Condition Assessment and Probabilistic Analysis to Estimate Failure Rates in Buried Pipelines

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Condition Assessment and Probabilistic Analysis to Estimate Failure Rates in Buried Pipelines

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ABSTRACT

Pipe condition assessment can provide useful information to assist rehabilitation and replacement decisions. For those pipelines with only limited failure histories (such as critical mains) condition assessment can be used to quantify the level of deterioration and estimate the variation in failure probability over time. Interpretation of this failure probability will in turn allow selection of an appropriate rehabilitation strategy that will be capital cost effective, have minimal externality cost and be environmentally friendly. Whilst commercially available electromagnetic techniques and emerging technologies such as gamma ray back-scattering (using radioactive probes) provide direct information on pipe wall condition, geochemical and geophysical techniques provide condition information indirectly through measurement of surrounding soil properties. Alternative methods of condition assessment are being developed for non-metallic pipes, such as plastic and asbestos cement, which are generally incompatible with the techniques described above. As more techniques are developed, it is expected that procedures will be available to generate information on pipe condition for any type of underground pipe asset through trenchless, limited trench or minimal surface disruption techniques. For many techniques, assessment is limited to specific locations and high cost or difficult pipe access precludes continuous assessment over large pipeline areas. To address this limitation, this paper presents an overview of the condition assessment process, highlighting the importance of planning and statistical analysis of condition data and using data to forecast future failure rates. The paper examines a statistical basis for extrapolating pipe condition data from discrete sampling positions to estimate the condition of the longer pipeline. A technique is presented to extrapolate the Weibull distribution function based on the ratio between an initial sample area over which pipe condition data is obtained, and a larger target area, such as a pipe or pipeline length. Structural reliability methods are then used to illustrate how the statistical distribution of pipe condition can be used to estimate pipe failure probability. A practical example of a buried Mild Steel pipeline is analysed to illustrate the value of this approach. By including this analysis in the condition assessment process, a complete solution is proposed, which allows long-term pipe rehabilitation strategies to be developed based on a well-planned program of limited condition assessment.

1. INTRODUCTION

Faced with increasing economic pressures to satisfy the requirements of regulatory compliance (Ofwat 2002, VIC. Regulator 2002), 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). Whilst trenchless rehabilitation is central to most rehabilitation programs, the ability to map the condition of pipelines and forecast future failures is a key prerequisite in the decision process (Burn *et al.* 2001). Numerous models that combine water distribution system performance, rehabilitation options, financial constraints and regulatory requirements have been proposed (Andreou and Marks 1986, Deb 1994, AWWARF 1998), and predicting failure is an important element in all of them. Whilst most models are based on failure history (Jarrett *et al.* 2001, Lei and Sægrov 1998, Eisenbeis *et al.* 1999, LeGat and Eisenbeis 2000) the availability of failure information is often limited for critical mains. 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 and Rajani, 2001).

Although continuous condition assessment is ideal, it is usually 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.

2. PIPE DETERIORATION MECHANISMS

The typical causes of pipe deterioration are shown in
Figure 1. Galvanic corrosion is the primary mechanism of deterioration in metallic pipe brought about by cathodic and anodic areas on the pipe, in the presence of moisture and a supply of oxygen (aeration). Whilst internal or external forces precipitate structural failure, the inability of the pipe to resist these forces is essentially due to deterioration of pipe wall strength. Thus, the primary focus of condition assessment is the pipe wall, although the embedment support and external loading play important secondary roles.

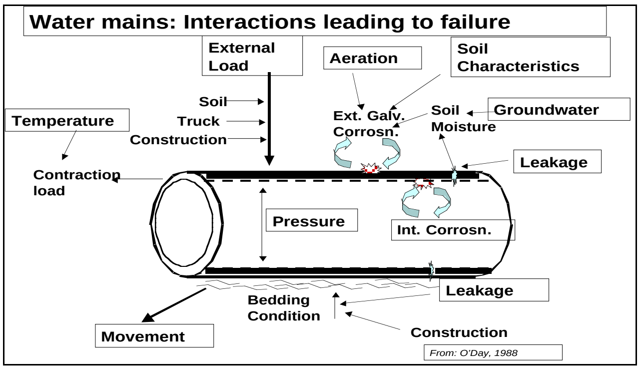

Figure 1: Failure causes in water pipe

It is estimated that two thirds of distribution water mains in most developed countries are metallic, while asbestos-cement (A-C) forms about 15 percent of pipelines and the balance plastic (Kirmayer *et al* 1994). About 66% of metal pipes are cast iron (CI) and the remaining 34% is ductile iron (DI) (Smith et al, 2000). Since CI water mains form the majority of relatively old pipe networks, they are also the focus of renewal programs in many countries. Their deterioration through pitting corrosion and graphitisation has been the subject of many previous investigations (Romanoff 1964, Makar and Rajani 2000, Makar *et al*. 2001). A-C pipes are of a similar vintage and are also targeted for renewal in many cities.

3. CONDITION ASSESSMENT OF PIPE

Condition assessment of metallic pipelines is standard practice in the oil and gas industry and usually forms part of a license requirement to demonstrate an operational risk that is “as low as practically possible” (Jones and Dawson 1998). The relatively low failure consequences of water pipelines means that the water industry has been slow in utilising the available technology. Whilst recent developments have produced in-pipe technologies tailored specifically for water mains, they still remain relatively expensive (Rajani and Kleiner, 2001). For non-metallic pipe such as A-C and plastic, instrumented techniques are not available, and direct examination of the pipe wall is required. The high cost of assessment techniques and the associated civil works for launching in-pipe probes or exposing pipe has led to the development of indirect assessment methods. One of the promising indirect methods uses the relationship between the electrochemical properties of pipe bedding soil and pipe deterioration (Nicholas *et al.* 2001).

3.1 Metallic pipes

Although some metallic pipes have coatings to eliminate or reduce the risk of galvanic corrosion, perforations, poor quality and installation damage can still induce corrosion. The criteria essential for corrosion (oxygen supply, moisture, soluble salts, cathodic and anodic sites on the metal surface) ensure that corrosion of a pipe surface is rarely uniform, and examination of a small section of pipe may not indicate the extent of deterioration over an entire pipeline. Therefore with ferrous pipelines, it is usually necessary to monitor the condition of significant lengths of the pipeline for an accurate assessment of the most severe corrosion damage.

Whilst corrosion depth and width are easily measured on exhumed pipe samples, their determination by non-destructive techniques is typically through electromagnetic methods which require interpretation of the strength of an induced magnetic field, generated by a permanent magnet or an exciter coil supplied with a sinusoidal current. Acoustic methods of condition assessment are also under development. The permanent magnet methods are referred to as Magnetic Field Leakage (MFL) tools and the exciter coil methods as Remote Field Eddy Current (RFEC) tools. Signal interpretation in both these methods requires skill and experience as it depends on pipe material, conductivity, permeability, orientation of corrosion defects and frequency (RFEC).

3.1.1 RFEC Techniques

Remote Field Eddy Current technology has been used to assess the condition of pipes for more than 50 years (Hoshikawa *et al.* 1989). However, it is only in the last 10 years or so that it has been used successfully, and extensively, to determine the remaining wall thickness of CI pipes in the water industry. Essentially, the technique involves the generation of an electromagnetic field from an exciter coil, as the tool (or pig) travels along the pipeline, and the measurement of amplitude and phase components of the signal, at a distance greater than 2.4 x internal diameter from the exciter coil (Ferguson *et al.* 1996). This is shown schematically in *Figure 2*.

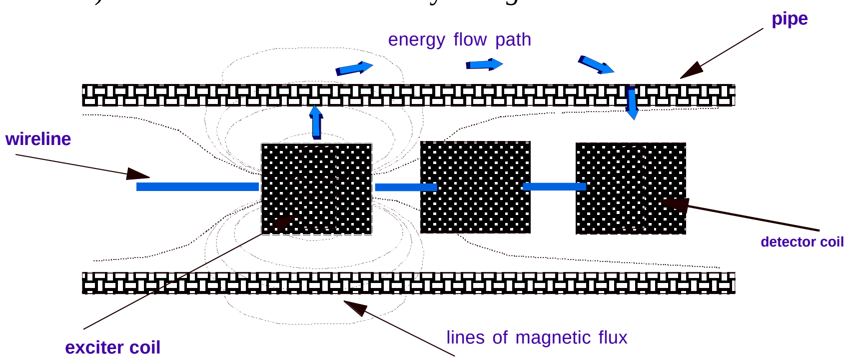

Figure 2: Schematic of RFEC Technique (from Ferguson et al, 1996)

A new tool developed in Australia measures the full-wave secondary magnetic field resulting from a transient input signal. By recording the full waveform response it is possible to obtain information on both the magnetic and electrical properties of metallic pipes. The transient input signal generates multiple frequencies, typically 50Hz to 50kHz. The wide acquisition bandwidth negates the requirement for tuning or setting fixed frequencies depending upon pipe-wall thickness and composition.

An example of the calibrated processed output obtained from a machined section of CI pipe is provided in

Figure 3. Currently development is focused on improving anomaly discrimination and providing a means to confidently assess not only wall thickness, but also the extent of graphitisation.

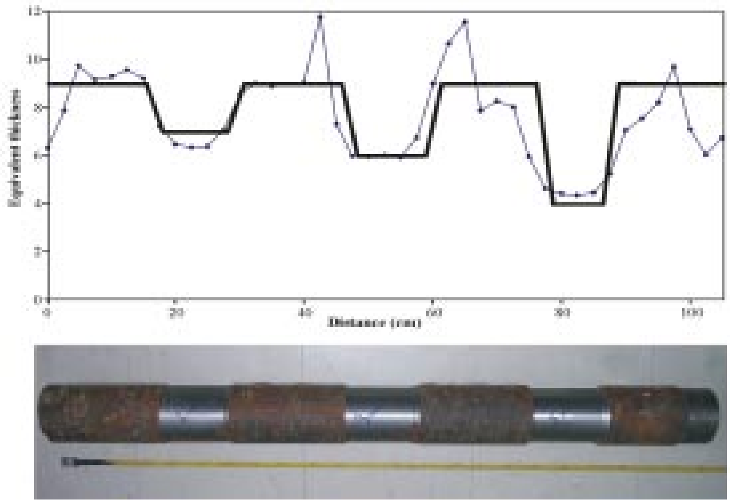

Figure 3: Trace from the TESTAU in-pipe tool (thin irregular line) superimposed on the actual wall thickness (the heavy black line) of a test pipe with the wall machined to different depths

3.1.2 MFL Techniques

Magnetic flux leakage (MFL) technologies utilise a permanent magnet to generate a static field in the pipe wall. Used extensively on gas and steam pipes, where sensors can be held at a constant offset from the wall, these devices provide a means to rapidly assess pipe walls for fractures and pitting. However, water pipes are rarely smooth and clean, with tuberculous and manganese deposits on the wall. This represents a severe limitation to MFL techniques, which are extremely sensitive to offset variations between the sensor and the pipe inner surface, unless cleaned internally prior to assessment. In addition, it is not possible to distinguish differences between graphitisation and general pipe thinning and further, there is a dramatic reduction in sensitivity as the wall thickness increases. However, simple small sensor packages combined with modern high speed acquisition systems means MFL based techniques can be used for high-resolution sampling at low costs.

3.2. Cementitious pipes

Whilst the techniques for metallic pipes have advanced though the stringent requirements of the oil and gas industries, applications for cementicious pipes used in the water and wastewater industries have not. However, some useful data can be obtained with high frequency radar equipment (designed by Monash University Geophysical Research Laboratories) for operation on long cables (> 500 m). Several ground penetrating radar (GPR) surveys have now been completed within large diameter non-ferrous pipes with encouraging results. The technique was able to image both the wall thickness and also provide information about embedment conditions such as cavitation and compaction level.

More accurate information is available through direct mechanical testing of core samples, a technique developed specifically for A-C pipe. Though not strictly non-destructive, it inflicts minimal damage to the pipe and is easily repaired by clamps. The core is removed using standard equipment that makes openings in A-C pipe for installation of service connections or hydrant attachment. The indirect tensile strength of this core can be obtained from a splitting compression test in accordance with AS 1012 Pt.10(1972)/ASTM C-496-90, along the circumferential axis of the core. The pipe hoop strength can then be determined and related to information from a phenolphthalein indicator test on the core sample *(figure 4)* (De Silva *et al*. 2002).

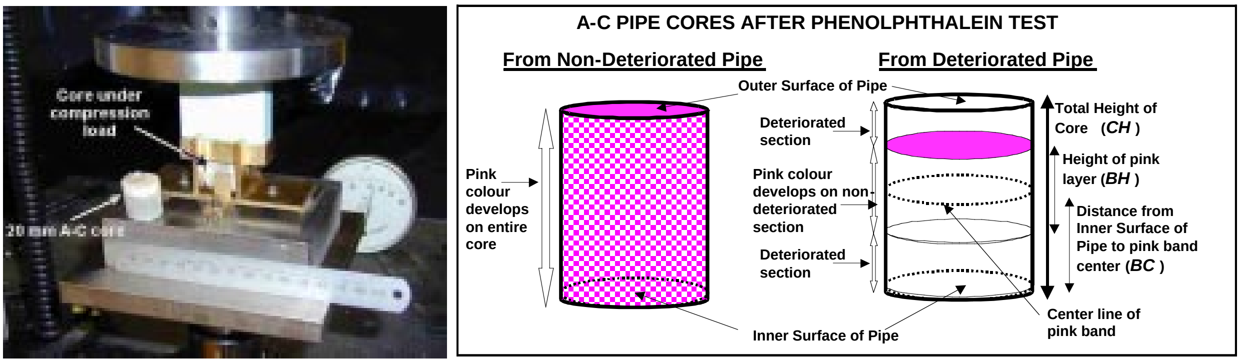

Figure 4: Test rig for splitting tensile strength test and colour development after phenolphthalein test, and measurements on core

3.3. Soil properties and Pipe Deterioration

The link between external corrosion of a pipe and relevant soil properties is well established (O'Day 1985). Whilst the electrochemical activity of a soil can be quantified by several parameters (pH, conductivity/resistivity), Linear Polarisation Resistance (LPR) has been shown to correlate well with corrosion rates in metallic structures (Scully and Bundy, 1985, Ferguson *et al* 1996, Millard *et al* 2001). However, to use soil LPR measurements as a condition assessment tool, it is necessary to identify those areas of a pipe network where results can be applied.

4. THE CONDITION ASSESSMENT PROCESS: OVERVIEW

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

4.1 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 (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 which are contained within highly corrosive soils which also exhibit high shrink-swell indices.

4.2. 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: Examples of appropriate degradation properties

Pipe type:	Property:	Typical sampling method:
Metallic pipes	*Corrosion pit depth*	*Direct measurement of wall thickness*
Metallic pipes	*Corrosion rate*	*Soil Linear Polarisation Resistance*
Asbestos-Cement	*Cement strength*	*Core strength, cement pH etc*
Plastics	*Defect size*	*Direct pipe examination*

4.3. 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 such as:
  - Random variation along the pipe length
- Systematic variation such as:
  - Variation between soil types
  - Variation due to varying pressure levels
  - Variation due to varying materials

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, etc. 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 in the section 5.

4.4. 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 2*.

Table 2: Failure analysis input

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

Outputs from a structural reliability analysis, which can be used to design rehabilitation plans are given in *table 3*.

Table 3: Failure analysis output

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

The condition assessment process stages are illustrated schematically in *Figure 5* and the input requirements and output of the various stages can be seen.

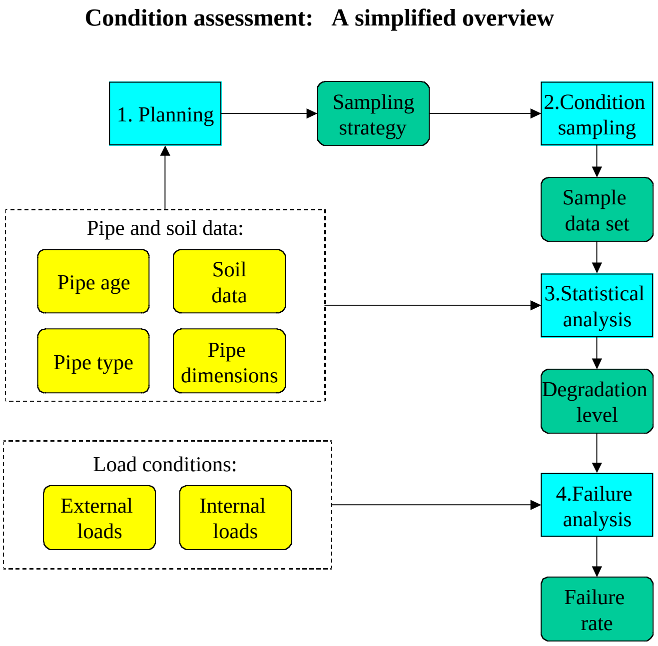

Figure 5: Condition assessment process overview

Note how additional information (ie 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.

5. 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.

5.1. 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 wall thickness is smallest, e.g. where the corrosion is deepest. Therefore we are interested in the maximum corrosion pit depth.

In practice, the family of *Generalised Extreme Value Distributions (GEV)* (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[1] is fitted to maximum pit depth data obtained from each sample area.

$$F(x) = P(X \le x) = 1 - e^{-\left(x/a\right)^c} \qquad (1)$$

a is called the *Scale parameter*
c is a called the *Shape parameter*

The parameters of the Weibull distribution, *a* and *c* are estimated using the Maximum Likelihood Method (Crowder 1991, Blom, 1989). Sampling measurements should be a grouped into a set of numbers x_i: i=1…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 parameters that we need to fit. In other words, the parameters *a* and *c* are chosen such so that the actual sample result is the most probable outcome.

$$Likelihoodfunction = \prod_{i=1}^{n} f\left(x_i \mid a, c\right) \qquad (2)$$

f(x |a, c) is the probability density function. Whilst there are alternatives to the Maximum Likelihood method, it is usually both relatively efficient and simple. The statistical significance will depend on the number of samples that are available. Optimally, 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.

5.2. Extrapolation of pit depth data in space

Having fitted the results to an appropriate distribution, it remains to determine how we can extrapolate these results 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 we are modelling Extreme Values (e.g. minimum or maximum values) 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.. etc; the interesting quantity is

$$Y(n) = \min(X_i) \quad i = 1...n,$$

which is the minimum quote found after *n* queries. *Y(n)* can be assumed to be distributed according to some extreme value distribution (such as Weibull). Intuitively, the probability of finding a good price increases as 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, we choose a number of sample areas and retrieve a set of sample data from each, giving the maximum pit depth. We then estimate an Extreme Value distribution for the maximum pit depth within the sample area, which has an assumed number of pits equal to *n* (this is the same to making *n* queries in the pricing example above). If we want to find the distribution for a larger pipe segment (which has a larger area and a greater number of pits) it follows that we must find the related distribution based on the quota between the relevant areas.

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[1] See equation (1) for the cumulative probability distribution of a two-parameter Weibull distribution. The Weibull distribution is an Extreme Value Distribution and a special case of the general family of GEV distributions.

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). The target area 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

$$Y(k) = \max[X_i] \quad i = 1 \ldots k \tag{3}$$

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 the theory for Weibull distributions (Blom, 1989), the probability distribution function for the maximum pit depth within the target area can then be found using the transformations in equation (4) and (5).

$$a_Y = a_X k^{1/c} \tag{4}$$

$$c_Y = c_X \tag{5}$$

The Weibull distribution parameters a_X and c_X in eqs. (4) and (5) apply to A_s and the parameters c_Y and a_Y apply to A_t. 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 etc). Substantial estimation errors can be made if this recommendation is not followed.

5.3. 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:

<u>Assumption 1: Pit growth function:</u> 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 (ie always increasing) function of time, *p(t)*, describing the pit depth (Aziz, 1956).

<u>Assumption 2: Order preservation</u>: 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:

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

where T is some initial time period.

<u>Assumption 3: Initial pit creation stage:</u> 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 approximation 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, we can assume that we actually sample the pit depth growth rates *d*, during condition assessment.

If pit growth is assumed to be constant in time[2] (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, we get 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 equation (7) is usually assumed to describe the degradation process (note that in this case, assumption 2 above is only valid for $t > T = 1$):

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

The parameters *q* and *d* must be estimated using subsequent measurements on the maximum pit depth at a particular sampling site (according to Laycock, (Laycock et al, 1990) *d* is typically in the range 0,33 to 0,5). If only one measurement is available, we assume a linear model as a first approximation:

$$p(t) = dt \quad (8)$$

The pit depth growth rate, *d*, is a stochastic variable described by some probability distribution with mean $E(d) = \mu$ and variance $V(d) = \sigma^2$. As the pit depths, *p*, are observed, we estimate a distribution for the maximum growth rate parameter $d_{\max}$. The maximum pit depth can then be extrapolated over time as:

$$p_{\max}(t) = p(t, d_{\max}) \quad (8)$$

6. FORECASTING FAILURES BASED ON CONDITION ASSESSMENT

Having outlined several techniques for pipeline condition assessment and the sampling requirements to extrapolate limited data, we now go on to illustrate how condition assessment information can be used to forecast failures. Regardless of material, failure mechanisms in buried pipes can be idealised by the balance illustrated in Figure 6.

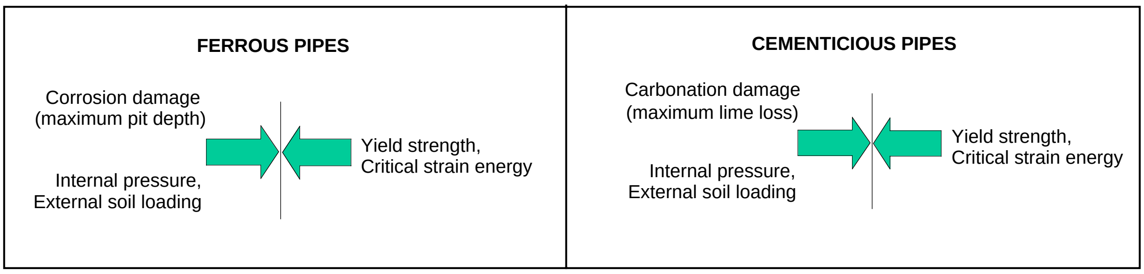

Figure. 6. Failure balance in ferrous and cement based pipes

[2] Assuming that the time is known.

As shown, in-service loading can be split into contributions from internal pressure and external soil loading, attributed to 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 or carbonation in cement based pipes. It follows that failure will occur when both these factors combine to exceed a critical property of the pipeline, such as its yield strength or critical strain energy.

6.1. Probabilistic failure models

Whilst deterministic failure models can be developed to predict remaining service lifetime (Rajani, et al), a range of pipe conditions and loading types will be encountered in a realistic pipe network. To combat this problem, models can be modified to determine the variation in the probability of failure over time (Ahammed and Melchers).

In its simplest form a deterministic failure criterion can be defined for a pipe in service as

$$z = s_f - s_a \tag{9}$$

where s_a is the maximum stress that is imposed in service and s_f is the stress that the pipe can resist without failing. Clearly, s_f will be a function of pipe condition, and s_a will be a function of loading. For example, assuming that a pipe is subjected to internal pressure only, Eq. (9) is re-written as

$$z = s_f - \frac{pr}{b} \tag{10}$$

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 uniform, linear corrosion in metallic pipes, equation (10) can be written as

$$z = s_f - \frac{pr}{(b_0 - d_{\max} t)} \tag{11}$$

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 progresses, the decreasing wall thickness results in an increasing applied stress until failure occurs. Whilst a ‘limit state’ is defined by setting $z = 0$, 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

$$P_f = P(z < 0) \tag{12}$$

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 and Baker, 1982), Level II First-Order-Second-Moment (FOSM) reliability techniques are well suited to this type of problem (Ahammed and Melchers, 1995). In all probabilistic methods, the basic variables that govern failure are assumed to be stochastic, and hence the limit state (eq. (11)) is re-cast in the form

$$Z = f(X_1, X_2, ...X_n) = f(\overline{X}) \tag{13}$$

Z is the stochastic limit state variable and $\overline{X}$ is a random vector of the n stochastic basic variables that comprise the limit state function (ie s_f, p, $d_{\max}$ etc.). Whilst $d_{\max}$ was described by the Weibull distribution in section 5.1, 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 and Baker, 1982). Furthermore, 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, the ‘Normal tail’ transformation is perhaps best suited to Extreme Value distributions (Ahammed and Melchers, 1995). With this assumption in place, all the basic variables can 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

$$P_f = P(z < 0) = \Phi(-\frac{\mu_z}{\sigma_z}) \tag{14}$$

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 and Baker, 1982):

1. Convert all stochastic basic variables in the limit state function (eq. (11)) to equivalent standard normal variables
2. Linearise the limit state function (eq. (11))
3. Use the normal distribution laws for linear functions (Melchers, 1999) to determine μ_z and σ_z and hence calculate P_f from eq. (14)

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 and Baker, 1982).

6.2. A practical example – Mild Steel pipe subjected to external surface corrosion

To illustrate the value of FOSM analysis, let us consider a practical example of a buried Mild Steel Cement Lined (MSCL) pipeline subjected to external surface corrosion. Figure 7 schematically illustrates the layout of the pipeline, which required condition assessment and failure forecasting.

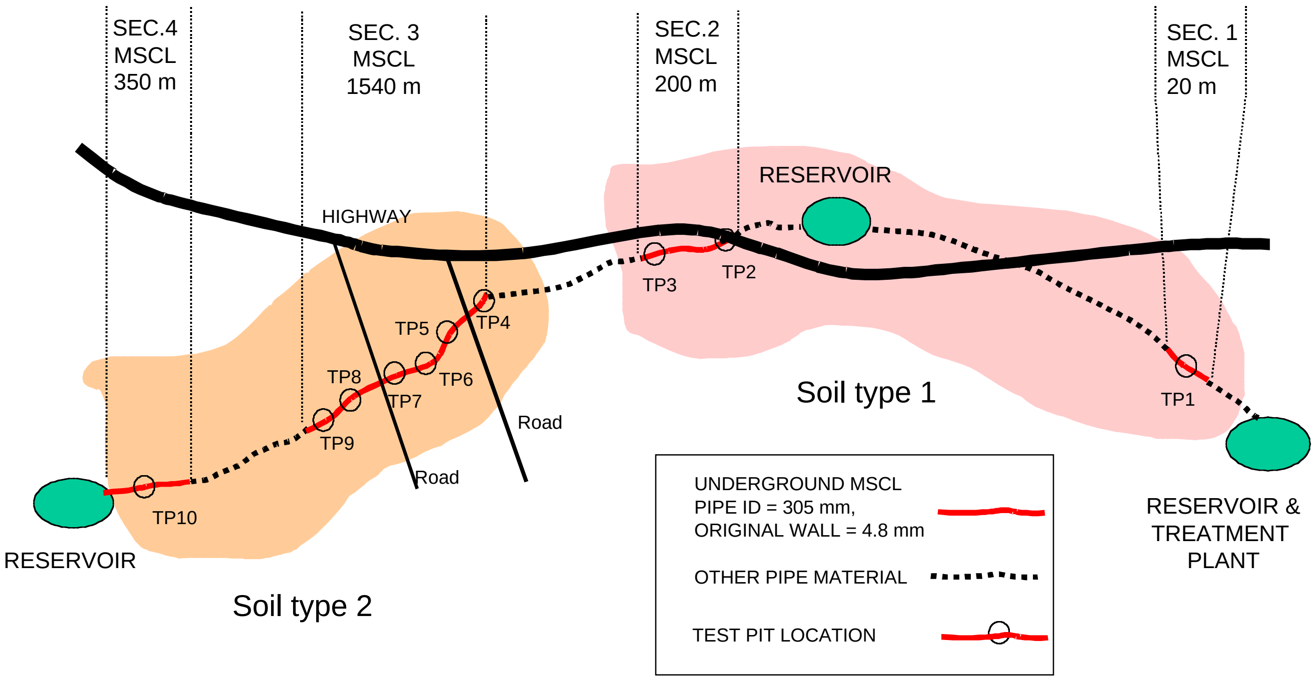

Fig. 7. Schematic layout of Buried Mild Steel Cement Lined pipeline subject to external surface corrosion

As shown, 4 sections of buried Mild Steel Cement Lined (MSCL) pipes were identified, each of different lengths. Those properties that were assumed to be constant within each section of the pipeline are given in Table 4.

Table 4: 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 to 4*	0.169
Original wall thickness, b_0 (mm)	*1 to 4*	4.80
Material yield strength, s_f (MPa)	*1 to 4*	423.0

Whilst these properties were treated as single-valued, the remaining basic variables in eq. (13) were assumed to be stochastic and required condition assessment. As shown in figure 7, geological terrain mapping indicated that the pipeline was buried in two different soil types, (denoted by the shaded areas). Within each soil type, a series of pipe condition assessments were conducted to determine the variation in remaining pipe wall thickness b. Test pits (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 was known, the minimum remaining wall thickness at each test pit location could be converted into a maximum linear corrosion rate $d_{\max}$.

The Weibull probability distribution function outlined in section 5.1 (eq. (1)) was then applied to results from test pits within each soil type, allowing distribution functions to be estimated for $d_{\max}$ (*Table 5*).

Table 5: Distribution parameters for maximum linear corrosion rate, d, within the condition sampling area of 1.5 m^2

MSCL pipe section	TP #	Soil Type	Weibull Distribution parameters for maximum linear corrosion rate *d(mm/year)* $F(d) = P(D \le d) = 1 - e^{-\left(d/a\right)^c}$			
			a	c	*Mean value* $\mu(d)$*(mm/year)*	*Standard deviation* σ_d *(mm/year)*
1 and 2	*1,2 and 3*	*1*	0.070	1.75	0.062	0.037
3 and 4	*4 to10*	*2*	0.034	2.60	0.034	0.012

As shown in table 5, the maximum linear corrosion rate $d_{\max}$ was well represented by the Weibull distribution function with the parameters as shown. Clearly, as reflected in the mean values sections 1 and 2 of the pipeline lie in a more aggressive soil environment than sections 3 and 4.

As outlined in section 5.2, it should be noted that the Weibull distributions given in table 5 apply only to the *sampling area* A_s = 1.5 m^2, and must be extrapolated to describe the distribution over a larger *target area* A_t. For example, if we target an individual MSCL pipe (with an outer diameter of 314.6 mm, and a pipe length of 12 m) for extrapolation, then A_t = 11.89 m^2. Therefore, applying equations (4) and (5) gives the extrapolated distribution of maximum corrosion rates within an individual MSCL pipe (Table 6).

Table 6: Weibull distribution parameters for maximum linear corrosion rate, d, within an individual pipe target area A_t = 11.9 m^2

MSCL pipe section	TP #	Soil Type	Weibull Distribution parameters for maximum linear corrosion rate *d(mm/year)* $F(d)=P(D\le d)=1-e^{-(d/a)^c}$			
			a	*c*	*Expected value* $\mu(d)(mm)$	*Standard deviation* σ_d *(mm/year)*
1 and 2	*1,2 and 3*	*1*	0.228	1.75	0.203	0.112
3 and 4	*4 to10*	*2*	0.075	2.60	0.067	0.028

Following the argument in section 5.2, extrapolating the maximum linear corrosion rate for sections 1 and 2 to the individual pipe area increases the expected value from 0.062 and 0.034 mm/year to 0.203 and 0.112 mm/year. An increase is also observed for pipeline sections 3 and 4.

Having obtained the Weibull distribution function for d_{max}, the next stage of the analysis was to convert it to an equivalent approximate normal distribution functions in order to determine the mean and standard deviation of the limit state variable z in eq. (13). As stated above, the 'normal tail' transformation was used, the details of which are in the literature (Melchers, 1999). Level II FOSM analysis was then used in conjunction with eqs. (11) and (14) to determine the probability of failure, P_f, for an individual pipe in each section. The cumulative failure probability curves are given in Figure 8.

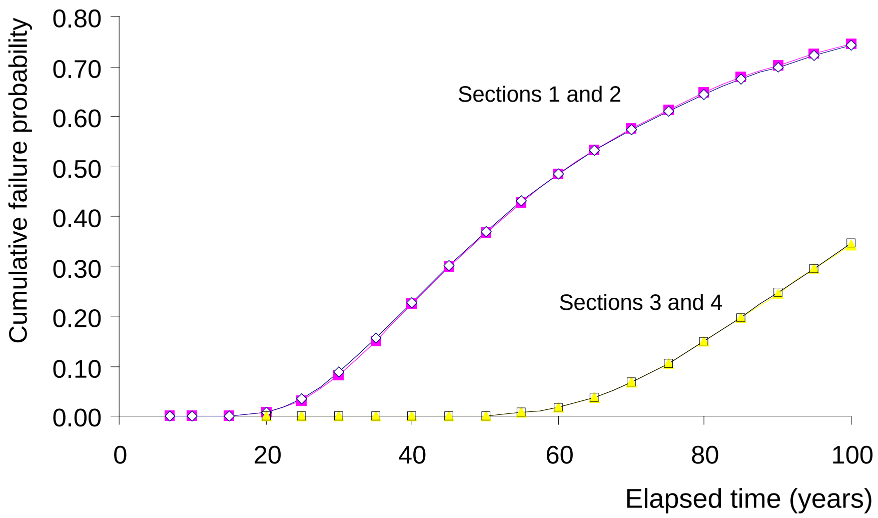

Figure. 8. Cumulative failure probability for an individual MSCL pipe 12 m long

As shown, the relatively high corrosion rate in sections 1 and 2 is reflected by a rapid increase in P_f with elapsed time. Note that this is projected from the time of initial condition assessment. After an elapsed time period of 100 years, P_f = 0.72 compared to 0.3 for sections 3 and 4. Whilst P_f curves for individual pipes are useful, assuming that failures along a complete pipeline follow a binomial probability process (Melchers, 1999) allows the expected failure rate (per km/per year) to be forecast. For example, if each individual pipe sustains one failure, and is assumed to be independent of others, then the expected number of failures in a pipeline *E(N)* is given by

$$E(N)=nh(t) \tag{18}$$

where n is the number of individual pipes in the pipeline; *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 P_f (Melchers, 1999, Thoft-Christensen and Baker, 1982). Therefore, in a 1km length of pipeline, there will be a total of 83.3 (rounded down to 83) individual pipes, and over a 1-year time interval, eq. (18) can be used to determine the expected failure rate *E(N)* (per km/per year) (*figure 9*).

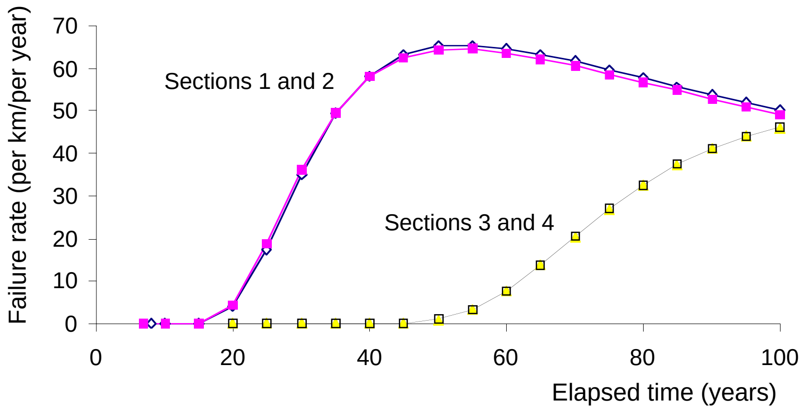

Fig. 9. Cumulative failure probability for MSCL pipeline

As shown in figure 9, the higher corrosion rate in sections 1 and 2 is again evident in a relatively sharp increase in 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.

Clearly if the costs associated with pipe failure are known, then curves of the type shown in *figure 9* can assist the development of long-term pipe replacement and rehabilitation strategies. Therefore, by including statistical analysis of condition data and reliability modelling in the condition assessment process, a complete solution can be obtained.

7. 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.

This paper outlined the statistical basis for extrapolating pipe condition data from a limited number of samples to a wider network. A procedure was described where a pipeline network is initially zoned according to the soil type classification and a sampling program is developed. The distribution of data from a limited number of samples within each zone can then be described using Extreme value statistics. Where appropriate these distributions can be extrapolated to a larger area of pipe network, based on the ratio of actual sample and intended target areas. Level II first-order-second-moment reliability analysis was also combined with condition assessment data to illustrate how pipe failure probability and future failure rates can be estimated. A practical example of a Mild Steel pipeline subjected to external corrosion was used to illustrate the value of this technique in practice.

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.

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