Investigation of Bore Condition Assessment Methodologies and Determination of Remaining Service Life

Shi Ran (Sean) Ding

Jeremy Leggoe
School of Mechanical and Chemical Engineering

Venkat Coimbatore, Des McEwan
CEED Client: Water Corporation

Abstract

Many of the Water Corporation's water bores are nearing the end of their expected design life and the decision for repair or replacement must be made. Due to the anticipated spike in bore expenditure in 2016, it is desirable to reduce financial pressure by identifying bore expenses that can be delayed. This project focuses on developing a methodology for assessing the steel bores using a probabilistic mathematical model to predict the effects of pitting corrosion. The stochastic nature of pitting has been modelled using a Markov process, although the model can be improved using findings from the literature. As the model accounts for different environments, the corrosivity of different rock stratas were investigated and it was concluded that shale and clay were the most severe environments. The Markov model will be adapted to suit pitting corrosion in water as internal damage is of greater concern than external corrosion. Inspection techniques are required to assess the current bore condition and it was found that technology from the oil and gas industry can be adapted. The inspection technique and corrosion model are yet to be verified, and this is likely to be outside the scope of this project.

1. Introduction

The ability to accurately predict asset deterioration and failure adds value to a company, for example by reducing downtime or preventing potential safety incidents. Many of the steel bores at the Water Corporation are nearing the end of their design life of around thirty years, however it is proposed that due to varying environmental conditions, the true lifetimes will vary. It is in the Water Corporation's interest to change their reactive maintenance strategy with bores to a performance based strategy which allows maximisation of asset lifetime time without severely compromising reliability. There is an expected spike in bore expenditure in 2016, hence this project seeks to defer capital expenditure by determining which repairs/replacements can be postponed.

A mathematical model is being developed to predict the Remaining Service Life (RSL) by estimating bore-wall damage. The primary deterioration mechanism is pitting due to Sulphate Reducing Bacteria (SRB), although there are other deterioration mechanisms that need to be accounted for. Due to the stochastic nature of pitting (Caleyo et al. 2009), the model being used is a Markov process model which, theoretically has the ability to predict how a pit-depth distribution changes over time, however attempts are being made to incorporate models by different authors to improve accuracy.

In addition to the model, the Water Corporation is interested in a technique for inspecting pitting damage. There currently exists no specialised technique, so techniques from other industries are being investigated through trials. The trial tests will also play a crucial role for verifying the mathematical model as existing data in this area is scarce. Any successfully trialed techniques may be implemented as part of the company's condition assessment methodology.

2. Project Methodology

This project can be broken down into multiple phases. Stage one is a literature review of Microbiologically Induced Corrosion (MIC) and techniques for inspecting pitting corrosion. Since there are no specialised techniques for inspecting water bores, methods in the oil and gas industry for inspecting steel pipe corrosion were investigated. The techniques needed to satisfy certain requirements such as:

- Ability to do in-situ inspections
- High resolution
- Works on mild/stainless steel
- Accurate
- Relatively affordable
- Locally available

The next stage was compiling location, size, age and construction material data for all of the corporation's bores. Plotting the data helped visualise the number of bores nearing the end of their design life, and allows a rough prediction on short-term expenditure on these assets. Visualising the use of different materials in different regions is important for future inspection prioritisations by identifying regions requiring more attention.

Stage three was a review of the different corrosion environments in each region. Rock stratas at different depths were collated for each region (using bore logs) and investigated to determine their corrosivity to the external casing of ungrouted steel bores. A summary sheet on the corrosivity of each strata was compiled.

The software used for investigating the mathematical model is Mathematica, due to its superiority in visualisation and symbolic manipulation. Once finalised, model will be transferred to an Excel spreadsheet to be handed over as a deliverable. The current inputs for the model include environmental parameters such as pH, the concentration of sulphate and the water content. It also requires the initial pit distribution as measured by the inspection technique.

The final deliverable is a methodology that allows the Water Corporation to systematically decide whether or not to inspect a bore. The triggers for the inspection will be determined collaboratively with the aid of the predictions made by the mathematical model. One method is to use the point when a certain proportion of pits are predicted to be greater than a pre-determined value. The time of the inspection must give enough time for potential maintenance to be carried out before failure occurs.

3. Results and Discussion

3.1 Microbiologically Induced Corrosion (MIC)

It is known that the bores are susceptible to fouling, which subsequently leads to MIC. The mechanisms can be categorised into three groups: differential aeration, change of pH and anaerobic conditions. The uneven formation of a biofilm/scale causes differential aeration by limiting oxygen diffusion in some areas, leading to oxygen concentration cells. In the presence of oxygen, sulphate oxidising bacteria produce sulphuric acid which changes the pH and promotes corrosion. Anaerobic conditions form beneath the biofilm/scale, harbouring anaerobic bacteria like SRB. SRB generates sulphide ions and hydrogen – the sulphide reacts with iron to form mackinawite (scale) while the hydrogen can potentially diffuse into the steel, causing hydrogen attack (Silverman & Puyear 1987). The sulphur oxidising and reducing bacteria form a local ecosystem that survives off the sulphur cycle.

3.2 Inspection Techniques

There are three main categories of inspection techniques that can detect pitting corrosion. Table 1 summarises each category with their abilities. All three techniques are covered by two oil field service companies, which have been contacted to perform trial inspections.

Technique Category	Description	Application
Ultrasonic Techniques (UT)	These rely on the reflection times of acoustic waves to determine the position of interfaces. Interfaces include material changes and defects (NDE Associates 2015).	Mild Steel & Stainless Steel
Magnetic Flux Leakage (MFL) Technique	These rely on saturating a ferromagnetic material with magnetic flux and detecting perturbations in the field due to changes in thickness or defects (NDE Associates 2015).	Mild steel
Eddy Current (EC) Techniques	These rely on detecting the magnetic field generated by induced eddy currents. Because the exciting magnetic field oscillates, this technique works better on non-ferromagnetic materials (NDE Associates 2015).	Stainless steel

Table 1 A summary of the different categories of techniques that can be used to inspect pitting corrosion in steel water bores.

A disadvantage of the ultrasonic technique is it requires water coupling and hence cannot function above the water surface. The MFL and EC techniques operate without a medium but they are only effective on either mild or stainless steel (NDE Associates 2015).

3.3 Soil Strata Profiling

The predominant rock stratas identified were basalt, granite, shale, clay, sandstone and limestone. Conditions can be considered anaerobic a few metres below ground, hence the main parameters that determine the corrosivity of these strata are: water content, pH, resistivity, soluble ions and microbiological activity (Caleyo et al. 2009). After investigating the geobiology of these layers, it was concluded that clay had the greatest potential of harbouring bacteria that caused external pitting. The conditions for bacteria to thrive are: tolerable environmental conditions (e.g. temperature and pressure), the presence of a carbon and energy source and the presence of water (Bachofen et al. 1998). Clay has around 10% organic content, contain sulphur compounds (Hajj et al. 2010) and a high porosity for water and bacteria to reside (Bachofen et al. 1998).

3.4 Mathematical Model

For this project, pitting is modeled as a stochastic process, meaning the exact depth cannot be predicted exactly and a statistical approach must be used. A Markov process model is used to model the change in pit depth distribution over time. The model uses Markov states to represent a pit depth (a low state representing a shallow pit) and the transition between states represents the corrosion process. By constructing a probability density function that evolves with time, the proportion of pits between certain depth values can be tracked. With increasing age, the entire population will shift towards higher states and a threshold can be defined using the probability-of-exceedance of a particular pit depth. The probability density function for a pit being in state n at time t is (Caleyo et al. 2009):

$$p_n(t) = \sum_{m=1}^{n} p_m(t_0) \binom{n-1}{n-m} \left(\frac{t_0 - t_{sd}}{t - t_{sd}}\right)^{\nu m} \left(1 - \left(\frac{t_0 - t_{sd}}{t - t_{sd}}\right)^{\nu}\right)^{n-m}$$

$p_m(t_0)$: Initial pit distribution
n: Number of markov states
m: Current state of the pit
t_{sd}: Time of pitting initiation
t_0: Time of measurement of initial pit depth distribution
ν: Pitting exponent factor (function of environmental parameters)

The equation comes from solving a differential equation known as Kolmogorov's forward equation (also known as the Fokker Planck equation). Assumptions 2 and 3 (see below) enables simplification of the expression from state-transition probabilities to the pit-depth distribution (above). It is important to know the assumptions for this model as it leads to certain limitations. The implications of the four major assumptions are described below.

1. The model deals with identically, independently distributed (IID) random variables (Rivas et al. 2008): This assumes the depth of each pit is independent of all the others. This assumption is questionable for pits in the vicinity of each other however it is a necessary assumption. In fact this assumption means the answer is more conservative as a corroding pit reduces corrosion of surrounding pits (Liu 2013). Melchers and Jeffrey (2008) found cases of bi-modal pitting, where a group of 'stable' pits growth faster than the remaining 'meta-stable' pits, resulting in two peaks in the distribution.
2. The empirical mean pit-depth follows the power law (Caleyo et al. 2009): The time evolution of the average pit depth is known to take the form $D(t) = \kappa(t - t_{sd})^{\nu}$.
3. Model follows a linear growth rate (Caleyo et al. 2009): The physical interpretation is that higher states (deeper pits) grow at a faster rate.
4. The system is memoryless (Caleyo et al. 2009): This means the current pit distribution is independent of the past and predictions for the future can be made using only current data. This is also known as the Markov property.

The model requires data for the initial pit distribution and some environmental parameters for rock corrosivity. According to Shibata (1994), pit depths generally follow the Gumbel distribution, hence a fictitious distribution was constructed for the purpose of visualisation of the model. Figure 1 shows the evolution of the distribution over time. Notice the spread of the curve increases with time – the result of assumption 3. The probability of the pit depth exceeding 9 mm at 30, 40 and 50 years are: 0.1%, 0.8% and 2.5% respectively. If a threshold of 2.5% is chosen, then with the current age being 30 years, the remaining lifetime is 20 years.

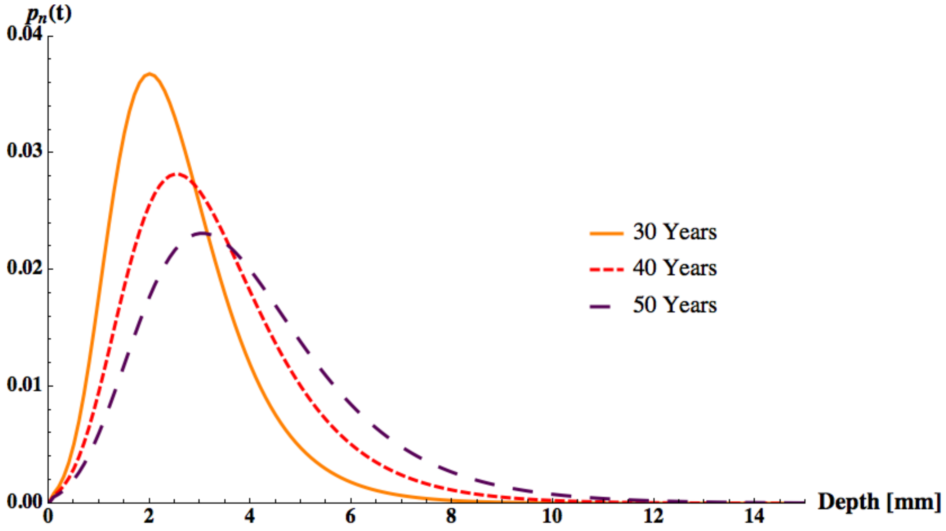

Figure 1 An arbitrary Gumbel distribution used to visualise the evolution of the pit-depth distribution. The age is relative to pitting initiation.

3.5 General issues to Consider

It is uncertain if the inspection techniques accurately detect subsurface cavities (Figure 2). If a significant number of these pits exist and cannot be detected, it will give the wrong impression for the pit-depth distribution.

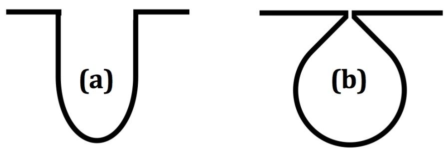

Figure 2 Different pit geometries. It is unknown if subsurface pits (type b) can be accurately measured.

The current model was designed for pitting in soil (Caleyo et al. 2009) so there needs to be a slight adaption for a water environment. In addition, Melchers and Jeffrey (2008) questioned if the power law (assumption 2) for pitting corrosion is applicable to SRB induced pitting. The power law was derived from laboratory experiments and according to Melchers, field data shows the corrosion rate increased significantly upon the onset of pitting due to bacteria.

This paper only outlines one possible approach out of multiple identified possibilities not explained in this paper (for example the block maxima method). These methods can be explored and combined with the findings from Melchers to improve the predictions.

4. Conclusions and Future Work

The aim of this project is to develop a condition assessment methodology to predict the RSL of steel water bores. It is known that pitting corrosion due to SRB is of primary concern and viable techniques for inspection haave been (with trials organised). A Markov process model was reproduced to predict the change in pit-depth distribution over time and this allowed an estimate of the RSL. Even though the methodology will be developed by the end of this project, both the inspection technique and mathematical model need to be verified. The confidence intervals for the predictions should be investigated, similar to what is presented by Liu and Meeker (2015). The complexity of the model can be increased by accounting for pit generation, or it can be refined through synthesis with other models. Overall, the objectives for this project will be achieved and the models can even be extended to manage other assets such as steel pipes and tanks.

5. Acknowledgements

In addition to the direct supervisors, the author would like to acknowledge John McAvan, Luke Zappia, Robin Milne and Melinda Hodkiewicz, who have given advice and/or have inputted some of their own time into this project.

6. References

Bachofen, R., Ferloni, P., Flynn, I. (1998) “Review: Microorganisms in the Subsurface”, *Microbiological Research*, Vol. 153(1), pp. 1-22

Caleyo, F., Velazquez, J., Valor, A., Hallen, J. (2009) “Markov chain modelling of pitting corrosion in underground pipelines”, *Corrosion Science*, Vol. 51(9), pp. 2197-2207

Hajj, H., Abdelouas, A., Grambow, B., Martin, C., Dion, M. (2010) “Microbial Corrosion of P235GH steel under geological conditions”, *Physics and Chemistry of the Earth*, Vol. 35, pp. 248-253

Liu, S. (2013) *Statistical Methods for extreme values and degradation analysis*. Ph.D. Iowa State University.

Liu, S., Meeker, W. (2015) “Statistical Methods for Estimating the Minimum Thickness Along a Pipeline”, *American Statistical Association and the American Society for Quality*, Vol. 57(2), pp. 164-179

Melchers, R., Jeffrey, R. (2008) “Probabilistic models for steel corrosion loss and pitting of marine infrastructure”, *Reliability Engineering and System Safety*, Vol. 93(3), pp. 423-432

NDE Associates (2015) Selection of NDT Techniques for Inspection of Heat Exchanger Tubing. [Online] [Accessed 29th August 2015] <http://www.nde.com/paper54.htm>

Rivas, D., Caleyo, F., Valor, A., Hallen, J. (2008) “Extreme value analysis to pitting corrosion experiments in low carbon steel: Comparison of block maxima and peak over threshold approaches”, *Corrosion Science*, Vol. 50(11), pp. 3193-3204

Shibata, T. (1994) “Application of Extreme Value Statistics to Corrosion”, *Journal of Research of the National Institute of Standards and Technology*, Vol. 99(4), pp. 327-336

Silverman, D., Puyear, R. (1987) ‘Effects of Environmental Variables in Aqueous Corrosion’. In Destefani, J., Frissell, H., Jenkins, D. (eds.) *ASM Handbook Volume 13: Corrosion*. 9th Ed., Materials Park, Ohio: ASM International, pp. 71-88