Practical Paper

Modelling asset lifetimes and their role in asset management

S. Burn, D. Marlow and D. Tran

ABSTRACT

Utilities throughout the world are faced with the challenge of how best to manage their existing asset stock to provide satisfactory customer service with limited funds. Effective asset management helps utilities to meet this challenge; however, this requires the utilization of cost-effective approaches for assessing asset condition, performance and remaining service life. A key component of these approaches requires an understanding of asset lifetimes. This paper discusses the role of asset lifetimes in asset management and the current state of the art for prediction of remaining life using different approaches. It discusses very simple approaches based on assumed lives, as well as sophisticated mathematical approaches using deterministic, statistical, physical/probabilistic and artificial intelligence models. In analysing both asset management strategies and lifetime prediction methodologies, a key factor identified as missing is a standardized technique for the incorporation of lifetime models into the probability side of risk analysis. For asset management to become a valued and readily utilized tool, this issue needs to be urgently addressed.

Key words | assets, failure, lifetimes, pipelines, risk, service life

S. Burn (corresponding author)
D. Marlow
CSIRO Land & Water,
Water for a Healthy Country Flagship,
Highett Victoria,
Australia
Tel.: +61 392526032
E-mail: *Stewart.Burn@csiro.au*

D. Tran
Institute for Sustainability and Innovation,
Victoria University,
Werribee,
Australia

INTRODUCTION

The provision of water and wastewater services involves numerous assets of many types with design lives that range from a matter of years, to hundreds of years. The life of many of these assets could potentially be extended if we were able to improve our understanding of what influences the asset life and how this can be incorporated into effective asset management strategies: for example, via enhanced knowledge of economic and risk factors, or via improved operational and maintenance practices. Extending the life of assets by even a small proportion has the potential for saving significant amounts of money, thus allowing utilization of these savings elsewhere for the benefit of customers and the environment: for example, Australia with A$94 billion of water assets could save over A$9 billion with a 10% extension of lifetimes. Management of remaining asset life is therefore a key component in the overall asset management challenge.

The need to gain a better understanding of remaining life of capital assets for clean and potable water sectors in the USA was outlined in the US EPA's study of investment gaps (US EPA 2002*a*). In this 'gap report', it was noted that better knowledge of the remaining life of capital assets would greatly improve decision-making relating to investment needs for maintaining, upgrading and expanding infrastructure. A fact sheet produced by the US EPA (2002*b*) also indicates the central role of remaining asset life (or residual life) to planning the replacement of assets.

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The key challenge is how to define when an asset has reached the end of its useful life, especially when varying customer service requirements are taken into account. For example, many assets are repairable, so loss of function does not imply end of asset life. At the other extreme, a critical asset can be considered to have reached the end of its life well before any failures actually occur, due to the relative balance between risk and replacement, or rehabilitation costs, or redundancy due to capacity constraints. In this context we define the end of asset life and remaining life in the following ways:

- End of asset life: the time at which a significant (capital rather than operational) investment is made.
- Remaining life: the time left before a significant capital intervention is required.

As shown in Figure 1, asset management can be considered at a range of scales, from the management of an individual asset to a whole utility concept. From the perspective of utility operations, this is effectively seen as a progression from operations and maintenance (O&M), through tactical asset management (TAM), to strategic asset management (SAM), as described below.

OPERATIONS AND MAINTENANCE (O&M)

O&M encompasses day-to-day asset management activities which include operational risk management, capital delivery and/or maintenance, all of which require asset specific data; for example, for a specific pipe of interest (Marlow & Burn 2008). Within this aspect of asset management, activities that relate to remaining asset life include undertaking inspection and monitoring tasks, responding to failure events and service issues, making repairs, collecting data for these failure events, and determining which of the failed assets need replacing.

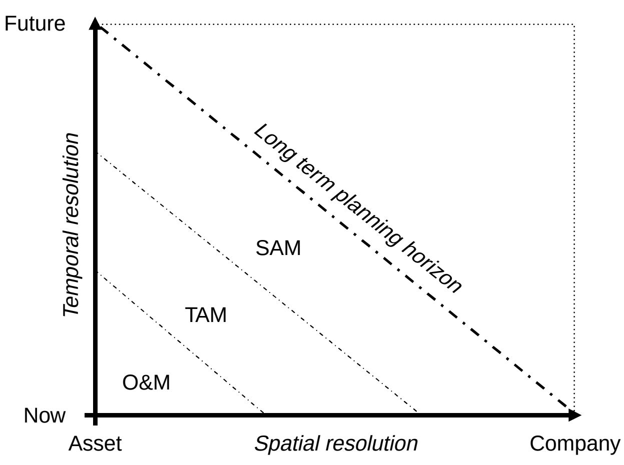

Figure 1 | Different scales of asset management (after Marlow & Burn 2008).

TACTICAL ASSET MANAGEMENT (TAM)

TAM is used to refer to asset management practices with a medium-term view and is generally concerned with the delivery of capital solutions, including the setting of priorities and determining how, when and where to intervene in the asset stock. TAM is applied at a broader resolution than O&M, so more refined data is needed: for example, detailed cohorts of assets and information at the individual asset level (Marlow & Burn 2008).

Within TAM, activities that relate to remaining asset life include prioritization and justification of planned replacement work, as well as developing business cases for proposed capital works projects. These activities require identification of specific assets that are approaching the end of their life and need to be either replaced or rehabilitated in the short to medium term owing to financial, service, risk or other drivers. These decisions may necessitate the utilization of condition assessment, inspection of the asset, or the application of other screening tools (McDonald & Zhao 2001; Marlow *et al.* 2007*a*; Davis & Marlow 2008) and includes the selection of appropriate rehabilitation technologies where appropriate (NGSMI 2003).

STRATEGIC ASSET MANAGEMENT (SAM)

The expression strategic asset management (SAM) is often used to refer specifically to asset management practices with a long-term view. SAM is concerned with setting overall strategy and budgets using broad estimation tools, and is generally applied to assets such as distribution assets, transmission assets and treatment works assets at a coarse resolution using spatially aggregated data and broad management units (Marlow & Burn 2008). Within SAM, remaining asset life is considered as a critical component of budget setting and assets valuation.

Determining budgets requires the remaining life of facilities, large individual assets or cohorts of smaller assets to be determined, along with potential intervention options. These options are increasingly being developed within a risk-based methodology where both the probability (or frequency) and consequence of risk are incorporated into the assessment criteria (Faber & Stewart 2003; ABS 2004; IPWEA 2006; Burn *et al.* 2007; Marlow *et al.* 2010).

Risk concepts

At all levels of asset management, risk is decreased by either reducing the likelihood of failure and/or limiting the potential consequences of an incident/event. Asset managers therefore need to understand both the likelihood-side and consequence-side of risk.

Likelihood side of risk

The likelihood-side of risk can be expressed either as the probability that an event occurs or as the frequency that the event occurs, with both factors significantly affecting the residual life of an asset, depending upon the levels of customer service required. As discussed by Buckland (2000), when considering likelihood of failure, the level of service provided to the community and the environment, and the 'value for money' represented by that level of service must be considered. For example for a specific customer, an asset may fail three times in a year and still give a satisfactory level of service, yet for another customer this frequency of failure may not be suitable.

The aim of a successful asset management methodology is to achieve an optimal (or at least acceptable) balance between intervention costs (including repair and replacement) and the costs associated with asset maintenance and operation, through the consideration of risk; thus obtaining the optimal residual life for the asset. The need to balance the costs associated with risks (risk-costs) against other costs can be illustrated by considering the theoretical balance between total intervention costs (inspection, maintenance and renewal) and risk-costs associated with asset failure. For example, in the literature relating to the maintenance of manufacturing and process equipment, plots such as that shown in Figure 2 are often used to demonstrate that there is a trade-off between the levels of maintenance (preventive costs), the corresponding costs associated with equipment failures (risk exposure) and total cost (Woodhouse 1999). Similar plots have been produced that show the trade-off between costs and the level of pipe-asset renewals (Shamir & Howard 1979; Burn *et al.* 2007), and the cost trade-offs involved in asset operation, inspection and rehabilitation (Madryas & Przbyla 2007).

As shown in Figure 2, it is theoretically possible to balance maintenance expenditure against risk-cost such

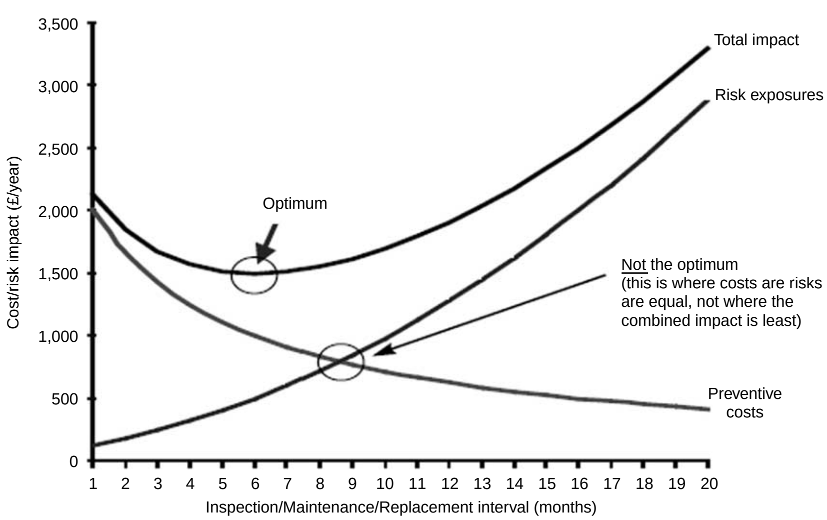

Figure 2 | Optimal timing of intervention (after Woodhouse 1999).

that the overall cost of asset ownership is minimized and this is the critical factor determining asset lifetimes. Importantly, increased reliability (reduced risk-costs) can be achieved through higher maintenance expenditure, but only by accepting an increase in total costs. However, in purely financial terms, the increase in expenditure to achieve this level of asset performance would not be justified, though it may be justified in broader economic terms.

Consequence side of risk

In general, unless there is a major change in the use, service duty or service parameters for a given asset, the potential consequences of failure are likely to remain fixed for its service life (ABS 2003). This allows the consequence of failure to be used as a constant measure of asset importance and to specify the management strategy for an asset. For example, the higher the potential consequences of asset failure, the more important the asset and the more effort can be justified to prevent the occurrence of failure and the more important the determination of remaining asset life becomes. In this case the remaining asset life would be determined, not by failure of the asset, but by determining the probability of failure of the asset and assessing the increasing risk as the asset ages.

While various terms can be used to categorize assets in terms of asset importance (e.g. 'critical asset' and 'asset criticality'), we propose that we should categorize assets solely from the perspective of the strategy adopted to manage the asset. Assets can be managed using a 'reactive' strategy, a 'proactive' strategy, or a 'mixed' strategy depending on the relative balance between potential consequences and the cost of risk mitigation. The concepts underlying this categorization are illustrated in Figure 3 (Burn *et al.* 2007; Marlow *et al.* 2007*a*).

As discussed by Buckland (2000), Burn *et al.* (2007) and Marlow *et al.* (2007*a*) and illustrated in Figure 3, an asset with low consequence of failure is generally managed reactively; such assets are left to operate until failures start to occur and in general the end of asset life is not reached at the first failure, but when the asset fails to provide the necessary level of service. In this context the first failure is often used to flag an asset as potentially needing major intervention; once the asset fails to meet the required level of service or other performance characteristics, a decision is then made to repair and maintain or replace the asset, with this decision normally being expanded to consider the replacement of similar assets at the same time. The decision to retain or replace the asset(s) would include consideration of budget constraints, the economics of continuing to operate the existing asset, externality costs (van Beuren & McDonald 2004; Marlow & Burn 2007) the levels of customer service needed, and operational strategies that can be economically implemented to reduce the impact of retaining a failing asset (Burn *et al.* 2007).

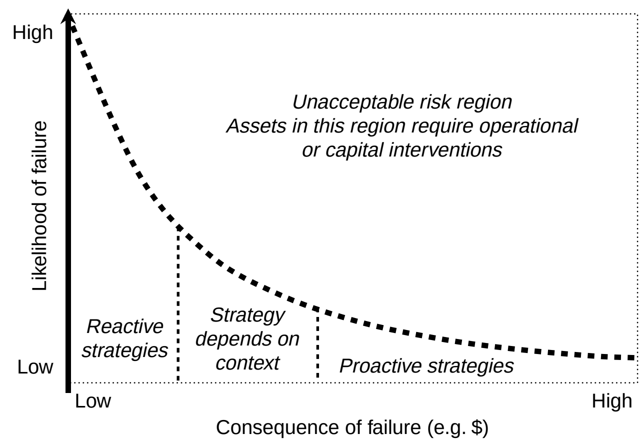

Figure 3 | Risk-based management strategies.

As shown in Figure 3, proactive strategies are generally applied to assets when the consequences associated with failure are large, and there is thus the potential for authorities, municipalities and other segments of society to incur high costs (tangible and/or intangible). For such assets, the economics of preventing failure are advantageous (Marlow *et al.* 2007*b*) and effective lifetime modelling is a critical input into the decision-making process.

It should be noted that the criteria used to assess end of life are different for reactively and proactively managed assets. In particular, a reactive management strategy is characterized by the use of failure events or failure history in decision making; individual assets may be run to failure or be replaced because of the failure history of similar assets. In contrast, for proactively managed assets, end of life criteria are judged in terms of level of deterioration and predictions of failure, rather than through asset failures.

DETERMINING REMAINING ASSET LIFE

As shown in Figure 1 there are varying levels of asset management that require the use of asset lifetimes. Determining the remaining asset life depends critically upon the current state of the asset, thus assessing the current state is a key input into the process of determining remaining asset life. With this in mind, three approaches can be used to determine remaining asset life:

- A simplified approach in which assumed or expected asset life is determined and used in conjunction with current age as a measure of asset state.
- An observation approach in which the current condition of an asset and the anticipated deterioration of condition with time is used to determine the remaining life.
- A more complex modelling approach in which asset lives are modelled using advanced mathematical and scientific approaches.

A simplified method for determining remaining asset lives

If the age of an asset is known and its expected service life is relatively well defined, then the remaining asset life can be calculated simply by determining the difference between these two figures; that is:

Remaining asset life = (expected service life) − (asset current age)

While somewhat simplistic, this approach is based on the recognition that it is possible to specify average expected lifetimes for a range of asset types. While in practice the actual life of a specific asset may be higher or lower than the assumed average, over a reasonably sized population of assets, the average will still be meaningful.

In addition to its use in calculation of depreciation, the assumed or 'book' life of an asset can be used in decision making with respect to the replacement of assets. For example, Hoskins *et al.* (1998) refer to the use of book lives to determine the age at which oil-filled circuit breakers should be replaced (a book-life of 35–40 years is given). However, the actual life of an asset can often exceed the book-life. Furthermore, replacement of an asset in accordance with its book-life does not explicitly consider the other economic factors that can drive asset replacement, so such approaches do not align with the asset management principles generally outlined in this paper.

The role of condition assessment in determining remaining life

As an asset ages and deteriorates it passes through a range of condition and/or performance states and these can be labelled in qualitative terms (new, fair, etc.). Depending on the factors that influence asset life, an asset will transition between states more or less quickly. The likelihood of asset failure tends to increase as the asset condition deteriorates. In many respects, an ideal assessment of asset state would thus be a measure of failure probability. Unfortunately, in many instances it is impractical or too costly to develop an assessment of failure probability with any reasonable degree of accuracy. As an alternative, asset condition can be used as a surrogate measure for failure probability (Marlow *et al.* 2007*a*; Marlow & Burn 2008). In this approach, acceptable asset condition states are defined, which characterize the threshold above which risk is deemed to be unacceptable (Hoskins *et al.* 1998). Condition assessment can then be used to determine whether the current state of an asset, implicitly expressed in terms of failure likelihood, is acceptable; that is, an asset in condition grade 'derelict', for example, may be considered to have reached the end of its useful life.

Ongoing condition monitoring which includes assessment of asset condition and/or performance, is undertaken to provide assessments of asset state over time. This also provides time series data from which the rate of deterioration can be estimated and the time to critical condition extrapolated, which in turn gives the remaining service life. To this end a number of approaches can be used to aid interpretation of condition and performance data, including:

1. The use of expert opinion.
2. Condition grading, for example grades 1–5.
3. Detection of critical defects.
4. Performance monitoring compared to thresholds.

All of these approaches are discussed in significantly more detail by Marlow et al. (2010) and will not be considered further in this paper.

Modelling approaches to the determination of remaining asset life

Sophisticated approaches to asset management normally require significant levels of data and a range of models to utilize this data, to allow prediction of asset failures and thus determination of the remaining asset life. Deterioration models for predicting asset lifetimes in infrastructure systems can be grouped into the following four categories as detailed in Table 1.

Deterministic models are often used for phenomena where relationships between components are certain. While statistical models also assume that component relationships exist, they attempt to account for inherent uncertainties that exist in model variables. Physical probabilistic models predict degradation and failure of infrastructure assets from knowledge of the actual degradation and failure mechanisms that occur in service. However, they also attempt to include realistic uncertainty in these processes by using appropriate probability distributions for model variables.

These first three categories describe the 'model-driven' approaches, in that some form of relationship is assumed between input and output data. In contrast, artificial intelligence-based models discriminate output patterns from a set of inputs by learning from past data, generalizing these lessons and predicting future targets (Smith 1996). These approaches in the fourth category are therefore 'data-driven' in that the model structure is determined by the data and no prior relationships are assumed. This category of models are occasionally referred to as 'black-box' models since they seem to be only concerned with input and output data without specifying the underlying mechanism (Taylor 1993). Table 1 lists the different techniques that are discussed in this paper. However, space limitations limit the amount of discussion that can occur here, and a more complete discussion is available in Marlow et al. (2010).

Table 1 | Approaches for predicting asset failure rates and service lifetimes

Generic approach	Specific approach
Deterministic	Empirical
	Physical
Statistical	Failure event data-based
	Service lifetime-based
	Cohort-survival
	Ordinal regression
	Markov chain
	Bayesian
Physical probabilistic	Monte Carlo simulation
	Structural reliability theory
Soft-computing, artificial intelligence	Artificial neural networks (ANNs)
	Fuzzy logic

Deterministic models

As stated above, deterministic models are often used in those instances where relationships between components are certain. Examples include physical or mechanism-based models and empirical models that relate failure rates to asset attributes. Empirical deterministic models involve fitting some form of equation to observations of asset failure while physical models are based on a physical understanding of the degradation mechanisms that influence the load bearing capacity of an asset and as a result its service lifetime. In principle physical deterministic models are usually developed to predict service lifetimes of an individual asset rather than failure rates of cohorts which are predicted by empirical deterministic models. A comprehensive review of empirical and physical deterministic models is given in the literature (Kleiner & Rajani 2001; Rajani & Kleiner 2001*a*). Specific applications of deterministic models in the literature include those of Shamir & Howard (1979) who used regression analysis to obtain a prediction of failure rates for water pipes in the USA via empirical deterministic models. For physical deterministic models, Randall-Smith et al. (1992) proposed a linear corrosion model based on the assumption that corrosion pit depth has a constant growth rate. Rajani & Kleiner (2001*a*), in a similar area, used physical deterministic models to predict the corrosion and structural failure of individual buried cast iron water pipes.

While empirical deterministic models may provide a reasonable fit to observed failure data, it is noted that they can only be applied to homogeneous groups (or cohorts) of pipes. Criteria for selection of these cohorts are rarely documented in detail in the literature. Furthermore, empirical models do not provide an improved understanding of the actual causes of deterioration and eventual failure. They also do not reflect the inherently uncertain nature of asset failures, which are caused by a combination of time-dependent deterioration process and random damage events (Morcous *et al.* 2002).

In comparison, physical deterministic failure models may provide insights into degradation and failure mechanisms; however, there is a trade-off between model complexity and usability. For example, while simpler models developed by Shamir & Howard (1979) as described in Kleiner & Rajani (2001) may be useful screening tools, they also include key simplifying assumptions that cannot be validated. An example is the assumption of linear corrosion in cast iron pipelines. At the other extreme, while the more sophisticated physical models, such as that of Rajani & Makar (2000), accurately capture degradation and failure processes, their input variables may be difficult to obtain. Regardless of their complexity, it is noted that physical deterministic models can only be applied to individual assets and do not provide estimates of failure rates for asset cohorts, unless all the factors across the cohort are constant.

Statistical models

In recent years many of the approaches to predicting asset failure have concentrated on the development of statistical models. This approach has occurred because of the unavailability of the fundamental science required for deterministic models and the availability of significant amounts of failure data collected by some utility organisations around the world such as UKWIR (UK Water Industry Research) and WSAA (Water Services Association of Australia), who have amalgamated the data water utilities typically collect on most water main failures. Failure patterns in water mains can be affected by many factors, and factors such as pipe material and size, soil type and installation practices, are considered static factors that do not vary with time, while climatic conditions (temperatures, precipitation) as well as operational practices (cathodic protection, pressure regimes) are considered dynamic, or time-dependent, factors because they change (or can change) over time. Statistical models try to account for natural randomness and variability in the two types of data.

As detailed in Table 1 statistical models can be considered in terms of: (i) failure event data-based, (ii) service lifetime-based, (iii) cohort-survival, (iv) ordinal regression, (v) Markov chain, and (vi) Bayesian. A full analysis of each of these methodologies can be found in Marlow *et al.* (2010), unfortunately space limitations preclude a detailed analysis of each type in this paper and only a general summary of the application of each type of model can be given.

Statistical models: failure event data approaches

Historical data-based models can be applied to forecast future failure rates of assets, provided sufficiently large volumes of historical failure data are available. In general, the occurrence of failures over time is treated as a stochastic process, and is represented by an appropriate probability distribution, such as variations on the Poisson process (Jarrett *et al.* 2001). The underlying stochastic process model is then used to estimate expected failure rates, with model parameters set up to describe the influence of variables such as material, asset size/geometry and surrounding environmental conditions which can include time-dependent covariates such as the effects of climate. The model is calibrated using maximum likelihood fitting methods to provide the best match between model predictions and recorded failure data. Goodness of fit between model forecasts and actual observations is then demonstrated by comparison with a blind data set that was not part of the calibration process.

The majority of models of this type have been tailored to water pipeline assets: for example, Shamir & Howard (1979) proposed a two-parameter (single variate, age) exponential function to represent the increase in water main failure rates with pipe age. This approach or variants of this approach were subsequently used by others in similar studies on water pipelines (Clark *et al.* 1982; Walski & Pelliccia 1982; Kleiner *et al.* 1998; Kleiner & Rajani 1999;

Kleiner & Rajani 2000, 2002), while Savic (2009) applied evolutionary polynomial regression to both water and wastewater pipelines. In contrast, Jarrett *et al.* (2001, 2002) proposed an alternative method based on a non-homogeneous Poisson process to forecast failure rates of individual buried water pipelines, based on previous research conducted by Constantine & Darroch (1993) and Veevers & Hussain (1999). In this approach it is assumed that failure rates are influenced by attributes such as pipe diameter, soil type and pipe age, among others.

While statistical-based models can be applied to assets with sufficient historical failure or condition data, their applicability is limited when considering newer assets or assets located in areas where relatively severe consequences would be incurred upon failure. In these cases, insufficient historical data exists for confident forecasts of future performance.

The partitioning of data into homogeneous populations or 'groups' warrants careful attention because two conflicting objectives are involved. On the one hand the groups have to be small enough to be uniform, but on the other hand the groups have to be large enough to provide results that are statistically significant. Pipe characteristics that are most likely to significantly affect water main failure patterns need to be identified, and subsequently used as grouping criteria. Ideally, candidate characteristics for grouping criteria include pipe material, vintage and diameter, soil type, operating pressures (if static), road type, road surface condition, material and density of service connections, among others. The typical utility, however, will rarely have all these data available in a usable form. The extension of the cohort-type models to better predict failures in individual assets has clear advantages, but to date limited examples such as Jarrett *et al.* (2002) have been documented in the literature.

Statistical models: service lifetime approaches

In addition to models that forecast failure rates based on observed failure events in assets, statistical techniques are also available to analyse recorded service lifetime data. In these techniques, service lifetime is usually defined as the time from asset installation to first failure. In general, these techniques involve fitting the variation in observed service lifetime data within a cohort of assets to an appropriate probability distribution. If a suitable distribution can be chosen and goodness of fit demonstrated, it can then be used to estimate expected remaining lifetime for a representative asset in the cohort and to estimate expected average failure rates across the asset cohort.

Examples of this type of cohort approach include that of Crowder *et al.* (1991) who considered that exponential distributions could be applied; however, the corresponding failure rate calculated from this distribution is independent of age, which often contradicts the observed pattern of asset failures in service. Herz (1996) assessed various mathematical distributions for modelling probabilistic lifetimes in infrastructure components; however, in his approach lifetime was defined either by the age the pipe was replaced or by the use of expert opinion. To aid this process, D'Agostino & Stephens (1986), in a comprehensive study, considered the most appropriate probability distribution for asset lifetime data and statistical test procedures for assessing goodness of fit.

In contrast to those approaches that analyse failure event data for individual assets, service lifetime approaches consider only the time to first failure. As such they cannot be considered as a fully fledged failure rate prediction model nor can they be used to incorporate the implications of customer service levels where information on the individual failure of assets is needed.

Similar to failure event data approaches, service lifetime models can only be applied to asset cohorts. The criteria used to segregate assets into cohorts must reflect their influence on asset failure.

Statistical models: cohort survival approaches

The process of asset deterioration can be described by a cohort survival model. In this model, cohorts are pipelines of the same period of construction sharing some other features, such as material, diameter, bedding and subsoil characteristics, which are assumed to influence their service life. Within their life-span they pass through different categories of condition, from best upon initial installation to worst as service use and lifetime increases. With some probability, they survive a number of years within a category of condition. These survival curves are transition curves into increasingly worse categories of condition. They can be determined from inspection data and used to forecast the number of years it takes until a specific type of asset will enter a critical category of condition.

Typical examples of this approach include those developed at Karlsruhe and Dresden Universities (Herz 1996; Hochstrate 2000; Baur & Herz 2002) as well as investigations in a Norwegian case study (Hörold 1998). A disadvantage is the use of cohorts, which requires a substantial amount of data to make it a 'homogeneous' cohort or group (Kleiner *et al.* 2007). Since this data is often not available, assumptions are required and the predictive results of these models could be imprecise. Cohort models also suffer the disadvantage similar to service lifetime models, that customer service levels on individual assets cannot be calculated.

Statistical models: ordinal regression

The ordinal regression methods are similar to the cohort-survivor approaches and have become popular statistical models when dealing with a relationship between an integer-valued output and one or more explanatory variables (Johnson & Albert 1999). The integer values are sometimes meaningfully ranked in increasing or decreasing order; the condition grading system for sewers is a typical example. Some common functions used in the ordinal regression models are logistic and probit functions (Tabachnick & Fidell 2001). The maximum likelihood method is the commonly used calibration technique for the ordinal regression models (Johnson & Albert 1999).

Examples of the application of ordinal regression include that of Ariaratnam *et al.* (2001) who developed a logit model using 19 pipe factors for prioritizing sewer inspection for the City of Edmonton in Canada. In a similar study conducted by Koo & Ariaratnam (2006), a deficiency logit model for prioritizing sewer inspection for the City of Phoenix was developed. Davies *et al.* (2001) conducted a similar study in the UK in which condition records were reduced to 'poorest condition' (condition grade 5) and 'not poorest condition' (condition grades 1–4), and the result was subject to a regression analysis. Pohls (2001) documented an investigation of sewer blockages in Australia using a similar approach.

Statistical models: Markov chain approaches

An alternative technique to modelling the change in condition for infrastructure assets is the application of Markov chain models. As with cohort and ordinal regression approaches, these are inspection-based models and rely on asset condition indicators. However, rather than ageing and deterioration through a continuous increase in recorded failure rate, Markov chain models assume that deterioration occurs by series of 'jumps' from one observed condition state to a more severe state over time. The probability of a jump occurring depends on the asset age and operating environment. As with statistical models for failure rate forecasting, inspection-based models are based on assumed probability distributions that describe the underlying stochastic deterioration process. Model calibration is again conducted by matching predictions of condition state to observations from CCTV inspection.

According to Morcous *et al.* (2002), the Markov chain theory is still the most frequently used method in many statistical models for the deterioration of infrastructure facilities. Examples of studies where Markov chain approaches have been applied include those of Micevski *et al.* (2002) and Tran *et al.* (2006*a*,*b*) for storm water pipes, Baik *et al.* (2006) and Le Gat (2008) for sewers.

From the theoretical point of view, the Markov model is attractive because it can handle the uncertainty of condition change of pipe assets while considering maintenance, repair and condition assessment using CCTV inspection. However, generally, regular inspections are not carried out for storm water and sewer pipes in developed countries such as the USA and the UK, which results in lack of regular data for calibrating Markov models for individual assets. This means that for the snapshot type of data, the Markov model cannot be applied to predict the condition change of individual pipes. Despite this, some studies attempted to calibrate the Markov model for individual pipes by using optimization (Wirahadikusumah *et al.* 2001) and ordered probit (Baik *et al.* 2006) techniques. However, the outcomes of those studies are in doubt because the Markov models were inadequately tested as a result of irregular data. According to Madanat & Ibrahim (1995) and Wirahadikusumah *et al.* (2001), at least three consecutive inspection data sets should be collected for testing the Markov model.

Statistical models: Bayesian approaches

Bayes' theorem provides a relationship between the likelihood that an initial theory is correct after the addition of new data and the previous perceived likelihood, before the new data were added. Bayesian statistics enables 'prior estimates' of the condition of the assets to be combined with any available site inspection data to make the best possible inference about the condition of the entire asset group.

Examples of the application of Bayesian approaches to the prediction of asset lifetimes include those of Kulkarni *et al.* (1986) who developed a maintenance system for cast iron gas pipelines, and Watson *et al.* (2001) who developed a Bayesian approach to modelling failure rates in water pipelines.

Bayesian approaches to modelling infrastructure asset failures are based on some simple and robust mathematical principles. As with other statistical techniques, assets are usually partitioned in homogeneous groups (or cohorts) and the criteria for this segregation must be carefully defined. To calibrate and apply the models, the failure ratios in these groups are systematically compared and evaluated. As noted by Kleiner & Rajani (2000) the model of Kulkarni *et al.* (1986) is 'flat' with respect to time and does not consider the time of breakage occurrence, just the empirical number of breaks to the time of analysis. Although no details are supplied, Watson *et al.* (2001) suggested that their Bayesian approach solves this limitation.

For a simple Bayesian analysis, only asset lengths and failure history are needed. Following Kulkarni *et al.* (1986), a detailed analysis requires partitioning of assets into an extensive list of condition states. As noted above, the appropriate criteria for this portioning must be available and chosen carefully.

Physical probabilistic models: Monte Carlo simulation

In contrast to purely statistical approaches, physical models are based on the actual degradation and failure processes that occur in service and are generally developed where historical failure data or inspection data is limited or unavailable. Examples are the modelling of time-dependent pitting corrosion in newer metallic pipes such as ductile iron, cement leaching and strength loss in cement-based assets and fracture from inherent defects in plastic pipes. While these physical models are developed and calibrated using small samples at laboratory scale (Rajani & Makar 2000; Burn *et al.* 2005; Davis *et al.* 2007*a*,*b*), they can be extrapolated to the network-wide scale through the incorporation of uncertainty in key variables. One technique is to represent key variables (i.e. degradation rate and operating loads) by appropriate probability distributions and use Monte Carlo (MC) simulation to generate projected service lifetimes for large numbers of assets. In this way, the details of physical degradation processes are retained but realistic uncertainty in this degradation is also accounted for. Outputs from these MC simulations are forecasts of time-dependent failure probability or estimated network-wide failure rates, both of which can assist risk assessment and asset planning.

At the core of a physical probabilistic model is the underlying degradation and failure model, which is often based on load-capacity relationships. Recent examples of physical probabilistic models are those developed using a fracture mechanics theory to relate the critical loading conditions to the extent of crack growth for polyvinylchloride (PVC) and polyethylene (PE) water pipes (Burn *et al.* 2005; Davis *et al.* 2007*b*; Burn *et al.* 2008) and corrosion of cast iron water mains (Rajani & Tesfamariam 2004; Sadiq *et al.* 2004; Tesfamariam *et al.* 2006). For metals, the underlying physical model uses fracture mechanics theory to relate the critical loading conditions to the extent of pitting corrosion that a pipe has experienced in service. If the rate of pitting corrosion is known, the model can then be used to predict when fracture failure will occur in service (Rajani & Makar 2000; Deb *et al.* 2003; Moglia *et al.* 2008). Similar models have been developed that predict failure from the rate of cement leaching and strength loss in asbestos cement pipes (Davis *et al.* 2008). For those cases where flexibility in developing and changing the underlying physical model is an imperative, Monte-Carlo simulation is preferable.

Physical probabilistic models: structural reliability-based methods

If suitable probability distributions can be selected for model variables, there are a number of approaches to accommodating this uncertainty in the underlying physical failure model. For example, methods such as the first-order second moment (FOSM) and first-order reliability method (FORM) are elementary methods in structural reliability theory. To apply these methods, the physical failure model is first re-formulated in the form

$$M = L - R$$

where L represents the load experienced by the asset, R represents its ability to resist that load and M represents the limit state of the asset with failure predicted to occur when $M < 0$.

Ahammed & Melchers (1997) demonstrated how L and R can be expressed in terms of an underlying physical model for combined corrosion and fracture of mild steel pipelines. Burn *et al.* (2005) and Davis *et al.* (2007*a*,*b*) demonstrated how a similar limit state equation can be set up to predict crack initiation and fracture for PVC and PE pipelines using FOSM and Monte Carlo simulation, while Rahman (1997) also used FORM/SORM (second-order reliability methods) and Monte-Carlo simulation in a probabilistic fracture analysis of circumferential through-walled-cracked pipes subject to bending loads.

While FOSM reliability-based methods may offer analytical solutions to failure probability problems, they can also result in over-simplification. For example, they require stochastic variables (such as defect sizes) to be 'normally' distributed and underlying failure models to be linear. In reality these assumptions may not always hold. In fact, complex loading conditions experienced by infrastructure assets means that linear failure models rarely exist. As a consequence of these assumptions, realistic physical failure mechanisms can be lost in order to obtain a solution. However, it should be noted that extensions to reliability theory have produced first-order reliability methods and second-order reliability methods, which largely sidestep such limitations. However, for those cases where flexibility in developing and changing the underlying physical model is an imperative, Monte-Carlo simulation is preferable.

Soft computing methods: artificial neural networks (ANNs)

Artificial neural networks (ANNs) belong to the class of artificial intelligence modelling techniques. In contrast to statistical or physical probabilistic approaches, ANNs are data driven rather than model driven. ANNs predict output from input information in a manner that simulates the operation of the human central nervous system. Within the model, processing elements (or nodes) receive information, which is then manipulated and passed on to other nodes in the network. ANNs consist of layers of nodes, which provide a functional relationship between input information and predicted output. They are trained on historical data sets, which demonstrate the actual relationship between input and output information and are then tested on independent data.

Examples of ANN application include those of Tran *et al.* (2006*a*,*b*), who applied ANN to predict deterioration and structural condition in storm water pipelines. In another example, Achim *et al.* (2007) developed an ANN to predict the average failure rate (number of failures/length/year) for cast iron pipes in a water reticulation network.

While ANNs are being increasingly used to solve complex problems, they are also often treated as 'black box' solutions. Data pre-processing, methods for determining adequate model inputs and the internal workings of ANNs are seldom considered during their application. In addition to expertise concerning the problem at hand, background knowledge in ANN development is also a prerequisite.

According to Maier & Dandy (2001), during pre-processing of input data, any trends or heteroscedasticity (differing variances between model variables) should be removed prior to the training of an ANN. Another crucial issue is the number of model parameters or nodes included in the input layer. An insufficient number of inputs may result in difficulties reaching a minimum root mean squared error (RMSE) during training. Conversely, if too many model parameters are used in relation to the number of training samples available, the ANN may lose its ability to predict outcomes from independent input data. Another issue that should also be considered is the number of training samples and the increment in nodal weights that are used during ANN training. Maier & Dandy (2001) demonstrate how an ANN can show divergent behaviour and never reach an optimal training level if increments in nodal weights during the training process are too large.

Soft computing methods: fuzzy logic

As with ANNs, the use of fuzzy logic theory to predict infrastructure deterioration is also part of the soft computing and artificial intelligence modelling category. Rajani *et al.* (2006) propose that the physicochemical processes that govern infrastructure deterioration are often not sufficiently well understood to merit the development of a physicochemical model (based on mechanics, electrochemistry, or microbiology, for example). Furthermore, converting deterioration observations to an infrastructure condition rating is inherently imprecise and often involves subjective judgement (Rajani *et al.* 2006). Fuzzy logic-based techniques are able to incorporate engineering judgement and experience in a model development process. Specifically, they are proposed to be well-suited to infrastructure problems in which:

- Data are scarce.
- Cause-effect knowledge is imprecise.
- Observations and model criteria are expressed in vague terms such as 'poor', 'average', 'good' condition, etc.

As discussed by Kleiner *et al.* (2004), fuzzy logic-based techniques allow the propagation of these attributes through a model, therefore yielding more realistic results.

The majority of research toward the development of fuzzy logic-based deterioration modelling for pipe assets has originated from the Buried Utilities Research Group in the National Research Council of Canada. For example, Rajani *et al.* (2006) collated relevant distress indicators for prestressed concrete cylinder pipe (PCCP) and cast/ductile iron pipe. Rajani *et al.* (2006) also developed the fuzzy synthetic evaluation method and demonstrated how a fuzzy condition rating could be determined for PCCP. Kleiner *et al.* (2005, 2006) developed a Markovian fuzzy rule-based deterioration model. This model is calibrated for a given asset, using fuzzy condition ratings that are discerned from historically observed distress indicators. The model was tested on a limited number of large water mains, for which data were available.

As part of the artificial intelligence/soft computing modelling category, fuzzy logic-based approaches also risk being treated as 'black box' solutions. Without a thorough grounding in the background fuzzy set theory, models can be developed that are inaccurate and unrealistic; however, the developments currently being undertaken in this area are generally transparent and need relatively few data for calibration. Since the application of fuzzy set theory to pipe deterioration is relatively new, significant further work is required to explore its robustness. In particular, as with all Markov-based approaches, pertinent data with historical depth (i.e. consecutive condition ratings spanning several years of a given pipe) is required for refinement and validation. For example, Kleiner *et al.* (2006) report that in one case, adding extra observed condition data to the model calibration actually degraded the accuracy of forecasting rather than improving it.

It should also be noted that the fuzzy logic-based approach to deterioration modelling is essentially a vehicle to incorporate and handle expert opinion. As described by Rajani *et al.* (2006), the weighting parameters required to translate distress indicators into condition are assigned through expert opinion. As such, it is essential that an appropriate surveying technique is employed to extract this opinion. One such approach is the Delphi method, which employs a series of questionnaires designed to elicit and develop individual responses to the problem posed to a pre-selected panel of experts (Rajani *et al.* 2006).

APPLICATIONS OF LIFETIME MODELLING IN ASSET MANAGEMENT

As discussed above there are a large number of modelling techniques that can be utilized to predict remaining asset lifetimes. Of these modelling approaches only a limited number have been incorporated into asset management frameworks or application tools to allow planning and prioritization of assets and in each case the approach taken has been different.

For example, the software approaches developed by the Commonwealth Scientific and Industrial Research Organization (CSIRO) in Australia and the National Research Council in Canada for their PARMS (planning, priority and risk) and D&I-WARP models utilize failure event-driven statistical models to allow planning and prioritization of pipeline assets (Rajani & Kleiner 2001*b*; Burn *et al.* 2003, 2004; Marlow *et al.* 2006; Moglia *et al.* 2006; Kleiner & Rajani 2007, 2009). While PARMS models all pipe types commonly seen in water reticulation systems, D&I-WARP models were designed to consider time-dependent covariates, one of which is effective cathodic protection of water mains. An initiative in the United Sates also uses failure event-driven statistical models (Rogers & Grigg 2009) to assign the break risk to individual assets. Using multi-criteria decision analysis, this allows them to be ranked according to the risk of breaking, a simple but increasingly popular approach.

In contrast, the European CARE-S, CARE-W and KANEW projects relied heavily on cohort survival and Markov chain approaches for the water and sewerage mains commonly installed in Europe, although further refinement of CARE-W does include failure predictions based on failure event-driven statistical models (Herz 1996; Hochstrate 2000; Deb *et al.* 2003; Saegrov 2005, 2006; Le Gat 2008). Deb *et al.* (2009) also details the American approach to a cohort asset management structure based on the KANEW method and earlier work by Loganathan *et al.* (2002) and Jun *et al.* (2008) on identification of pipes and valves of high importance for replacement, which is similar to the European approach.

A recent emergence is the utilization of physical/probabilistic models in asset management strategies (Burn *et al.* 2009), which has only been possible with the development of the physical models that allow asset deterioration to be predicted (Burn *et al.* 2005; Davis *et al.* 2007*a*,*b*). These methodologies effectively predict the failure or condition of each asset in the network and allow the utility to plan its financial strategy based on these failures or condition states.

Methodologies based on fuzzy logic and neural networks are also being developed (Rajani *et al.* 2006; Tran 2006*a*,*b*) but their application in asset management has so far been limited.

While each of these approaches has its merits and has been adopted to different degrees by industry (for example PARMS-Planning is utilized by most of the major water utilities in Australia), there is no standardized approach that will allow utilities to identify the right approach for their level of asset management sophistication and ensure that the customer service requirements are incorporated into the decision-making process. As utilities develop their asset management approaches, they need guidance on the types of data, model utilization and asset management strategy they should be developing, to ensure optimum management of their assets and reduce the future costs for the communities they serve. At the moment these strategies are generally driven by the researchers, rather than the needs of industry, which is leading to confusion and competition, rather than a collaborative approach to meet the future needs of the water industry. Thus it is imperative that a cohesive framework for utilization of asset lifetimes be developed by researchers, in collaboration with industry, to evaluate the validity of the models for their application into asset management. This framework should be based on the following definition of asset life: 'end of asset life–the time at which a significant (capital rather than operational) investment is made' rather than solely utilizing the failure of individual assets.

CONCLUSIONS

Water authorities are increasingly being required to manage their assets more efficiently in an era of reducing budgets, decreasing technical capacity and increasing requirements for the provision of appropriate levels of service. In such an environment, they are increasingly utilizing more sophisticated levels of asset management to allow them to plan and implement strategies to meet these needs.

A critical component in any asset management strategy is the ability to determine the remaining useful life of assets. As presented in this paper, a significant number of approaches are available for calculating asset remaining life; each methodology has different benefits and disadvantages. There currently does not appear to be any definitive work that allows determination of the most suitable approach for the analysis of remaining asset life at different levels of spatial and temporal resolution to meet the needs of strategic asset management (SAM), tactical asset management (TAM) and operations and management (O&M); the choice of approach is currently determined by the technical expertise available to the utility. Although a number of methodologies for using deterioration modelling in asset management are available, each applies a different approach and thus it is proposed that deterioration modelling in terms of service provision (rather than asset deterioration) needs to be developed and incorporated into a guidance framework to allow utilities to select the best modelling method based on their level of asset management sophistication. This would allow the optimum collection of data to meet these needs and remove much of the confusion that currently exists regarding the use of deterioration and lifetime modelling in asset management. Although not discussed in this paper, asset management should also ultimately include network reliability and water quality issues, a topic for future discussion.

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