

Failure prediction and optimal scheduling of replacements in asbestos cement water pipes

Paul Davis, Dhammika De Silva, David Marlow, Magnus Moglia, Scott Gould and Stewart Burn

ABSTRACT

Asbestos cement (AC) pipes are among the oldest assets in many water supply networks. With increasing failure rates and cost consequences, asset management tools are required to pre-empt unplanned failures and schedule future replacement at the most cost-effective time during service. This paper develops a physical probabilistic failure model for AC pipes under combined internal pressure and external loading. Uncertainty in the degradation process is accounted for using the Weibull extreme value probability distribution. Monte Carlo simulation is then used to estimate the probability of pipe failure as ageing proceeds. In the final stage of the model, a cost/benefit analysis is conducted to determine optimal scheduling of future inspection and replacement activities. The end result is a potentially useful asset management methodology in which both the probable physical lifetime and the economic lifetime of an AC pipe can be estimated.

Key words | asset, degradation, economic, lifetime, pipelines, probability

Paul Davis (corresponding author)
Dhammika De Silva
David Marlow
Magnus Moglia
Scott Gould
Stewart Burn
Commonwealth Scientific and Industrial Research
Organisation (CSIRO),
Division of Land and Water,
37 Graham Road,
Highett,
Victoria 3190,
Australia
E-mail: paul.davis@csiro.au

NOMENCLATURE

| | | | |
|----------------|---|------------|--|
| a, b, c | fitting parameters for Herz probability distribution | P | internal pressure of pipe (Pa) |
| B_t | probable failure costs for existing pipe asset at time t (AU\$) | p_c | internal pressure required for failure with no external load (Pa) |
| $C^{INSPECT}$ | cost of inspecting existing pipe asset (AU\$) | s | standard deviation |
| $C^{INSTALL}$ | cost of installing new pipe asset (AU\$) | s_0 | original, as-produced tensile strength (MPa) |
| C_t | probable failure costs for new pipe asset at time t (AU\$) | SEM | standard error of mean |
| d | discount rate for future cash flows | s_f | residual tensile strength at failure (MPa) |
| D | goodness-of-fit test statistic | s_R | degradation (strength loss) rate (MPa/year) |
| $F(s_R), F(t)$ | cumulative probability distributions for degradation rate and pipe lifetime | T_{MAX} | maximum physical lifetime of pipe (years) |
| $f(s_R), f(t)$ | probability density functions for degradation rate and pipe lifetime | w | external load ($N\ m^{-1}$) |
| F_m | bedding factor | w_c | external load required for failure with no internal pressure ($N\ m^{-1}$) |
| H | soil cover depth (m) | Z_{AC} | known cost of failure in existing pipe asset (AU\$) |
| $h(t)$ | hazard (failure rate) function | Z_{NEW} | known cost of failure in new pipe asset (AU\$) |
| N | number of trials in Monte Carlo simulation | α | scale parameter for Weibull extreme value probability distribution |
| NPV | net present value (AU\$) | γ | soil unit weight ($kN\ m^{-3}$) |
| | | δt | time step for analysis (years) |
| | | η | shape parameter for Weibull extreme value probability distribution |

INTRODUCTION

Since the development of asbestos cement (AC) pipes approximately 90 years ago, the total length of AC pipelines in service has increased to approximately 2.4 million kilometres worldwide (NAS 1982). In 1992, AC pipes accounted for an estimated 15% of all pipes installed in North American water supply networks (Kleiner & Rajani 2001). In Australia, a significant fraction of water and sewer networks comprises AC pipes, which were installed between the 1930s and the late 1970s. These pipes are among the oldest assets in many water networks and exhibit relatively high failure rates compared with other pipe materials. In some cases, the consequences of these failures can be severe. At a minimum, direct costs are incurred from trenching, pipe replacement and surface reinstatement. Indirect costs associated with customer service interruption, insurance claims and negative publicity are also often incurred. While difficult to quantify in monetary terms, externalities associated with environmental damage and traffic disruption can also be significant.

To address the problem of ageing water infrastructure and increasing failure consequences, pipeline asset management tools have been developed to prioritise maintenance and rehabilitation in pipe networks (Burn *et al.* 2004; Moglia *et al.* 2006). The essential components of a successful asset management methodology are the ability to predict the time-dependent deterioration and failure of a pipe asset and techniques to quantify the consequences that are incurred upon failure. The level of risk associated with a particular asset can then be quantified and used to schedule future intervention. This paper describes an asset management methodology for AC water pipelines, which comprises the following components:

- A simple probabilistic model to estimate degradation rates in buried AC water pipes
- A service life simulation model to estimate the probability of pipe failure with ageing
- A cost/benefit analysis to help determine the time for future intervention

Each of these individual components is presented in more detail below.

PROBABILISTIC MODELLING OF DEGRADATION IN AC WATER PIPES

For a buried AC pipe in service, internal surface degradation can occur through contact with soft water (Al-Adeeb & Matti 1984) and external surface degradation can occur through contact with high sulphate content soil environments (Davis *et al.* 1998). When in contact with soft water, the loss of strength in cement-based materials is mainly attributed to the increase in cement matrix porosity as cement is leached to the surrounding environment (Saito & Deguchi 2000). In contact with acid sulphate soil environments, expansive degradation products such as gypsum and ettringite can also be produced. While these degradation products offer no structural support, they occupy considerably more volume than the original cement matrix and can cause swelling and, ultimately, pipe fracture (Davis *et al.* 1998).

Residual strength is also influenced by the behaviour of reinforcing asbestos fibres, which are dispersed throughout the cement matrix on pipe manufacture. According to Katz (1996), these fibres are typically short, randomly dispersed and inclined at an angle to any cracks that may develop in the cement matrix due to strength loss. Consequently, the asbestos fibres are subjected to bending stress as these cracks open, which in turn can lead to flexural fibre rupture before the fibre attains its full capacity in direct tension (Katz 1996). As a result, the reinforcing efficiency of these fibres may be reduced as degradation proceeds (Katz 1996). Densification of the cement matrix can also occur through carbonation and can decrease cement matrix porosity (MacVicar *et al.* 1999). This can also increase fibre bending stresses, reducing reinforcing efficiency (Katz 1996).

Although previous experimental research has produced models that predict the decrease in residual strength with cement leaching, the majority of these studies are based on accelerated cement leaching tests conducted under well-controlled laboratory conditions (Carde & Francois 1997; Saito & Deguchi 2000). Consequently, the applicability of these models to AC pipes in service is limited. The problem of residual strength prediction is further complicated by the inherent uncertainty in the environmental conditions that a buried AC water pipe is exposed to. For example, water quality parameters such as pH, alkalinity and calcium

hardness may vary along a pipeline resulting in uncertain cement leaching rates at the pipe inner surface. Variations in soil pH and sulphate content can also influence the rate of degradation at the pipe outer surface (Dorn *et al.* 1996). In addition to uncertainties at the pipe/environment interface, the inherent microstructure of the pipe wall (characterised by cement porosity and asbestos fibre distribution) may also vary along a pipeline due to variations in the manufacturing process and/or different manufacturing methods. Since water quality and soil environment cannot be completely specified along a pipeline, the best approach is to accept that uncertainty in degradation exists and to account for it using an appropriate probability distribution.

To illustrate how a probabilistic model for degradation can be developed, residual tensile strength was measured at various locations along a 600 metre long, 100 mm diameter AC water pipeline. According to water authority data, the pipeline was 40 years old and was installed in clayey, sandy soil. In the absence of non-destructive test methods, residual tensile strength was measured using small coupons extracted from the pipe wall with a tapping tool. Each cylindrical core sample was approximately 20 mm in diameter with its length aligned in the pipe wall thickness direction (Figure 1). At all sampling locations, the pipe wall thickness (and hence core length) was approximately 15 mm.

To determine the residual tensile strength of the pipe wall, core samples were tested according to AS 1012 (Standards Australia 1972). As shown in Figure 1, each sample was compressed by a uniformly distributed load applied along its length while using end constraint. In each

specimen, an indirect tensile stress σ_{xx} is generated in the direction shown, which corresponds to the residual tensile strength at failure s_f . The orientation of core samples was chosen such that the indirect tensile stress was applied in the circumferential direction of the pipe, as is the case under combined internal pressure and diametrical deflection loads. As demonstrated by Davis *et al.* (2005), measured residual tensile strength values can be converted to a linear rate of strength loss (referred to as the 'degradation rate' s_R) given by $s_R = (s_0 - s_f)/Age$ where s_0 is the original, un-degraded tensile strength (Davis *et al.* 2005). According to Katz (1996), a value of $s_0 = 27.0$ MPa is a good first approximation for as-produced, undegraded AC pipe. The degradation rates measured at different locations along the inspected AC pipe are shown in Figure 2.

As shown, measured degradation rates vary significantly from 0.17 MPa year⁻¹ to 0.69 MPa year⁻¹. In previous studies of degradation in AC pipes, this uncertainty has been represented using the Weibull extreme value probability distribution (Davis *et al.* 2005), which has a cumulative probability distribution function $F(s_R)$ given by

$$F(s_R) = 1 - \exp\{- (s_R/\alpha)^\eta\} \quad (1)$$

$F(s_R)$ is the probability that the measured degradation rate is less than a particular value s_R , and α and η are the scale and shape parameters of the Weibull distribution. Taking double logarithms of Equation (1) indicates that a plot of $\ln[-\ln\{1 - F(s_R)\}]$ vs. $\ln(s_R)$ should be roughly linear if the Weibull distribution is appropriate. Following

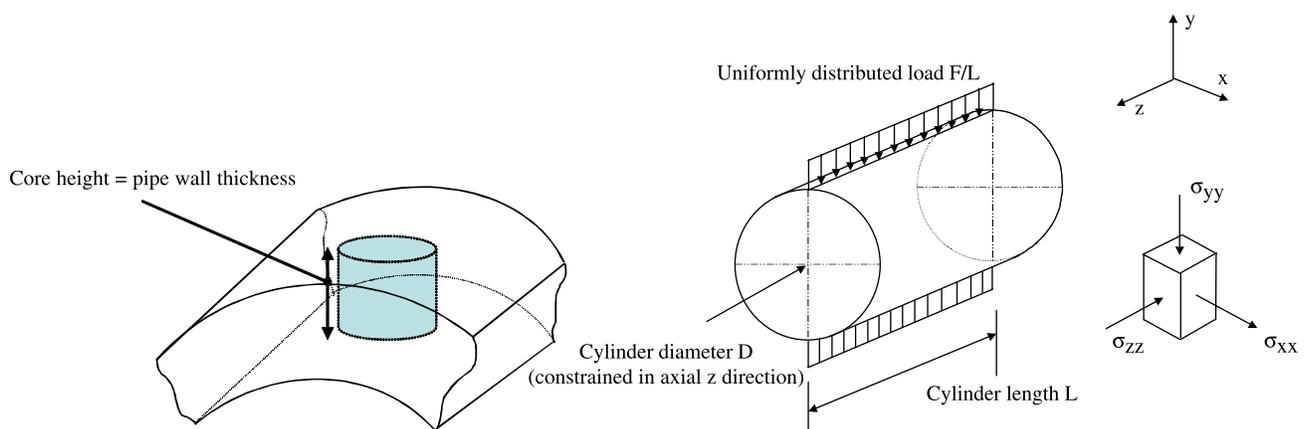


Figure 1 | Orientation of core samples removed from AC pipes in service.

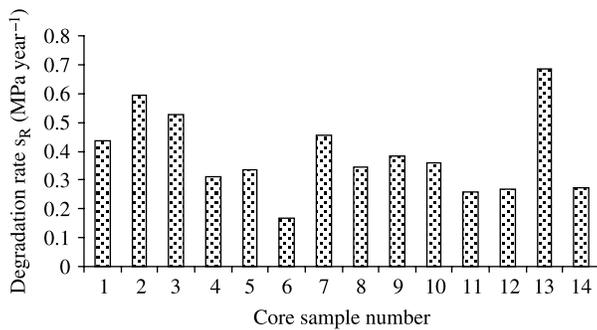


Figure 2 | Variation in measured degradation rate in 100 mm diameter AC water pipe.

Crowder *et al.* (1991), an empirical estimate of $F(s_R)$ can be obtained from the degradation rate data in Figure 2. Figure 3 shows a graphical plot to test the applicability of the Weibull distribution for measured degradation rate. As shown, a linear fit to the data can be achieved with an r^2 coefficient of 0.96. Based on the straight line fit in Figure 3, Weibull scale and shape parameters were calculated as $\alpha = 0.43$ and $\eta = 3.26$. In addition to graphical plotting, a formal goodness-of-fit test was made using the Kolmogorov-Smirnov D -statistic, which is the maximum difference between the proposed cumulative probability distribution (in this case the Weibull distribution) and the empirical distribution based on raw data. Following a procedure outlined by McCuen (2002), a goodness-of-fit test using the estimated values of α and η resulted in a D -value of 0.152, which corresponds to acceptance of the Weibull distribution. The corresponding probability density function for degradation rate was determined by differentiating the cumulative distribution function (Equation (1)) with respect to time to give:

$$f(s_R) = \frac{dF(s_R)}{ds_R} = \eta \alpha^{-\eta} (s_R)^{\eta-1} \exp \{ - (s_R/\alpha)^\eta \} \quad (2)$$

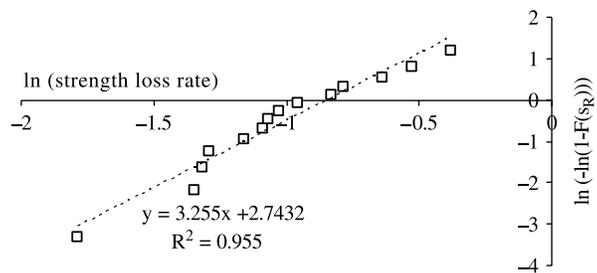


Figure 3 | Weibull plot for degradation rate in 100 mm diameter AC water pipeline (linearity indicates that the Weibull distribution is applicable).

where the probability that the strength loss rate lies within a small interval $[s_R, s_R + \Delta s_R]$ is given by:

$$\Pr(s_R \leq SR < s_R + \Delta s_R) = f(s_R)[\Delta s_R] \quad (3)$$

The probability density function for strength loss rate is shown in Figure 4. As shown, for this particular pipeline, the expected strength loss rate is $0.39 \text{ MPa year}^{-1}$ and the standard deviation is $0.13 \text{ MPa year}^{-1}$.

ESTIMATING FAILURE PROBABILITY WITH PIPE AGEING

Having quantified the uncertainty in degradation rate, a simple failure prediction model was developed for an AC pipe under typical operating loads. Based upon experimental load tests conducted on cast iron pipes, Schlick (1940) demonstrated that, for a brittle pipe subjected to combined internal pressure and uniform external three-edge loading along its length, failure will occur when the following criterion is satisfied:

$$\left(\frac{p}{p_c}\right) + \left(\frac{w}{w_c}\right)^2 > 1 \quad (4)$$

In Equation (4), p is the actual applied internal pressure; p_c is the critical pressure that would cause failure in the absence of any external loading; w is the actual applied external load (in Newtons per metre) and w_c (in Newtons per metre) is the external load that would cause failure with no internal pressure. Although Schlick's (1940) experimental work was originally conducted on cast iron water and gas pipes, the criterion in Equation (4) is used generally to design against failure in all rigid pipeline materials (Watkins & Anderson 1999).

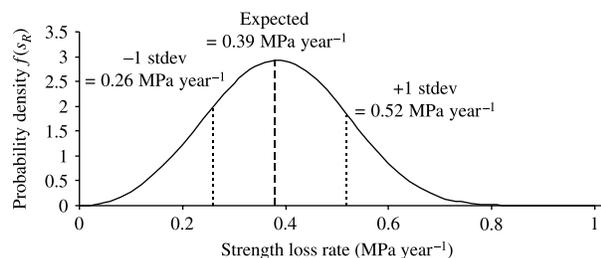


Figure 4 | Weibull probability density function for strength loss rate in 100 mm diameter AC water pipeline.

The critical pressure p_c and critical external load w_c can be written in terms of the current residual tensile strength of the pipe wall as:

$$p_c = \frac{2s_f b}{D}, \quad w_c = \frac{1.048F_m s_f b^2}{D} \quad (5)$$

where s_f is the tensile strength of the pipe wall, b is the pipe wall thickness, D is the pipe mean diameter and F_m is a 'bedding factor' which is equal to 2.5 for gravel beds and surrounds and 1.5 for other soil surrounds (Olliff & Rolfe 2002). Substituting Equation (5) into Equation (4) gives the failure criterion in terms of s_f .

$$\left(\frac{pD}{2bs_f}\right) + \left(\frac{wD}{1.048F_m b^2 s_f}\right)^2 > 1 \quad (6)$$

For a buried pipe in service, the applied external load w comprises an earth load from the surrounding soil and a live surface load from overhead traffic.

$$w = (\gamma H + P_s)(D + b) \quad (7)$$

In Equation (7), γ is the unit weight of the surrounding soil (in kN m^{-3}), H is the pipe cover depth (in metres) and P_s is the live surface load (in kPa). Using the previously defined linear rate of strength loss $s_R = (s_0 - s_f)/\text{Age}$, the time since installation (t) can also be incorporated into the failure criterion.

$$\left(\frac{pD}{2b[s_0 - s_R t]}\right) + \left(\frac{wD}{1.048F_m b^2 [s_0 - s_R t]}\right)^2 > 1 \quad (8)$$

As before, s_0 is the original, undegraded tensile strength of the AC pipe wall. Therefore, if the loading conditions are known along a pipeline, the measured degradation rate can be used to estimate the time to first failure based on Equation (8).

However, since degradation rate is uncertain, the corresponding predicted service lifetime from Equation (8) will also exhibit uncertainty that must be accounted for. A relatively straightforward technique is to use Monte Carlo simulation in conjunction with the physical failure criterion for AC pipes described above. The Monte Carlo simulation samples failure times by repeatedly generating random numbers for degradation rate (based on the Weibull probability distribution) and using these to predict the

time to failure for a set of trials. A number of service lifetimes are predicted, which then allows the mean and standard deviation of pipe lifetime to be estimated. The steps required for Monte Carlo simulation of the physical failure model are outlined below:

1. Set up a hypothetical population of pipes (or trials)
2. Randomly assign degradation rates in each trial based on the Weibull probability distribution function
3. Calculate/assign operating loads for each trial

Time marching loop

4. Increment time
5. Calculate reduction in nominal tensile strength after corrosion
6. Calculate reduced critical pressure and load bearing capacity
7. Check all pipe segments for failure using the criterion in Equation (8)
8. Record all pipe failures before returning to step 4
9. Estimate the expected lifetime and standard deviation from the predicted lifetimes in all trials
10. Calculate the standard error of the mean (SEM) lifetime and check that the number of simulated pipes assigned in step 1 is sufficient

In step 10, it must be demonstrated that the number of trials simulated (i.e. the number of hypothetical pipes chosen in step 1) is sufficient. One commonly used approach is to base this decision on the *standard error of the mean (SEM)* statistic,

$$SEM = \frac{\sigma}{\sqrt{N}} \quad (9)$$

where σ is the standard deviation of the variable of interest (in this case the predicted pipe service lifetime), and N is the number of trials in the simulation.

Case study: 100 mm AC water pipeline subjected to combined internal pressure and external loading

To illustrate how this simulation can be used in practice, a case study of a buried AC water pipe subjected to combined internal pressure and external loading is now analysed. The pipe attributes in Table 1 apply. As shown in Table 1, the previously derived Weibull distribution for degradation rate (Figure 4) is assumed to apply. The results from Monte

Table 1 | Attributes for hypothetical case study: AC pipe under combined internal pressure and external load

| Attribute | Value |
|--|---|
| Diameter (mm) | 100 |
| Wall thickness (mm) | 15 |
| Installation year | 1972 |
| Internal pressure (MPa) | 0.45 |
| Burial depth (metres) | 1.4 |
| Surrounding soil unit weight (kN m^{-3}) ^a | 18 |
| Live surface load from traffic (kPa) ^b | 16 |
| Degradation rate (MPa year^{-1}) | Weibull distribution with $\alpha = 0.43$ and $\eta = 3.26$ |

^aAccording to the Australian standard AS/NZS 2566.1 (Standards Australia 1998), a soil unit weight of $\gamma = 18 \text{ kN m}^{-3}$ can be assumed for sandy, clayey soils.

^bCorresponding to single lane traffic loading in AS/NZS 2566.1 (Standards Australia 1998).

Carlo simulations of this case are summarised in Table 2 for a range of different trials (N). As expected, as the number of trials in each simulation increases, the ratio of SEM/mean lifetime decreases. This is also illustrated by the level of reproducibility in the empirical cumulative probability distribution ($\hat{F}(t)$) that can be determined from the set of lifetimes in each Monte Carlo simulation. Suppose that all predicted lifetimes from a Monte Carlo simulation have been put in ascending order $t_{(1)} < t_{(2)} \dots < t_{(N)}$, where N is the number of trials in the simulation. The empirical cumulative probability distribution is given by $\hat{F}(t) = i/N$; where i is the position of the i th lifetime in the list arranged in ascending order (D'Agostino & Stephens 1986). Figure 5 illustrates how the number of trials N influences the level of reproducibility in $\hat{F}(t)$ attained over ten Monte Carlo simulations. As shown in Figure 5, as the number of trials

N increases, the empirical cumulative distribution becomes more reproducible, with $\hat{F}(t)$ curves effectively collapsing onto a single line for $N = 5,000$.

Having set up a Monte Carlo simulation of service lifetime, the final step in this stage of the methodology is to quantify the probability of pipe failure with ageing. To solve this problem, the probability distribution function for predicted lifetime must be specified. As discussed by Herz (1996), various mathematical distributions can be considered for modelling the probabilistic lifetimes of buried pipelines and some are more applicable than others. For example, the range of application of the normal distribution ($-\infty$ to $+\infty$) permits a negative lifespan, which is unrealistic. Although the logarithmic normal distribution is skewed towards the positive range of lifetimes, the residual life expectancy calculated from this distribution can increase with age, which is also unrealistic (Herz 1996). The exponential distribution could also be applied but, as described by Crowder *et al.* (1991), the corresponding failure rate calculated from this distribution is independent of age, which contradicts failure rates for AC pipes observed in service. While the distributions discussed above are rejected because of their unrealistic outcomes, the Weibull distribution remains and may be suitable for modelling pipe lifetime data (Herz 1996). The suitability of the Weibull distribution to predicted lifetimes from the Monte Carlo simulation is assessed in Figure 6, which shows a Weibull plot for predicted service lifetimes from Monte Carlo simulation #5 ($N = 5,000$). As with the degradation rate data in Figure 3, with service lifetime denoted as t , a plot of $\ln[-\ln(1 - F(t))]$ vs. $\ln(t)$ should be roughly linear if the Weibull distribution is applicable. As shown, predicted

Table 2 | Results from Monte Carlo simulations on 100 mm diameter AC pipe

| Simulation number | Number of trials in simulation, N | Expected (mean) lifetime (years) | Standard deviation of lifetime (years) | Standard error of mean lifetime (SEM) | SEM/mean lifetime (%) |
|-------------------|-------------------------------------|----------------------------------|--|---------------------------------------|-----------------------|
| 1 | 50 | 71.62 | 24.73 | 3.50 | 4.88 |
| 2 | 100 | 72.87 | 24.83 | 2.48 | 3.41 |
| 3 | 500 | 74.08 | 41.61 | 1.86 | 2.51 |
| 4 | 1,000 | 76.45 | 37.87 | 1.20 | 1.57 |
| 5 | 1,500 | 76.44 | 42.66 | 1.10 | 1.44 |
| 6 | 2,000 | 75.21 | 40.56 | 0.91 | 1.21 |
| 7 | 5,000 | 75.80 | 43.46 | 0.61 | 0.81 |

lifetime data clearly departs from the straight line prescribed by the Weibull distribution, indicating that the Weibull distribution is not applicable. A possible alternative is the so-called ‘Herz distribution’, which was specially developed to model uncertainty in water pipeline service lifetime (Herz 1996). The Herz cumulative probability distribution for service lifetime is written as:

$$F(t) = 1 - \frac{a + 1}{a + \exp[b(t - c)]} \quad (10)$$

where a , b and c are constants. Whereas the applicability of the Weibull distribution to a particular data set can be assessed using a linear plot (as in Figure 5), the applicability of the Herz distribution is analysed using the empirical cumulative probability distribution. The parameters a , b and c in Equation (10) are chosen to provide the best match between empirical and proposed distributions based on the Kolmogorov-Smirnov D -statistic (i.e. the maximum difference between the proposed cumulative distribution and the empirical distribution). Using the Microsoft Excel

Solver add-in tool, the parameters a , b and c can be chosen to minimise this D -statistic. A goodness-of-fit test requires the Kolmogorov Smirnov D -statistic to be determined and compared with a maximum allowable value of $D = 1.95$ for acceptance of the distribution. D -values greater than this threshold indicate rejection of the Herz distribution. As outlined by D’Agostino & Stephens (1986), the D -statistic obtained from fitting the empirical distribution to the Herz distribution is multiplied by $(N^{0.5} + 0.12 + 0.11/N^{0.5})$ to account for sample size. Values of Herz parameters and corresponding scaled D -statistics are given in Table 3. Although the reproducibility of each Monte Carlo simulation improves with increasing trial numbers (indicated by a decreasing SEM /mean lifetime ratio), the Herz distribution becomes less appropriate indicated by an increasing scaled D statistic. This is due to the scaling factor required for the number of trials N which provides a stricter test for larger sample sizes (D’Agostino & Stephens 1986). Referring to Table 3, it can be seen that the Monte Carlo simulation

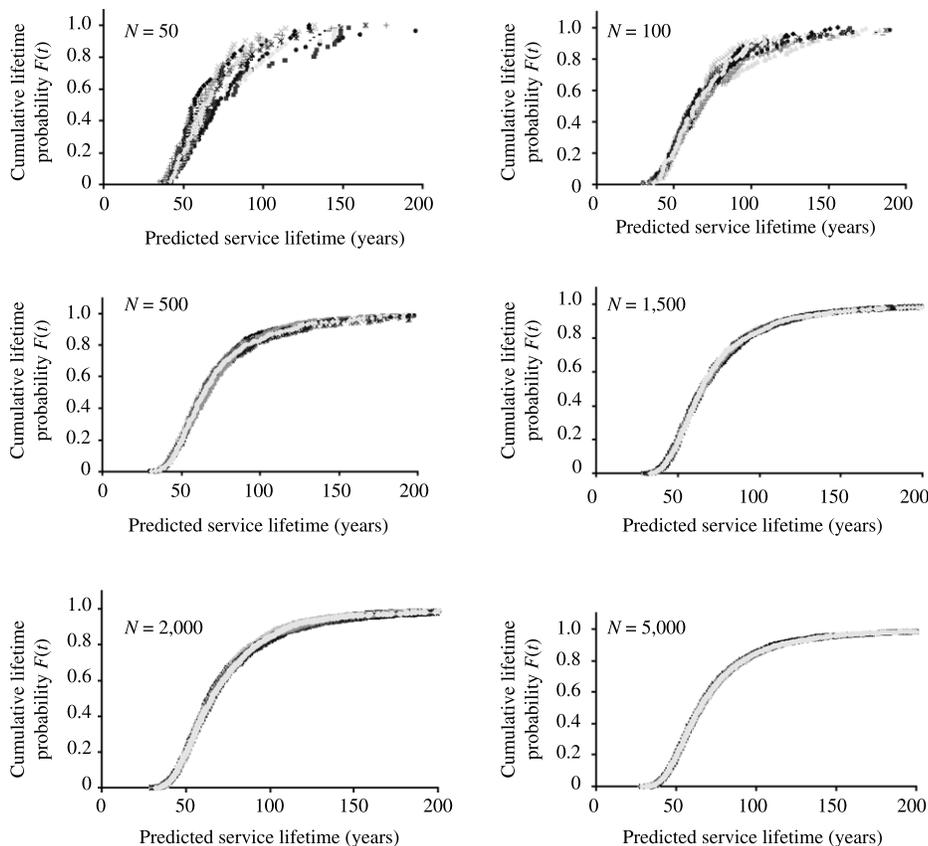


Figure 5 | Influence of number of trials over reproducibility in empirical cumulative probability distribution $\hat{F}(t)$ (ten Monte Carlo simulations were run to construct each graph).

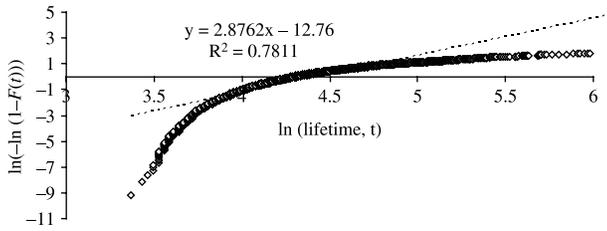


Figure 6 | Weibull plot for predicted service lifetimes in simulation #4 with $N = 5,000$ (non-linearity indicates that the Weibull distribution is not applicable).

with 1,500 trials passes the goodness-of-fit test for the Herz distribution and results in a *SEM*/mean lifetime ratio of 1.44%. Although this is slightly higher than the recommended 1% stopping rule which has been previously specified for Monte Carlo simulations (Schuyler 1997), the level of reproducibility attained from simulations with $N = 1,500$ trials (Figure 5) is deemed sufficient for this study. Although the 3-parameter Weibull distribution could also be explored, the Herz distribution has the advantage of a failure rate that increases with age approaching a boundary value (Herz 1996). This trend is frequently observed in historical failure rate data for water pipelines. Figure 7 compares the fitted Herz distribution with the empirical cumulative distribution obtained from the Monte Carlo simulation with $N = 1,500$ trials.

The corresponding lifetime probability density function $f(t)$ for the Herz distribution is obtained by differentiating Equation (10) to give

$$f(t) = \frac{dF(t)}{dt} = \frac{(a + 1)b \exp [b(t - c)]}{\{a + \exp [b(t - c)]\}^2} \quad (11)$$

The probability density function $f(t)$ is plotted in Figure 8 together with the arithmetic mean and standard deviation

in predicted service lifetimes obtained from the Monte Carlo simulation with a trial number $N = 1,500$. The probability that the predicted service lifetime lies within an interval $[t, t + \Delta t]$ is given by:

$$\Pr(t \leq T < t + \Delta t) = f(t)[\Delta t] \quad (12)$$

Another useful measure of ageing is the hazard function $h(t)$ given by:

$$h(t) = \frac{f(t)}{1 - F(t)} \quad (13)$$

where, as described above, $f(t)$ is the probability density function in Equation (11) and $F(t)$ is the cumulative distribution. As described by Crowder *et al.* (1991), the hazard function is a natural indicator of the ‘proneness to failure’ of a unit after time t has elapsed. For a time interval $[t, t + \Delta t]$, the conditional probability of failure at time t , given that failure has not yet occurred, is given by:

$$\Pr(t \leq T < t + \Delta t | T \geq t) = h(t)[\Delta t] \quad (14)$$

The hazard function for the AC pipe in this study is obtained from Equations (10) and (11) and shown in Figure 9.

As demonstrated by Herz (1996), the hazard function can also be interpreted as the renewal rate for a particular pipeline; $h(t)$ corresponds to the percentage of the current pipe length that will require rehabilitation at a given age (Herz 1996). As shown in Figure 8, the renewal rate for the AC pipeline in this study increases to approximately 5% at an age of 100 years and then remains effectively constant.

Table 3 | Goodness of fit D -statistics for representing simulated service lifetimes by the Herz distribution

| Simulation number | Number of trials in simulation, N | <i>SEM</i> /mean lifetime from MC simulation (%) | Herz parameter a | Herz parameter b | Herz parameter c | Scaled goodness of fit D -statistic ^a (D^*) | Herz pass/fail ($D^* < 1.95$) |
|-------------------|-------------------------------------|--|--------------------|--------------------|--------------------|--|---------------------------------|
| 1 | 50 | 4.88 | 4.86 | 0.05 | 31.59 | 0.374 | Pass |
| 2 | 100 | 3.41 | 5.48 | 0.06 | 33.53 | 0.575 | Pass |
| 3 | 500 | 2.51 | 3.93 | 0.06 | 34.69 | 1.460 | Pass |
| 4 | 1,000 | 1.57 | 3.95 | 0.06 | 33.92 | 1.599 | Pass |
| 5 | 1,500 | 1.44 | 2.66 | 0.05 | 36.16 | 1.887 | Pass |
| 6 | 2,000 | 1.21 | 4.41 | 0.06 | 34.83 | 2.280 | Fail |
| 7 | 5,000 | 0.81 | 4.49 | 0.06 | 33.75 | 3.533 | Fail |

^a $D^* = D(N^{0.5} + 0.12 + 0.11/N^{0.5})$.

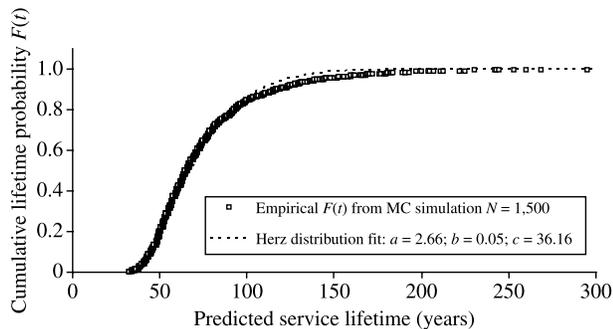


Figure 7 | Comparison between empirical service lifetime distribution (based on the Monte Carlo simulation with $N = 1,500$ trials) and the fitted Herz distribution.

While the hazard function $h(t)$ could be used to forecast the required renewal investment as a pipeline ages (Herz 1996), the precise scheduling of future interventions depends on the risk associated with the pipeline and the risk aversion level of the particular water authority concerned. For example, if the consequences of failure are perceived to be relatively low, the decision to intervene may be deferred until an upper limit (or optimistic) estimate of lifetime is reached. For example, this could correspond to 1 standard deviation after the expected time to failure in Figure 7. Alternatively, if the consequences of failure are perceived to be relatively high, a more risk-averse strategy may be adopted; that is, to intervene at a lower limit (or pessimistic) estimate of lifetime set by the lower limit of 1 standard deviation before the expected time to failure in Figure 7.

The models presented above relate only to the *physical* lifetime of an asset. As such, the models only consider some of the factors involved in scheduling future interventions; economic factors are not explicitly considered. By combining these physical lifetime models with failure cost consequences, however, the level of risk associated with a pipe can be estimated as it ages. The *economic* lifetime can

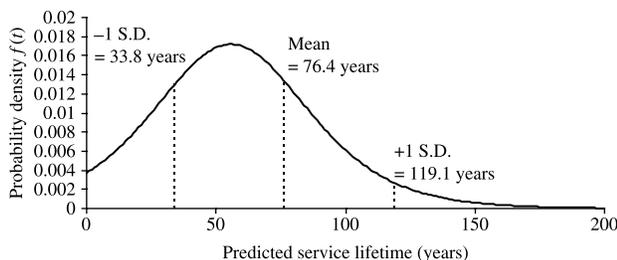


Figure 8 | Herz lifetime probability density function for AC water pipeline.

then be chosen to maximise the benefits accrued from a pipe in comparison with the cost of ownership. From this perspective, an intervention by the water utility can be seen as an investment that will reduce future costs and externalities. The following section of this paper proposes a methodology that uses the physical probabilistic model developed so far to schedule future interventions at the most cost-effective time.

COST/BENEFIT ANALYSIS TO SCHEDULE FUTURE INTERVENTIONS

The decision to intervene can be based on the net present value (*NPV*), and this indicator is used in the final stage of this asset management methodology, to give a measure of the economic lifetime of an AC pipe. *NPV* is taken to be the difference between benefits and costs ($B-C$) over time presented in terms of present day monetary values. The *NPV* is usually a measure of the total benefit of an investment. As such, a $NPV < 0$ would indicate that intervention is not value-adding. However, in this example, the benefits of owning the asset derived from its ability to provide service are assumed to be the same before and after the intervention. These benefits can therefore be ignored, given the assumption that the asset continues to serve a necessary function. It should also be recognised that the drivers for interventions are not purely financial, but also relate to regulations, key performance indicators and the responsibility to deliver a service to the community. As such, a negative *NPV* could be accepted in certain circumstances.

Since the decision horizon of buried pipe assets encompass many years, the time value of money is considered by discounting future cash flows. The discount rate, d , allows the present value of future cash flows to be

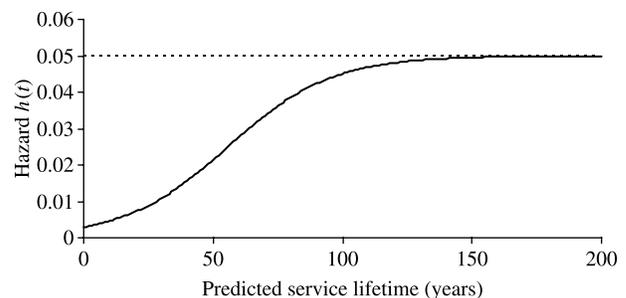


Figure 9 | Herz hazard function for AC water pipeline.

calculated and accounts for interest rate and an additional value for financial risk. In this case, the present value of a future cash flow is calculated using a discounting factor $(1 + d)^{-t}$ where t is the time (in years) from the present. The NPV of intervention at time, T , is therefore given by:

$$NPV = \underbrace{\left\{ \sum_{t=T}^{T_{max}} [B_t - C_t] \cdot (1 + d)^{-t} \right\}}_{Benefit} - \underbrace{\left\{ [C^{INSPECT} + C^{INSTALL}] \cdot (1 + d)^{-T} \right\}}_{Cost} \quad (15)$$

The first bracketed term in Equation (15) represents the benefit associated with the water authority’s intervention in the pipeline. This benefit is defined as the difference between those failure costs likely to be incurred by keeping the existing pipe in the ground, and those failure costs likely to be incurred by replacing the existing pipe with a new pipe at time T . B_t refers to the failure costs at time t predicted for the existing pipe asset (which would be removed by intervening), while C_t refers to the failure costs at time t predicted for the new replacement pipe used. These costs are summed up to the maximum physical lifetime of the existing AC pipe (T_{MAX}). Referring to Figure 8, a value of $T_{MAX} = 119.1$ years (1 standard deviation after the expected time to failure) is arbitrarily chosen for the example AC pipe in this study. Since failure costs from the present ($t = 0$) to the time of intervention ($t = T$) are the same with and without intervention, they cancel each other out in the benefit calculation and do not appear in the first bracketed term in Equation (15). The second bracketed term in Equation (15) contains the costs associated with intervention. $C^{INSPECT}$ is the cost of inspecting the existing pipe before replacement. It is assumed that a water authority would always precede pipe replacement by inspection since new information on the condition of an asset would allow the lifetime probability distribution to be refined. If this were not the case then $C^{INSPECT}$ would be zero. $C^{INSTALL}$ is the cost of installing a new pipe at time T .

At any time during the service life, the expected failure costs of the existing pipe (B_t) and the new replacement pipe (C_t) are defined over a time δt as:

$$B_t = f\left(t + \frac{\delta t}{2}\right)_{AC} \delta t \cdot Z_{AC}, \quad C_t = f\left(t + \frac{\delta t}{2}\right)_{NEW} \delta t \cdot Z_{NEW} \quad (16)$$

$f(t)_{AC}$ is described by the Herz lifetime probability density function derived above, and for simplicity is evaluated at the mid point of the time interval δt . Z_{AC} is the cost consequence of AC pipe failure. Similarly, $f(t)_{NEW}$ is the lifetime probability density of the new replacement pipe and Z_{NEW} is the failure cost consequence for this new pipe. These cost consequences should include the direct costs of repair and subsequent replacement. If possible, estimates of costs incurred by traffic and customer disruption (i.e. externalities) should also be included.

The schematic diagram in Figure 10 illustrates how the costs B_t and C_t are used to calculate the NPV of intervention. As shown, the failure cost (B_t) is incurred up to time $t = T$ regardless of intervention. Therefore, as stated above, these costs cancel each other in the calculation of benefit and do not appear in Equation (15). However, from the intervention time onwards, failure costs incurred by the new pipe (C_t) would be lower due to its relatively low failure probability. Costs associated with inspecting the existing pipe ($C^{INSPECT}$) and installing the new replacement pipe ($C^{INSTALL}$) are incurred at the time of intervention.

To illustrate how the economic lifetime of the AC pipe can be calculated, the previous hypothetical example is revisited with the assumption that costs in Table 4 apply.

Using the amounts in Table 4, the cost consequences of failure (Z_{AC} and Z_{NEW}) are given by the sum of the direct costs and indirect costs (i.e. negative impacts on third party or environment). Only the direct consequences (carried by the water authority) are subject to discounting. This assumption is made for two reasons: 1) indirect costs cannot be invested; and 2) externalities are carried by

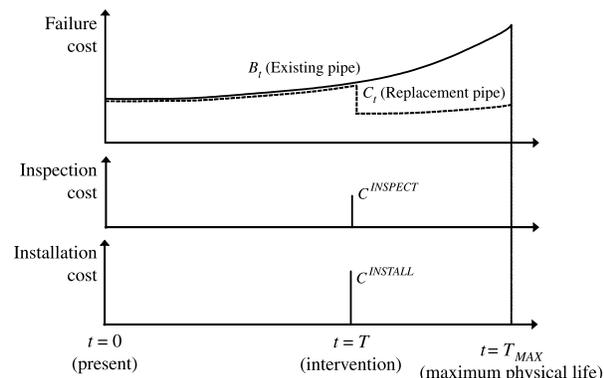


Figure 10 | Variation of failure for existing pipe (B_t) and replacement pipe (C_t) with time.

Table 4 | Costs of failure and inspection for AC pipeline

| Direct costs | Value (AUS) |
|--|-------------|
| Repair costs | 3,000 |
| OH&S cost ^a | 500 |
| Trench excavation costs ^b | 1,500 |
| New pipe installation cost ^c | 1,800 |
| Backfill and reinstatement cost ^d | 900 |
| Total replacement cost | 7,700 |
| Indirect costs | |
| Traffic disruption costs (\$/vehicle/hour) | 2.72 |
| Repair time (hours) | 3 |
| Traffic density (vehicles/hour) | 300 |
| Total traffic disruption cost over repair time | 2,448 |
| Number of connections to the main | 23 |
| Number of customers per connection | 5 |
| Percentage of failures that lead to interruptions (%) | 100 |
| Social cost per interruption (\$/customer/hour) | 7.77 |
| Total penalty cost per customer interruption (\$) | 2,680.65 |
| Inspection costs | |
| Cost of one core sample measurement of degradation rate (\$) | 500 |

^aOccupational health and safety cost paid to contractors handling AC pipe failures.

^bBased on 6 m long, 2 m wide and 4 m deep trench.

^cBased on 6 m of 100 PVC pipe.

^dBased on bitumen surface reinstatement.

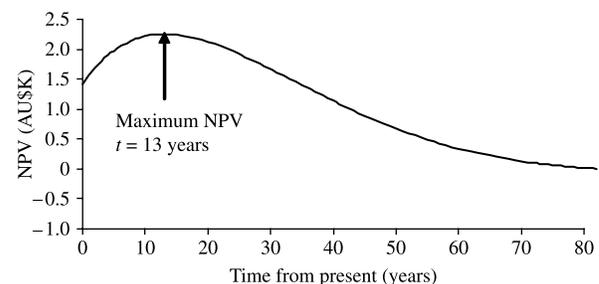
a third party who may not be in a position to invest any lost money alternatively. For this particular example, the direct costs per failure for the existing AC pipe are equal to AU\$7,700 and the indirect failure costs are AU\$2,448 + AU\$2,680.65 = AU\$5,128.65. With the exception of the health and safety cost of US\$500 (which is incurred by contractors handling asbestos), these direct and indirect consequences are also assumed to apply to any failure in the new replacement pipe. The inspection cost ($C^{INSPECT}$) is given by the cost of inspecting the existing pipe wall for degradation using one core sample to measure degradation (= AU\$500). The direct cost of new pipe installation ($C^{INSTALL}$) is given by the sum of trenching, pipe installation and surface reinstatement costs (AU\$1,500 + AU\$1,800 + AU\$900 = AU\$4,200).

The variation of intervention NPV can now be plotted against pipe age using Equation (15). A 1-year time step ($\delta t = 1$) is adopted for all calculations together with a discount rate of 7%, which is representative of discount

rates currently adopted by Australian water authorities. The ageing of the existing AC pipe is characterised by the Herz lifetime probability distribution derived previously. It is assumed that failed AC pipes are replaced by new PVC pipes, which exhibit a lifetime probability density ($f(t)_{NEW}$) that follows the Weibull extreme value distribution. Previous research has shown that, for the pipe size and operating conditions specified in Table 1, Weibull scale and shape parameters of $\alpha = 395$ and $\eta = 1.3$ represent the variation in predicted service lifetime for PVC pipes reasonably well (Davis et al. 2006). Figure 11 shows the variation in calculated NPV of intervention for this hypothetical example. As shown, over the service lifetime of the pipe, the net present value of intervention (NPV) reaches a maximum of AU\$2,255 at 13 years from the present time. Referring back to Table 1, it can be seen that the AC pipe under investigation was installed in 1972, which means that it is currently 34 years old. Therefore, with the new information in Figure 10, a water authority could decide to run the main until it is 47 years old, with the knowledge that, after this time, it becomes less cost-effective should they replace the pipe. The economic and physical lifetimes for this hypothetical case study are compared in Figure 12.

DISCUSSION

The development of the modelling approach described above has been undertaken to help water authorities refine their approaches to asset management. Asset management is, in essence, a framework for delivering sustained service provision through timely interventions in an asset stock. When available budgets and resources are limited, as is generally the case, formalised approaches to asset management can help a water authority to develop a

**Figure 11** | Calculated NPV of intervention for AC water pipeline.

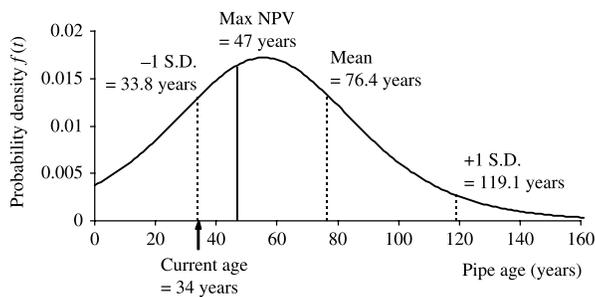


Figure 12 | Comparison of physical and economic lifetime of the AC water main.

replacement strategy that reduces the overall costs borne by customers, the wider community and the environment. One element of such a strategy is to defer asset replacement where possible, but only up to the point where this is economically justified. Ideally, this point would be identified explicitly through consideration of both the probability and consequences of asset failure, and the cost of asset replacement.

In many water authorities, replacement decisions are often made in the absence of asset-specific data using engineering judgement and/or with reference to historical practices. When the potential risks of asset failure are high, such approaches will tend to result in conservative decision making, which means an asset's maximum economic life may not be achieved. Conversely, excessive levels of risk might be carried by water authorities that defer asset replacement too much. Analytical techniques that explicitly consider all the significant risk factors involved are thus desirable, as these will, to the extent that is possible, allow a consistent analysis of risk to be applied to decision support, and help remove subjectivity and bias. The cost of any analysis undertaken should, however, be proportional to the level of investment and risk involved.

The first challenge for any water authority is to understand the risk profile across the entire asset stock, and to identify those assets where more detailed analysis is likely to accrue net benefit; that is, where the improvement in decision making realised by the analysis will justify the cost of undertaking that analysis. Once these assets are identified, asset-specific techniques are required to assess remaining economic life and thereby improve the timing of interventions.

This paper has sought to illustrate one approach to this asset-specific analysis, and the development of a model to

estimate the probability of failure in asbestos cement pipelines has been illustrated. This model was combined with cost consequence information to illustrate how the most cost-effective time of future intervention can be estimated. While the current model is useful, it is based on a number of assumptions and the following areas are identified for improvement:

Calculating degradation rate in the pipe failure model

In the absence of experimental data, the as-produced tensile strength required by the model was assumed from values in the literature and in previous Australian performance standards. However, it should be noted that manufacturing methods for AC pipes have changed since its original introduction to the water pipe industry. As described by Scott (1990), the use of autoclave curing and the addition of fine silica powder in 1954 produced pipes with increased mechanical strength compared with those manufactured by earlier methods. Further work is required to identify values of as-produced strength for each of the manufacturing methods used since the introduction of AC pipes. The pipe failure model also assumes that the as-produced strength of a pipe in service decreases linearly over time. This assumed constant rate of strength reduction also requires further investigation. For example, in tests on cement-based samples submerged in water, Saito & Deguchi (2000) reported a linear relationship between the amount of leaching and the reduction in compressive strength. However, their results also indicate that the amount of cement leaching was proportional to the square root of exposure time (Saito & Deguchi 2000). This suggests that the assumed constant rate of strength loss over time may not be applicable. Further experimental work is required to quantify the actual time dependence of strength reduction for AC pipes in service.

The sensitivity of economic lifetime

The estimated failure probability from the pipe failure model was combined with cost consequences to quantify the value of intervention over time. The economic lifetime of a pipe was assumed to expire at the time of maximum net present value (NPV) of intervention. Exploration of the

model indicates sensitivity to discount rate (d) with a reduction in economic lifetime observed as d decreases (a discount rate of 4% reduces the economic lifetime to 8 years from the present compared to 16 years at $d = 7\%$). In contrast, the economic lifetime appears to be relatively insensitive to increases in discount rate; with d increasing to 11%, the maximum NPV time remains at 15 years. While economic lifetime depends on discount rate, the most dramatic change was in response to the exclusion of external costs and externalities from the analysis. If those costs incurred from customer interruption and traffic disruption are ignored, negative NPV values are calculated over the service life of the pipe, suggesting that it is *never* cost-effective to intervene.

It should also be noted that the consequences incurred upstream or downstream of a failure were also omitted. In practice, failure of a large diameter water supply main will result in service interruptions elsewhere in the network in those locations that rely on supply from the failed main. To capture these remotely incurred, yet related consequences of a single main failure, the hydraulic connectivity of the pipe network needs to be defined. Further work is clearly required to identify an appropriate costing and discounting structure to model the costs of long-term failures in buried water pipelines.

CONCLUSIONS

As buried water pipeline assets age, their failure rates increase and they incur higher cost consequences. In Australia, asbestos cement pipes are among the oldest assets in many networks and, consequently, they exhibit the highest failure rates. To pre-empt unplanned failures and schedule future replacement and rehabilitation activities for AC pipes, an asset management methodology has been developed with three main components: 1) quantification of degradation rates in AC pipes; 2) prediction of service lifetime for an AC pipe under expected operating loads; 3) economic analysis for optimal scheduling of future interventions. While this preliminary study suggests that the methodology will be useful to support decision making by asset managers, further work can be undertaken to improve the academic rigour of the approach, namely:

- Identify changes in tensile strength for as-produced AC pipes manufactured by different processes
- Quantify the time dependency of strength loss rate for AC pipes in service
- Identify an appropriate costing structure and discount rate to model the cost consequences of pipe failures over time

Work in these areas is progressing at CSIRO.

REFERENCES

- Al-Adeeb, A. M. & Matti, M. A. 1984 Leaching corrosion of asbestos cement pipes. *Int. J. Cem. Compos.* **6**(4), 233–240.
- Burn, S., Ambrose, M., Moglia, M., Tjandraatmadja, G. & Buckland, P. 2004 Management strategies for urban water infrastructure. *Proceedings of the IWA World Water Congress and Exhibition*, 19–24 September 2004, Marrakech, Morocco.
- Carde, C. & Francois, R. 1997 Effect of the leaching of calcium hydroxide from cement paste on the mechanical and physical properties. *Cem. Concr. Res.* **27**, 539–550.
- Crowder, M. J., Kimber, A. C., Smith, R. L. & Sweeting, T. J. 1991 *Statistical Analysis of Reliability Data*. Chapman and Hall, London.
- D'Agostino, R. B. & Stephens, M. A. 1986 *Goodness-of-Fit Techniques*. Marcel Dekker, New York.
- Davis, J. L., Nica, D., Shields, K. & Roberts, D. J. 1998 Analysis of concrete from corroded sewer pipe. *Int. J. Biodet.* **42**, 75–84.
- Davis, P., De Silva, D., Gould, S. & Burn, S. 2005 Condition assessment and failure prediction for asbestos cement sewer mains. *Proceedings of the Pipes Wagga Wagga Conference*, 17–20 October 2005, Australia.
- Davis, P., Burn, S., Moglia, M. & Gould, S. 2006 Physical probabilistic model to forecast failure rates in PVC water pipelines. *J. Reliab. Eng. and Sys. Safety* **92**(9), 1258–1266.
- Dorn, R., Howsham, P., Hyde, R. A. & Jarvis, M. G. 1996 *Water Mains: Guidance on assessment and Inspection Techniques*. Report 162, CIRIA, London.
- Herz, R. K. 1996 Ageing processes and rehabilitation needs of drinking water distribution networks. *J. Wat. Suppl. Res. & Technol.-AQUA* **45**, 221–231.
- Katz, A. 1996 Effect of fiber modulus of elasticity on the long term properties of micro-fiber reinforced cementitious composites. *Cem. Concr. Compos.* **18**, 389–399.
- Kleiner, Y. & Rajani, B. 2001 Comprehensive review of structural deterioration of water mains: statistical models. *Urban Wat.* **3**, 131–150.
- MacVicar, R., Matuana, L. M. & Balatinecz, J. J. 1999 Aging mechanisms in cellulose fiber reinforced cement composites. *Cem. Concr. Composites* **21**, 189–196.
- McCuen, R. H. 2002 *Modelling Hydrologic Change: Statistical Methods*. Lewis Publishers, Boca Raton, Florida.

- Moglia, M., Burn, S. & Meddings, S. 2006 Decision support system for water pipeline renewal prioritisation. *ITcon* **11**, 237–256.
- NAS (National Academy of Sciences) 1982 *Drinking Water and Health*, (vol. 4). National Academies Press, Washington, DC.
- Olliff, J. & Rolfe, S. 2002 *Proceedings of the 20th International NO-DIG Conference. Copenhagen, Denmark, 28–31, May 2002*.
- Saito, H. & Deguchi, A. 2000 Leaching tests on different mortars using accelerated electrochemical method. *Cem. Concr. Res.* **30**, 1815–1825.
- Schlick, W. J. 1940 *Supporting Strength of Cast Iron Pipe for Gas and Water Service*, Bulletin No 146. Iowa Engineering Experimental Station, Ames, Iowa.
- Schuyler, J. 1997 Monte Carlo Stopping Rule, Part 1, <http://maxvalue.com/tip025.htm>, accessed June 2006.
- Scott, R. J. 1990 *Melbourne Water, Water Main Renewal Study: Reticulation Water Mains 1857-1990*. Internal report. Melbourne Water, Melbourne, Australia.
- Standards Australia 1972 *AS 1012, Part 10, Method for Determination of Indirect Tensile Strength of Concrete Cylinders*. Standards Australia, Sydney, Australia.
- Standards Australia 1998 *AS 2566.1, Buried Flexible Pipelines Part 1: Structural Design*. Standards Australia, Sydney, Australia.
- Watkins, R. K. & Anderson, L. R. 1999 *Structural Mechanics of Buried Pipes*. CRC Press, Boca Raton, Florida.

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