a different length), with an inner diameter of 305 mm and an original wall thickness of 4.8 mm. Those properties that were assumed to be constant (i.e. deterministic) within each section of the pipeline are given in Table 3.

Whilst these properties were treated as single-valued, the remaining basic variables in Equation (13) were assumed to be stochastic. As shown in Figure 4, geological terrain mapping indicated that the pipeline was buried in two distinctly different soil types (denoted by the shaded areas),

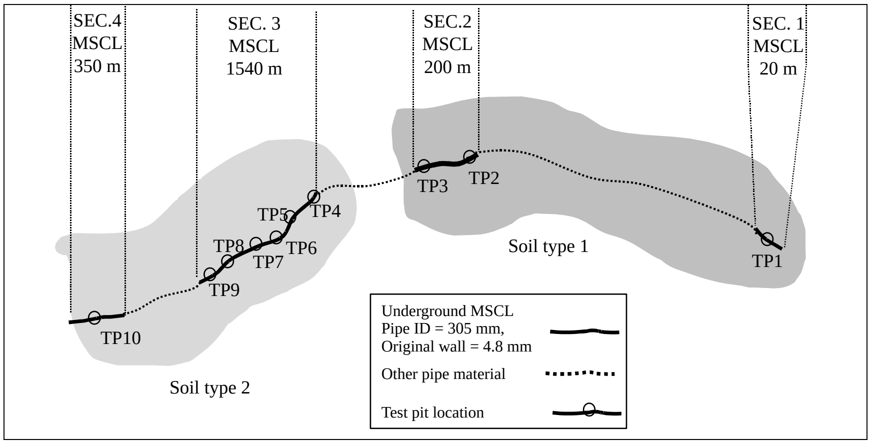

Figure 4 | Schematic layout of buried MSCL pipeline subject to external surface corrosion.

which formed the basis for segregating the pipe sections into two groups. Within each soil type, a series of pipe condition assessments were conducted to determine the variation in remaining pipe wall thickness b. Test points (denoted as TP1–TP10 in the diagram) indicate the location of individual assessments. For each assessment, a sample area $A_s = 1.5\,m^2$ (see section 5.2) was exposed and the minimum remaining wall thickness b was measured using a non-destructive electromagnetic technique. Since the pipe age and original wall thickness were known, the minimum remaining wall thickness at each test point location could be converted into an estimated maximum linear corrosion rate $d_{\max}$.

The Weibull probability distribution function outlined in section 5.1 (Equation (1)) was then applied to results from test pits within each soil type, allowing distribution functions to be estimated for $d_{\max}$. These are given in Table 4.

As shown, the maximum linear corrosion rate d_{max} was well represented by the Weibull distribution function with the parameters as shown. Clearly, the mean values of d_{max} indicate that sections 1 and 2 of the pipeline lie in a more corrosive soil environment than sections 3 and 4.

Following the discussion under the heading 'Extrapolation of pit depth data in space.', it was noted that the Weibull distributions given in Table 4 applied only to the sampling area $A_s = 1.5\,m^2$, and needed to be extrapolated to describe the distribution over a larger target area A_t. To this end, an individual MSCL pipe (with an outer diameter of 314.6 mm, and a pipe length of 12 m) was chosen for extrapolation, with a target area $A_t = 11.87\,m^2$. Applying Equations (4) and (5) to the sampled Weibull distribution gave the extrapolated distribution of maximum corrosion rates for an individual MSCL pipe, as detailed in Table 5.

As shown, extrapolating the maximum linear corrosion rate for sections 1, 2, 3 and 4 to the target area of an individual pipe increased the statistical expectation values from 0.062 and 0.034 mm/year to 0.203 and 0.067 mm/year respectively.

Having obtained the Weibull distribution function for $d_{\max}$, the next stage of the analysis was to convert these distributions to equivalent approximate normal distribution functions, in order to determine the mean and standard deviation of the limit state variable z in Equation (13). As stated in section 6.1, the "normal tail" transformation was used for this purpose (Melchers 1999). A Level II FOSM

Table 3 | Constant properties for each MSCL pipeline section

Property	MSCL pipe section	Value
Pressure, p (kPa)	1	78.0
	2	268.0
	3	604.0
	4	693.0
Pipe radius, r (m)	1–4	0.169
Original wall thickness, b_0 (mm)	1–4	4.80
Material yield strength, s_f (MPa)	1–4	423.0

Table 4 | Distribution parameters for maximum linear corrosion rate, d, within the condition sampling area of 1.5 m^2

			Weibull distribution parameters for maximum linear corrosion rate d (mm/year) $F(d) = P(D \le d) = 1 - e^{-(d/a)^c}$			
MSCL pipe section	**TP #**	**Soil type**	***a***	***c***	**Mean value $\mu(d)$ (mm/year)**	**Standard deviation σ_d (mm/year)**
1, 2	1, 2, 3	1	0.070	1.75	0.062	0.037
3, 4	4–10	2	0.034	2.60	0.034	0.012

Table 5 | Distribution parameters for maximum linear corrosion rate, d_{max}, for an individual pipe with target area $A_t = 11.9$ m^2

			Weibull distribution parameters for maximum linear corrosion rate d (mm/year) $F(d) = P(D \le d) = 1 - e^{-(d/a)^c}$			
MSCL pipe section	**TP #**	**Soil type**	***a***	***c***	**Statistical Expectation value $\mu(d)$ (mm)**	**Standard deviation σ_d (mm/year)**
1, 2	1, 2, 3	1	0.228	1.75	0.203	0.112
3, 4	4–10	2	0.075	2.60	0.067	0.028

analysis could then be applied in conjunction with Equations (11) and (14) to determine the probability of failure, P_f, for an individual pipe in each section. The cumulative failure probability curves which resulted from this analysis are given in Figure 5.

As shown, the relatively high corrosion rate in sections 1 and 2 is reflected by a rapid increase in P_f with time. After an elapsed time period of 100 years (from the time of initial condition assessment), $P_f = 0.72$ compared to 0.3 for sections 3 and 4. Whilst P_f curves for individual pipes are useful, assuming that the individual failures that occur along a pipeline follow a binomial probability process (Melchers 1999) allows the statistically expected failure rate (per km/

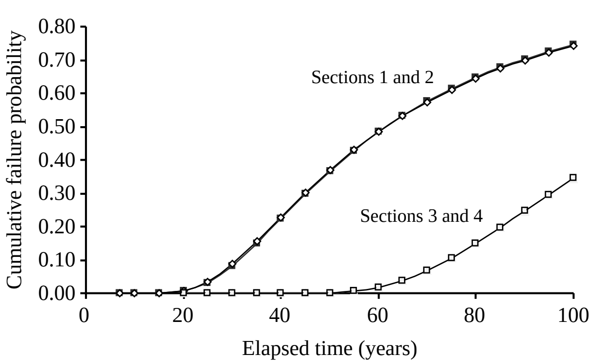

Figure 5 | Cumulative failure probability for an individual 12 m long MSCL pipe.

per year) to be estimated. For example, if each individual pipe sustains one failure, which is assumed to be independent of other failures, then the statistical expectation of the number of failures in a pipeline $E(N)$ is given by:

$$E(N) = nh(t) \tag{16}$$

where n is the number of individual pipes in the pipeline, and $h(t)$ is the hazard function for an individual pipe (Melchers 1999). $h(t)$ is the likelihood of an individual pipe failure in the time interval t to $t + dt$, given that failure has not yet occurred, and can be determined from the failure probability P_f (Melchers 1999; Thoft–Christensen & Baker 1982).

For the case examined in 1 km lengths of pipeline, there was a total of 83.3 (rounded down to 83) individual pipes and, over a one-year time interval, Equation (16) can be used to determine the statistical expectation of the failure rate $E(N)$ (per km/per year) (Figure 6).

As shown, the higher corrosion rate in sections 1 and 2 is again evident in a relatively sharp increase in statistically expected failure rate after a total elapsed time of 20 years. In contrast, an increase in failure rate for sections 3 and 4 is delayed until a total elapsed time period of 50 years. If the costs associated with pipe failure are known, then the failure rates in Figure 6 could assist the development of

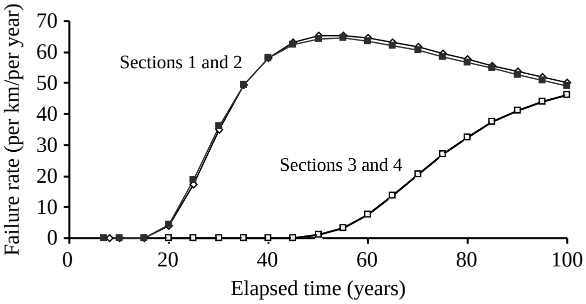

Figure 6 | Statistically expected failure rate for MSCL pipeline.

long-term pipe replacement and rehabilitation strategies. Alternatively, as a useful intermediate step, the timings of subsequent condition assessment programs in each section of the pipeline could be scheduled.

CONCLUSIONS

Whilst proactive maintenance strategies for water distribution networks are driving the development of condition assessment technologies, high cost has limited their use by water authorities. This has promoted the need for techniques which use information from a few sampling locations to reliably predict the condition of a larger pipeline area.

It is anticipated that the combined approach adopted in this paper can be used to provide long-term rehabilitation and replacement strategies based on a well-planned, limited sampling program of pipe condition. By including statistical analysis of condition data and reliability modelling in the condition assessment process, a complete solution can be obtained.

To illustrate these concepts, a case study of a mild steel pipeline was investigated. Using data from broadband electromagnetic condition assessment, probability distributions for corrosion rate were derived. A simple, net-section yielding failure model was then used with Level II first-order-second moment reliability analysis to forecast failure probability.

REFERENCES

Ahammed, M. & Melchers, R. E. 1995 Probabilistic analysis of pipelines subjected to pitting corrosion leaks. *Engineering Structures* **17**, 74–80.

Andreou, S. 1987 Maintenance decisions for deteriorating water pipelines. *Journal of Pipelines* **7**, 21–31.

Atherton, D. L., Jagadish, C., Storm, V., Ham, F. & Scharfenberger, B. 1990 Pipeline inspection speed alters MFL signals. *Oil & Gas Journal* **88**(5), 84–86.

Atherton, D. L. & Sullivan, S. 1986 Remote field through wall electromagnetic inspection technique for pressure tubes. *Materials Evaluation* **44**(13), 1544–1550.

Aziz, P. M. 1956 Application of the statistical theory of extreme values to the analysis of maximum pit depth data for aluminum. *Corrosion* **12**, 35–46.

Birks, A. S., Robert, E., Green, R. E., Jr. & McIntire, P. (eds) 1991 Nondestructive Testing Handbook, Vol. 7. Ultrasonic Testing, 2nd ed. American Society of Nondestructive Testing, Columbus, OH, USA, pp. 465–470.

Birring, A. S. 2001 Selection of NDT techniques for inspection of heat exchanger tubing. *Materials Evaluation* **59**, 382–391.

Blitz, J. 1997 *Electrical and Magnetic Methods of Non-destructive Testing*, 2nd edition. Chapman & Hall, London, UK.

Burn, L. S., Eiswirth, M., De Silva, D. & Davis, P. 2001 Condition monitoring and its role in asset planning. In: Proceedings Pipes 2001 – Asset Management & Control, City of Wagga Wagga, NSW, Australia. CD ROM, Available through www.cmit.csiro.au/research/papers/abstract.cfm/330.

Crowder, M. J., Kimber, A. C., Smith, A. C. & Sweeting, A. J. 1991 *Statistical Analysis of Reliability Data*. Chapman & Hall/CRC, Boca Raton, Florida, USA.

Deb, A. K. 1994 Water distribution system performance indicators. *Water Supply IWSA (Zurich)* **12**(3/4), 11–20.

Deb, A. K., Herz, R. K., Hasit, Y. J. & Grablutz, F. M. 1998 *Report Project 265: Quantifying Future Rehabilitation and Replacement Needs of Water Mains*. AWWA Research Foundation, Denver, Colorado, pp. 156–158.

Dingus, M., Haven, J. & Austin, R. 2002 *Nondestructive, Noninvasive Assessment of Underground Pipelines*. AWWA Research Foundation Denver, CO.

Englehardt, M. O., Shipworth, P. J., Savic, D. A., Saul, A. J. & Walters, G. A. 2000 Rehabilitation strategies for water distribution networks: a literature review with a UK perspective. *Urban Water* **2**, 153–170.

Evans, J. W., Johnson, R. A. & Green, D. W. 1989 *Two- and Three-Parameter Weibull Goodness-of-Fit Tests*. United States Department of Agriculture, Wisconsin, USA.

Fuchs, H. V. & Riehle, R. 1991 Ten years of experience with leak detection by acoustic signal analysis. *Applied Acoustics* **33**, 1–19.

Grant, K. 1972 *Terrain Classification for Engineering Purposes of the Melbourne Area, Victoria*. Division of Applied Geomechanics Technical Paper No. 11. CSIRO, Australia.

Gumbel, E. J. 1954 *Statistical Theory of Extreme Values and Some Practical Applications*. National Bureau of Standards Applied Mathematics Series No. 33. US Government Printing Office, Washington DC, USA.

Jarrett, R., Hussain, O., Veevers, A. & Van der Touw, J. 2001 A review of asset management models available for water pipeline

networks. In: *Proceedings Int. Conference of Maintenance Societies 2000*, Melbourne, *Australia Paper No. 49*.
Kiefner, J. F. & Vieth, P. H. 1990 New method corrects criterion for evaluating corroded pipe. *Oil and Gass Journal* **6**, 56–59.
Kleiner, Y. & Rajani, B. 2001 Comprehensive review of structural deterioration of water mains: statistical models. *Urban Water* **3**, 157–176.
Laursen, C. & Atherton, D. L. 1992 Effects of line pressure stress on MFL patterns. *British Journal of Non-destructive Testing* **34**(6), 285–288.
Laycock, P. J., Cottis, R. A. & Scarf, P. A. 1990 Extrapolation of extreme pit depths in space and time. *Journal of the Electrochemical Society* **137**(1), 64–69.
LeGat, Y. & Eisenbeis, P. 2000 Using maintenance records to forecast failures in water networks. *Urban Water* **2**, 173–181.
Makar, J. & Chagnon, N. 1999 Inspecting systems for leaks, pits and corrosion. *J. American Water Works Association* **91**(7), 36–46.
Melchers, R. E. 1999 *Structural Reliability Analysis and Prediction*. 2nd edition. John Wiley & Sons, Brisbane, Australia.
Mester, M. & McIntire, P. 1986 *Nondestructive Testing Handbook, Vol. 4, Electromagnetic Testing: Eddy Current, Flux Leakage and Microwave Nondestructive Testing*. American Society of Nondestructive Testing, Columbus, Ohio, USA.
Nicholas, D., Heathcote, M. & Moore, G. 2001 Condition assessment of buried water pipelines: which techniques work? In: *Proceedings. Pipes 2001 – Asset Management & Control*. City of Wagga Wagga, NSW, Australia, CD-ROM.
O'Day, D. 1988 Water main condition monitoring – A case study. In: *Proceedings. Conference on Pipeline Infrastructure, Boston, Mass. June 6–7 1988*. American Society of Civil Engineers, New York, pp. 274–286.
Ofwat 2005 http://www.ofwat.gov.uk (accessed August 2005).
Rajani, B. & Kleiner, Y. 2001 Comprehensive review of structural deterioration of water mains: physically based models. *Urban Water* **3**, 177–190.
Rajani, B., Makar, J., McDonald, S., Zhan, C., Kuraoka, S., Jen, C. K. & Viens, M. 2000 *AWWARF Project No. 280: Investigation of Grey Cast Iron Water Mains to Develop a Methodology for Estimating Service Life*. AWWA Research Foundation, Denver, CO. USA.
Romanoff, M. 1964 Exterior corrosion of cast iron pipe. *Journal of the AWWA* **56**, 1129–1143.
Rossum, J. R. 1969 Prediction of pitting rates in ferrous metals from soil parameters. *Journal of the AWWA* **61**, 305–310.
Sægrov, S., Melo Bapista, J. F., Conroy, P., Herz, R. K., LeGauffre, P., Moss, G., Oddevald, J. E., Rajani, B. & Schiatti, M. 1999 Rehabilitation of water networks: survey of research needs and ongoing efforts. *Urban Water* **1**, 15–22.
Schmidt, T. R. 1984 The remote field eddy current inspection technique. *Materials Evaluation* **42**(1), 225–230.
Sullivan, S., Atherton, D. L. & Schmidt, T. R. 1989 Comparison of conventional, through-wall and remote field eddy current techniques. *NDT International* **22**(4), 203–208.
Thoft–Christensen, P. & Baker, M. J. 1982 *Structural Reliability Theory and Its Applications*. Springer–Verlag, Berlin, Germany.
Vangdal, A. C. 2002 Rehabilitation planning based on technology for exact measurement of pipe walls in water networks. In: *Proceedings 20th Int. Conference NO-DIG*, Copenhagen, Denmark, *CD-ROM Paper No. 3*.
VIC Regulator 2005 http://www.reggen.vic.gov.au/water101.html (accessed Aug. 2005).
weibull.com 2005 http://www.weibull.com/ (accessed Aug. 2005).

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