SEPTEMBER 2014
ISSUE 3 ■ VOLUME 10

water asset management INTERNATIONAL

PAPERS

IWA PUBLISHING

water21 magazine of the International Water Association

Research finds common coagulant could corrode sewers

A research team at the University of Queensland have discovered that a common coagulant used in drinking water treatment can be a prime contributor to global sewer corrosion.

Aluminium sulphate (alum) is widely used as a coagulant as it is relatively cheap and widely available. The aluminium binds to particles in water and is removed as part of the treatment process, but the soluble sulphate remains in the treated drinking water.

The paper, published in the journal Science, reveals that the coagulant is the main source of over 50% of the sulphate found in wastewater, which in turn is indirectly the primary source of hydrogen sulphide. This gas is well known as the cause of rapid degradation in concrete sewers, sometimes reducing their life by up to 90%.

The mechanism for the degradation is the presence of microbes on sewer walls that take up the hydrogen sulphide and oxidise it to form sulphuric acid, an extremely powerful agent for corroding concrete.

The team, led by Professor Zhiguo Yuan, concluded that to reduce sulphide formation, it was necessary to reduce either the sulphate or the organics in wastewater, the latter not being a viable option. They recommended that utilities move to sulphate-free coagulants, in order to reduce concrete corrosion by 35% after just ten hours and up to 60% over a longer period of time, generating potentially large savings in sewer maintenance.

The research also discovered that the production process for desalinated or recycled water normally eliminates sulphate from the final produced water, creating a potentially valuable protective effect for sewers downstream.

The researchers undertook a two-year sampling programme in South East Queensland, conducted an industry survey across the country, and undertook a global literature review and a comprehensive model-based scenario analysis of the various possible sources of sulphate to reach its conclusions.

The team also recommends a more fully integrated approach to urban water management to identify other interactions, noting that the main reason the connection had not been realised earlier is the institutional separation of the urban water system into water and wastewater services, often run by separate organisations. ●

AWF grant agreed to improve South African water supplies

The African Water Facility (AWF) has agreed a €1.3 million ($1.7 million) grant to the Water Research Commission of the Republic of South Africa to improve water delivery services; an initiative that will be supported and driven by the beneficiary communities of Limpopo province. Over 20,000 people are expected to get improved access to water for domestic and agriculture purposes, among others.

The project proposes to implement the holistic Multiple Use Services (MUS) approach to overcome water challenges faced by many South African households. Most rural and peri-urban communities in South Africa rely on ill-suited, single-use water services to sustain a variety of activities such as small-scale agriculture, household chores and cooking, says AWF.

On the contrary, the MUS is a low-cost water service approach proposing systems that take into account people's multiple water needs as a starting point of planning, which leads to designs that can provide water services for a variety of uses all at once.

'The unreliability and unpredictability of access to water in Limpopo province, which is aggravated by climate change and population growth, poses tremendous water challenges to the most vulnerable communities,' explained Akissa Bahri, Coordinator of the African Water Facility. 'This project will not only bring much needed multiple-use water services for rural and peri-urban communities in the region, but create local knowledge of the MUS approach and of best practices in providing water services in line with the principles of integrated water resources management.' The infrastructure will be used to demonstrate the value of the multi-use approach, and develop models for future up-scaling throughout South Africa. In addition, the project is expected to strengthen capacities for water planning and development.

The estimated total cost of the project is €1.7 million ($2.2 million), of which the AWF will finance €1.3 million. A part of the AWF support will go into disseminating knowledge on MUS approaches and in supporting resources mobilization activities to attract downstream investments through the preparation of development plans as well as research. ●

water asset management INTERNATIONAL

Water Asset Management International is an international newsletter on asset management in water and wastewater utilities. The focus of the newsletter is on the strategic aspects of this developing field, providing utilities with international perspectives on infrastructure planning and maintenance as they seek to deliver cost-effective services to their customers.

Instructions for authors are available at: www.iwaponline.com/wami/default.htm

Papers for consideration should be submitted to the editors or to:

Catherine Fitzpatrick
Publishing Assistant
cfitzpatrick@iwap.co.uk

PUBLISHING

Associate Publisher
Keith Hayward
khayward@iwap.co.uk

Publisher
Michael Dunn

Water Asset Management International is published four times a year (March, June, April, December) by IWA Publishing. Statements made do not represent the views of the International Water Association or its Governing Board.

IWA Publishing
Alliance House,
12, Caxton Street,
London SW1H 0QS, UK
Tel: +44 (0)20 7654 5500
Fax: +44 (0)20 7654 5555
Email: publications@iwap.co.uk
Web: www.iwapublishing.com

SUBSCRIPTIONS

Water Asset Management International is available as either a print or an online subscription.

2014 price (4 issues):
£282 / €426 / $562
(IWA members: £217 / €326 / $413)

Contact
Portland Customer Services
Commerce Way, Colchester,
CO2 8HP, UK
Fax: +44 (0)1206 79331
Email: sales@portlandpress.com

Or visit: www.iwaponline.com/wami/subscriptions.htm

Design & print
Designer: David Parry
Printed by Hobbs The Printers, UK

ISSN (print): 1814-5434
ISSN (online): 1814-5442

World Bank continues Azerbaijan watsan development support

The World Bank has approved an International Bank for Reconstruction and Development loan of $150 million for additional financing of the Second National Water Supply and Sanitation Project (NWSSP 2) in Azerbaijan. The objective of the loan is to improve the quality and reliability of the water supply and to expand water supply and sanitation services in selected regional centres in the country.

Azerbaijan has a relatively extensive water supply and sanitation network. However, due to a lack of investment and maintenance, the quality of services has significantly deteriorated in rural regions of the country. Recently, the Government of Azerbaijan launched a programme to address infrastructure deficits and to ensure financial sustainability of the sector.

The Second National Water Supply and Sanitation Project has been under implementation since 2008, and has already helped improve the water supply and sanitation networks in three regional centres, with reliable piped water supply and sanitation services provided to more than 120,000 beneficiaries. The project has also introduced EU water supply and sanitation standards in Azerbaijan. ●

AECOM awarded Miami-Dade sewer-repair contract

AECOM has announced that it has been awarded a $91 million contract by Miami-Dade County commissioners in Florida to oversee $1.6 billion in federally mandated repairs to the county's sewer system.

AECOM will provide programme and construction management services for upgrades to the existing wastewater treatment plants and the collection and transmission system pipes and pump stations – including overseeing and supporting the early planning, design and construction phases of the capital programme. AECOM will also oversee the implementation of numerous capacity, management, operations and maintenance programmes required by a federal consent decree.

'We are pleased to be selected for this important project, which will benefit the residents and visitors of Miami-Dade County through major improvements to the county's wastewater system and facilities,' said Michael S Burke, AECOM president and chief executive officer. 'This is a great opportunity to again demonstrate AECOM's expertise in delivering complex and crucial projects, which includes numerous large water and wastewater projects throughout the world.'

AECOM was awarded a five-year contract, with two five-year extension options.●

EBRD announces support programmes to repair flood damaged Balkan infrastructure

The European Bank for Reconstruction and Development (EBRD) is intensifying its efforts to help Bosnia and Herzegovina overcome the damage caused by the floods in May this year. The Bank presented a new range of financial support programmes at a donor conference, where the official flood damage assessment report was also unveiled.

Devastating flooding hit the Balkans in May 2014, causing loss of life and forcing thousands to leave their homes across the region. According to the new report 'Bosnia and Herzegovina Recovery Needs Assessment', the damage to the Bosnian economy is now estimated at €2.03 billion ($2.6 billion).

In a move designed to help Bosnia and Herzegovina accelerate its recovery from this severe damage, the EBRD is ready to extend and reallocate funding to the public and private sectors. Up to €58 million ($75 million) can be made available to the public sector subject to request by the authorities and approval by the EBRD. In addition, up to €100 million ($129.4 million) of financing for small and medium-sized municipalities will be available from the Municipal Infrastructure Development Fund.●

Loan provides improved access to water and sanitation services in Guyana

The Inter-American Development Bank is providing a $16.8 million loan to Guyana to strengthen and improve access to water and sanitation services.

The programme to improve water and sanitation infrastructure and supply calls for infrastructure projects to build, upgrade and expand water treatment plants and enhance access to adequate sanitation. This will be achieved through measures to strengthen the supplier, Guyana Water Incorporated.

The work will also design and implement a programme to monitor non-registered water and a public awareness campaign on the use of water and hygiene.

The programme is expected to increase the number of households with 24-hour access to water, and water pressure in line with national standards, as well as a reduction in unaccounted-for water and an increased number of homes with improved access to drinking water and proper sanitation arrangements. ●

Environment Agency awards flood asset upkeep contract

The Environment Agency has awarded IPL and Manhattan Atrium a £9 million ($1.4 million) framework contract to implement a new system to manage the upkeep of its flood and coastal defence assets.

The first phase of work under the framework will implement Manhattan Atrium's Enterprise Asset Management System, which will streamline the management of these key assets.

The four-year programme will enable the Environment Agency to focus more funds on the upkeep of these assets by reducing the administrative cost of maintenance planning, delivery and reporting, the companies said in a statement.

The Environment Agency has over 150,000 flood and coastal defence assets across England and the new system will give it a single view of all maintenance activity nationwide, enabling it to prioritise based on local need and available funding.●

Sewer deterioration modelling for asset management strategies

Various issues and complicating factors make sewer deterioration modeling for asset management a challenging task. Nicolas Caradot, Hauke Sonnenberg, Ingo Kropp, Torsten Schmidt, Alexander Ringe, Stephane Denhez, Andreas Hartmann and Pascale Rouault look at the state of the art and perspectives, and introduce a new project that aims to clarify the situation.

Nicolas Caradot, Hauke Sonnenberg, Andreas Hartmann and Pascale Rouault
Kompetenzzentrum Wasser Berlin gGmbH, Berlin, Germany. Email: nicolas.caradot@kompetenz-wasser.de

Alexander Ringe
OEWA Wasser und Abwasser GmbH, Leipzig, Germany.

Stephane Denhez
Veolia Direction Technique 1, Saint Maurice, France.

Ingo Kropp
3S Consult GmbH, Dresden, Germany.

Torsten Schmidt
TU Dresden, Institut für Stadtbauwesen und Straßenbau, Dresden, Germany.

Recent infrastructure studies underline the general deterioration of sewer systems and the risk of reversing public health and environment gains, and increasing costs (ASCE, 2009). Ageing pipes have not been inspected, replaced or rehabilitated rapidly enough to prevent sewer deterioration and increasing system failures (Tuccillo et al, 2010).

According to a need survey conducted by EPA (2008), the total funding need in the US for replacing, rehabilitating and expanding existing collection systems over a 20-year period is $82.7 billion, that is, 28% of public agencies' total need for wastewater treatment and collection. In the last 30 years, most municipalities have invested in sewer system expansion and treatment plant upgrades, but a relatively small component has been allocated to improving sewer system condition.

Only a part of the funds needed to upgrade the condition of sewer systems will be generated through increases in municipal taxes and user fees (Allouche et al, 2002). Another strong effort will be required to reduce overall costs by using decision support systems to define cost-effective rehabilitation plans and optimise inspection and maintenance programmes.

A key element of decision support systems is the ability to assess and predict the remaining life of the assets (Marlow et al, 2009). For this purpose, deterioration models have been developed by research and water utilities to simulate the actual condition of non-inspected (or not recently inspected) sewers, and to forecast the future degradation of the network (Figure 1).

Modelling results are used to support the definition of long-term strategies and budget requirements, or to determine at a finer resolution how, when, and where to rehabilitate sewers. Input data to deterioration models are generally sewer condition data (condition evaluation from CCTV reports) and factors that influence sewer degradation (sewer characteristics and environmental factors).

Several modelling approaches are now available, but are not commonly used by sewer operators and municipalities to support their strategies. Indeed, their ability to model sewer deterioration with an acceptable accuracy is still to be demonstrated. This step is crucial for the further development of deterioration models, since their acceptance among water utilities depends mainly on the availability of proof of reliable forecasts (Ana and Bauwens, 2010).

Since decision makers may use information from model results to plan or justify public investments, they are highly concerned by the accuracy of the model predictions (Sargent, 1999). Validating deterioration models is therefore still a primary task to be done in order to build the confidence of end-users (utilities and municipalities) in their use, and to demonstrate the benefits of using modelling approaches to set asset management strategies.

In order to fill this gap, the recently started SEMA project aims to investigate the suitability of sewer deterioration modelling for simulating sewer deterioration. The main goals are to assess the accuracy of sewer deterioration models, the influence of the availability of CCTV data on the modelling quality, and the optimum data requirement to reach acceptable and satisfactory results.

This article explores the background of sewer condition assessment and sewer deterioration modelling that led to the development of SEMA. It aims to present the state of the art of condition classification methodologies and sewer deterioration models, discuss open questions and highlight key issues for the future development of deterioration models. Finally, some details are given about the objectives and strategy of the ongoing SEMA project.

Sewer condition assessment

A wide panel of condition classification methodologies has been developed over recent decades. These methodologies typically use algorithms to weight, combine and aggregate sewer defects recorded during CCTV inspection of sewer pipes to provide an overall condition score for each sewer segment (from manhole to manhole). The scores have very different meanings, and should be interpreted carefully. Several approaches can be distinguished.

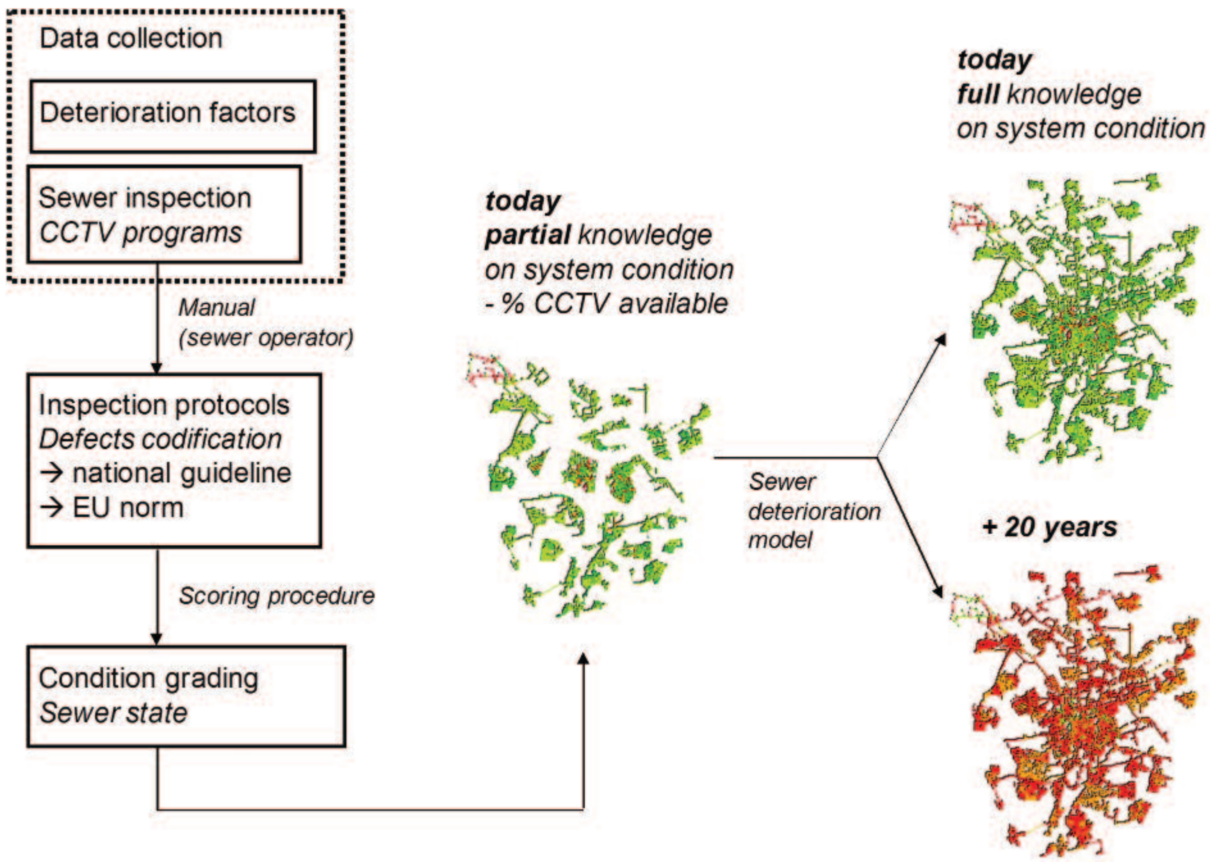


Figure 1
Figure 1: From CCTV inspection programmes to sewer deterioration modelling

Priority-based methodologies
These methods assign a final mark to each inspected sewer that represents the priority of rehabilitation, that is, the urgency of action regarding the probability of failure or collapse (Baur et al, 2005). The Water Research Center (WRc) in the UK proposed the first approach developed to assess the current condition of sewer pipes in 1986 (WRc, 1986). Based on or parallel to this original scheme, several approaches have been developed, particularly in Canada, the US, Australia, France (Le Gauffre, 2004) and Germany (DWA-M 149-3, 2011).

These methods focus on the structural condition of the sewers, but also consider operational and environmental factors (such as vulnerability of groundwater to pollution). Grades are calculated according to the most important damage within the sewer and / or the density of defects along the sewer line. Factors of vulnerability or failure consequences are often integrated (such as traffic flow above the sewer, and the location of services such as industry or highways) to evaluate the risk of failure or collapse (Le Gauffre et al, 2004; WRc, 2004). Thornhill (2008) suggests that data about failure consequences need to be considered in the condition assessment, since they are primary in the rehabilitation decision process. However, few utilities manage to implement full risk-based sewer condition evaluation, mainly because of the lack of standards and the expense of collecting such critical data.

Substance-based methodologies
Recent German projects (DWA T4, 2012; Hochstrate, 1999) stated that existing priority-based classifications do not allow for a pragmatic and accurate estimation of renewal needs. For that purpose, substance-based models have been developed. The goal is to rank sewer pipes in accordance with the amount and type of rehabilitation they need: replacement, renovation or repair.

These methods define a substance class for each sewer based on the repair length, that is, the length of sewer that will be affected by the rehabilitation actions. Depending on the type of defect, no-dig or open trench solutions will be required. Rehabilitation interventions will affect a specific sewer length longer than the defect itself. If defects are very close to each other, they may be rehabilitated together using fewer rehabilitation technologies, thus reducing the intervention costs. If much of the sewer is affected by rehabilitation interventions (for instance, if there are many severe defects spread over the sewer length), the substance of the sewer is considered to be very low since an expensive replacement will be the most cost effective solution. If only a small part of the sewer is affected (for example, if there is only one severe point defect or several small defects spread over the sewer length), the sewer has a better substance value as repair or renovation technologies will be appropriate.

What is the most appropriate condition classification for input data to deterioration models?
Condition classes from inspected sewers are used as input data to calibrate deterioration models. To reach a reliable calibration, the condition classification used should be appropriate to describe the degradation of the network. In other words, the degradation should be able to be modelled according to the chosen condition classification.

Substance-based classification can be more convenient than priority-based classification, as the grading considers the intrinsic value of the sewer (Baur et al, 2005). Indeed, priority-based classification is not adapted for deterioration modelling, since one grade can represent different degradation situations (such as one severe damage event or several small damages) that can hardly be reproduced or predicted by a model.

In addition, priority-based classification provides no advice on whether local repair will be sufficient for the sewer rehabilitation, or whether the replacement of the entire sewer line is justified (Schmidt, 2009). Investigations are needed to identify the most appropriate approach to classification for deterioration modelling. The influence of the choice of substance or priority-based classification on the quality of calibration and prediction in deterioration models should be investigated. Since classification methods combine and aggregate sewer defects to provide an overall grade, the possibility of using interim scores (for example structural or hydraulic condition) or single defect characterisation could be of interest.

How do uncertainties in condition classification influence the quality of modelling results?

The uncertainty of condition grading is a key issue for deterioration modelling, since condition classes are used as input data. Dirksen et al (2013) analysed findings from several European case studies on the accuracy and reliability of data obtained from CCTV inspections. Uncertainties originate mainly from subjectivity in recognising and describing defects, as well as the interpretation of CCTV inspection reports. The probability that an inspector would fail to recognise the presence of a defect was found to be about 25%. The group also found that the probability of an incorrect observation (defect recognition and description) for all defects was greater than 50%.

Finally, Hüben (2002) analysed the changes in condition scores between repeat inspections using data from a German municipality. The results indicated that over 50% of the sewers changed condition scores between the various inspections. Since there can be considerable uncertainty over condition grades, investigations are still needed to assess their influence on the quality of deterioration model predictions. In addition the robustness of deterioration models, considering the input data uncertainty, must still be demonstrated in large-scale case studies. The sensitivity of deterioration models to condition grade uncertainty has already been highlighted by Scheidegger and Maurer (2012), who used a synthetic dataset to generate several subsets of condition grades with inspection errors.

How does CCTV availability influence the quality of modelling results?

Due to the cost of CCTV inspections, few utilities have yet performed a full inspection of their entire sewer system. The amount of CCTV available (as a percentage of the network inspected) strongly influences the quality of calibration, and thus the quality of the modelling results. If too little data is available, the subset used for model calibration is probably not representative of the entire network and will lead to poor modelling results. In addition, as sewers with malfunctions and operational failures are often inspected as a priority, the CCTV available can overestimate a specific sewer condition and may not provide a representative distribution of the condition of the network. The influence of the amount of available CCTV on the prediction quality of deterioration models should be investigated. This step is crucial in informing sewer operators about the optimum data requirement for the successful use of deterioration models.

Deterioration factors

Since numerous factors affect sewer deterioration, it is obvious that pipes of different types and characteristics have different deterioration behaviours. These factors therefore need to be considered as variables or covariates in developing and calibrating sewer deterioration models. Due to the high costs associated with data collection, it is not cost effective for a sewer operator to collect data about all potential deterioration factors. Identifying and analysing the most important influencing factors is therefore crucial in reducing the amount of input data needed and improving the reliability of the deterioration models' predictions.

The sewer deterioration process can be divided into structural deterioration and hydraulic deterioration (WRc, 1986). Structural deterioration is characterised by structural defects (such as cracks and fractures) that may lead to structural failures such as a pipe collapse (Tran, 2007). Hydraulic deterioration is observed through hydraulic defects (such as tree root intrusion and deposits) that reduce the sewer transport capacity and may lead to hydraulic failures such as blockages and overflows. A defect can have consequences for both structural and hydraulic degradation (for example, tree root intrusion). In addition, the overall structural condition directly affects sewer flow capacity (Chughtai and Zayed, 2008), as deteriorated pipes with cracks and breaks have a rougher inner surface that increases the risk of debris accumulating.

Pipes generally deteriorate with age, but deterioration rates can vary significantly between pipes depending on pipe construction and operational and environmental factors. Therefore, an older pipe will not necessarily be in a worse state than a newer pipe. Numerous authors have analysed the influence of deterioration factors on sewer condition (Ana, 2009; Baur and Herz, 2002; Chugtai and Zayed, 2008; Davies et al, 2001; Müller, 2006; O'Reilly et al, 1989; Tran, 2007). The results of case studies are hardly directly comparable, because of the different construction practices, historical backgrounds and environmental conditions of the networks investigated. However, some trends regarding the most significant factors may be identified.

In most studies, the construction year and the sewer material were found to be the most influencing factors on the structural and hydraulic deterioration processes. The pipe size, the sewer depth, the sewage characteristics show a medium significance on sewer deterioration. These factors can be easily considered in deterioration modelling since data are usually available. The pipe slope was found to have a low significance for the structural deterioration but a high relevance on the hydraulic deterioration. On the other hand, the effect of pipe shape and pipe length was rarely investigated, although data of these factors are usually available.

What are the most relevant deterioration factors, and how can data be obtained?

Sewer operators do not systematically gather data on the factors that influence sewer deterioration. If the key data on age, material, size and location are largely available, other data that may have a significant influence on sewer deterioration rarely are. For example, the factors of pipe location (surface loading), soil type, sewer bedding and the presence of trees (the influence of roots) have rarely been investigated, as few data are available in operator databases.

As far as we know, the influence of other potential significant factors such as the installation method, standard of workmanship, joint type and groundwater level have not been investigated quantitatively. Data on these factors can be obtained from databases for other municipal services (for instance soil type, and the presence of trees) or from monitoring campaigns (such as sewer bedding (DWA-M 149-4, 2011)). Since these factors are often considered to have a major influence on sewer deterioration, further studies are needed to gather data and analyse their influence on sewer deterioration alongside the classical sewer characteristics.

How does the availability of data on deterioration factors influence the quality of modelling results?

Data on deterioration factors are rarely exhaustive. For example, information on sewer material or sewer construction year might only be available for part of the network. Incomplete data can be used to calibrate deterioration models, but the influence of partial information on the quality of modelling results should be carefully evaluated. As for CCTV data, research is needed to assess the optimum data requirement (the type of factor and amount of information available) to reach good model prediction quality.

Sewer deterioration modelling

A great variety of deterioration models have been proposed in the literature to

Study	City	Samples used	Model tested C	M	R	N	Results
Ana (2009)	Antwerp, Belgium	1539	+	-	-	-	C is appropriate at the pipe group level M fails at the pipe group level R and N fail at the pipe level
Tran (2007)	Greather Dandenong, Australia	417		+	-	+	M is appropriate at the pipe group level N is the best at the pipe level (percentage of correct prediction greater than 60%)
Ens (2012)	Canadian city	200			-		Very low prediction quality
Salman (2010)	Cincinnati, USA	11,373			-		Multinomial logistic regression has an overall good prediction quality but fails to predict sewer in medium condition
					+		Binary logistic regression has a good percentage of correct predictions (66%)
Chugtai and Zayed (2008)	Pierrefonds and Niagara Falls, Canada	-			+		Multiple regression model shows a good prediction quality (R2 between 0.72 and 0.88)
Khan et al. (2010)		-				+	Good prediction quality (R2 between 0.71 and 0.86)
Le Gat (2008)	Dresden, Germany	7042		+			Good prediction quality (50% of the pipes in the worst condition have the 20% worst predicted degradation scores)

Table 1
Validation results from applying different sewer deterioration models in the literature: C = cohort survival models, M = Markov-based models, R = regression based models (including discriminant analysis) and N = neural networks. (+) indicates that the validation results are rather satisfactory, (-) indicates that the model failed (or partly failed).

predict the deterioration processes, based on observed sewer conditions and factors influencing the deterioration process (Kley and Caradot, 2013). Three main approaches coexist to simulating the degradation of sewer condition: deterministic, statistical and artificial intelligence based models. Models can be further categorised into pipe group and pipe level models (Ana and Bauwens, 2010).

Pipe group models can be used to predict the condition of a group of sewers (cohorts), and are useful in supporting strategic asset management, that is, defining long-term strategies and budget requirements. These models enable the efficiency of several scenarios to be evaluated at network scale. Pipe level models can be used to simulate the condition of each individual pipe. They may be useful in setting priorities and justifying asset management operations and investments. Pipe level models are tools that can support utilities in mid-term planning and determining at a finer resolution how, when, and where to rehabilitate sewers. They can also be used at pipe group level for predicting the condition of groups of sewers and setting long-term budget requirements.

Deterministic models
These models aim to describe the deterioration process by evaluating physical ageing mechanisms. Some aspects such as corrosion can be modelled empirically, but general sewer deterioration is a very complex process that is not completely understood and depends on many factors (Schmidt, 2009). Deterministic models are often too simplistic to reflect the actual deterioration process, and the scarcity of available data required to simulate deterioration mechanisms decreases the applicability of such models (Ana, 2009).

Statistical models
To overcome this difficulty, statistical models relate sewer condition data history to pipe deterioration (Ana and Bauwens, 2010). According to Mehle et al (2001), since the ageing and deterioration of sewer systems is probabilistic, probability-based methods such as cohort survival models or Markov models are best adapted to simulating sewer condition.

These two models describe the deterioration process of homogenous sewer pipe groups (cohorts) sharing similar deterioration factors with transition functions. They both require extensive datasets to create cohorts with sufficient numbers of inspected sewers in each condition state. Data on repeat inspections that reflect condition changes of individual pipes over time are often missing, in particular. In the case of Markov models, the use of covariates can reduce the number of cohorts and thus the amount of data needed to calibrate reliable transition functions.

Other statistical models such as logistic regression and discriminant analysis can be used to analyse the relationship between independent variables (such as deterioration factors and sewer characteristics) and dependent outcomes (such as sewer condition states). They follow simple concepts, which support a better understanding of the deterioration process as deterioration factors are directly correlated to sewer condition. On the other hand, they require extensive datasets of CCTV data, and available data on the most relevant local deterioration factors (such as material, pipe, sewer bedding, ground water level, and so on).

Artificial intelligence models
These models can identify complex non-linear relationships between input (such as deterioration factors) and output (such as sewer condition state) data. Neural networks belong to this category of model. Their structure is determined by the available sample data (data driven). They investigate the mathematical relationships between deterioration factors and sewer condition classes by 'learning' the deterioration behaviour of pipes from inspection data. The knowledge obtained from the sample data is generalised to predict the condition of new pipes (Tran et al, 2007). However, these models require relatively complex and time-consuming training processes and extensive datasets of CCTV inspection and deterioration factors. They fall into the category of 'black box' models, since only the input and output data are specified but not the underlying processes.

Validation of deterioration models
For decision-making purposes, models need to have a good predictive capability and to be able to make reasonable estimates of the uncertainty of their predictions (Omlin and Reichert, 2007). The validation process aims to demonstrate whether the model possesses a satisfactory range of accuracy consistent with its intended application (Sargent, 1999). Since no observed data are available for the future, the accuracy of deterioration models is evaluated by comparing model predictions with already observed data.

Generally, the comparison is made with data not used during the calibration procedure. This can be done through splitting the available dataset in two, dedicated respectively to calibration and validation. Calibration and validation datasets can be chosen randomly from the entire dataset or chronologically (with CCTV divided into two periods of calibration and validation respectively). Due to the lack of extensive datasets, all too few case studies have managed to assess the quality of deterioration model prediction.

There is no clear conclusion about the best modelling approach. Results from the case studies are often contradictory and scarcely comparable as they differ in the size of their datasets and the methods used for model validation. Although several classical indicators for model validation have been proposed (efficiency, chi-square and so on), there is still no consensus about the most appropriate way to assess model prediction. Table 1 summarises the main results from the case studies investigated.

Ana (2009) found that the cohort survival model is the most useful at the pipe group level. Even considering the simplicity of the approach, few authors have applied the cohort model to observed CCTV data (Baur and Herz, 2002). The main reason could be the need for an extensive dataset to create sewer groups (cohorts) with sufficient inspected sewers in each condition state.

Ana (2009) noted that the Markov-based models show insufficient prediction quality due to overestimating the deterioration. On the other hand, Tran (2007) concluded that the Markov model is suitable for sewer deterioration modelling and Le Gat (2008) demonstrated the benefits of using a Markov-based approach for finding sewers in the poorest condition.

Multiple logistic regression and discriminant analysis (MDA) have been tested on several datasets but showed fairly low prediction performances (Ana, 2009; Ens, 2012; Salman, 2010). The low prediction ability of MDA could be explained by non-valid statistical assumptions about the normality of the input factors. More generally, the low performance could originate from a biased distribution of datasets in terms of the number of samples for each condition state, or from the lack of data for important deterioration factors (Ana, 2009).

On the other hand, Chugtai and Zayed (2008) managed to build multiple regression models using deterioration factors to predict sewer condition grades with pretty encouraging validation results. These findings underline the potential for regression methods to provide a better understanding of the deterioration process at pipe level if sufficient data on deterioration factors are available.

Neural networks have proven to be successful tools for predicting the deterioration of individual pipes (Khan et al, 2010; Tran, 2007). However, the results were not satisfactory in the Ana case study (2009). The main reason could be the lack of data to train the model: CCTV data were available for less than 15% of the network. More generally, an increased number of input factors such as sewer bedding or groundwater level should improve neural networks' predictive performance.

How should the quality of prediction of deterioration models be evaluated?
Further research is needed to define validation methodologies and indicators that are relevant for decision makers and stakeholders. Statistical indicators may be necessary to demonstrate the validity of modelling approaches, but are difficult for sewer operators to understand. Easily understandable and meaningful indicators are required to draw conclusions about the ability of deterioration models to simulate sewer deterioration, and to benchmark modelling results.

What is the most reliable approach to modelling sewer deterioration?
Several projects have set out to evaluate the quality of deterioration model prediction. However, since the modelling purpose, the amount of data available, the models tested and the validation method differ in each case study, it is still difficult to draw conclusions on the best modelling approach. Further research using extensive datasets is needed to draw conclusions on the most appropriate modelling approaches for a specific modelling purpose: pipe group or pipe level, short- or long-term planning, and so on.

Perspectives and ongoing project

This article has presented the state of the art of deterioration modelling and condition classification and has discussed key issues for further developing and applying these models.

The main open questions to be investigated concern the type of model and input data needed:

- What is the most reliable approach to model sewer deterioration?
- What is the most appropriate condition classification as input data?
- What are the most relevant deterioration factors?

Further studies are needed to assess the influence of the quantity and quality of input data available on the quality of modelling results. How does the availability of CCTV and data on deterioration factors influence the quality of modelling results? How do condition classification uncertainties influence the quality of modelling results?

Describing the sensitivity of deterioration models to input data is a key step in defining the optimum data requirement for model calibration and use. Since few utilities have inspected their entire system and collected comprehensive data on sewer deterioration factors, identifying the minimum input data requirement is key to reaching an acceptable prediction quality.

The SEMA project aims to address these challenges. Its main goals are to assess the accuracy of sewer deterioration models, the influence of available CCTV data on modelling quality, and the optimum data requirement to reach acceptable and satisfactory results. Within this project, several condition classification methodologies (priority and substance) and deterioration model approaches (cohort and Markov) will be tested using CCTV data from the cities of Braunschweig, Germany, and Montbéliard, France.

Braunschweig is an ideal case study for evaluating the sensitivity of sewer deterioration models, since the entire sewer system has been inspected once and 50% of the system has been inspected at least twice: about 60,000 CCTV inspection results are available covering a 15 year period. The prediction quality of cohort and Markov models will be evaluated by using a number of condition classification methodologies on the extensive Braunschweig dataset.

The sensitivity of the models and the optimum data requirements will be assessed using various configurations of input data for model calibration. Several calibration datasets will be created with different data availability setups (percentage of CCTV, percentage of information on deterioration factors) and data quality (a random assignment of condition classes within their range of uncertainties). Lastly, deterioration models will be applied in the city of Montbéliard to evaluate the possibility of applying model calibration from one case study to another where inspection data are scarce.

SEMA is investigating the suitability of sewer deterioration modelling for simulating sewer deterioration. In the next phase, the relevance of deterioration models to support inspection and rehabilitation strategies will be explored.●

References

Allouche, EN and Freure, P (2002), Management and maintenance practices of storm and sanitary sewers in Canadian municipalities. ICLR Research, Paper Series –No 18, www.iclr.org/images/Management_and_maintenance_practices.pdf.

Ana, EV (2009), Sewer asset management – sewer structural deterioration modeling and multicriteria decision making in sewer rehabilitation projects prioritization. Doctor in Engineering, Department of Hydrology and Hydraulic Engineering, Vrije Universiteit

Brussel, Brussel.
Ana, EV and Bauwens, W (2010), Modeling the structural deterioration of urban drainage pipes: The state-of-the-art in statistical methods. Urban Water Journal, 7, 47-59.
ASCE (2009), Report card for America's infrastructure. American Society of Civil Engineers, Available from www.infrastructure reportcard.org/index.
Baur, R and Herz, R (2002), Selective inspection planning with ageing forecast for sewer types. Water Science and Technology, 46 (6-7), pp389-396.
Baur, R, Herz, R and Kropp, I (2005), WP6 conclusive report. Project CARE-S, 2005.
Chughtai, F and Zayed, T (2008), Infrastructure condition prediction models for sustainable sewer pipelines. Journal of Performance of Constructed Facilities 22, pp333-341.
Davies, JP, Clarke, BA, Whiter, JT and Cunningham, RJ (2001), Factors influencing the structural deterioration and collapse of rigid sewer pipes. Urban Water 3, pp73-89.
Dirksen, J, Clemens, FHLR, Korving, H, Cherqui, F, Le Gauffre, P, Ertl, T, Plihal, H, Müller, K and Snaterse, CTM (2013), The consistency of visual sewer inspection data. Structure and Infrastructure Engineering, 9 pp214-228.
DWA-M 149-3 (2011), Advisory Leaflet DWA-M 149-3 – Conditions and assessment of drain and sewer systems outside buildings – Part 3: condition classification and assessment. ISBN: 9783942964111. German original published 2007, English translation published 2011.
DWA-M 149-4E (2008), Advisory Leaflet DWA-M 149-4E – Conditions and assessment of drain and sewer systems outside buildings - Part 4: detection of bedding defects and cavities by means of geographical techniques.
DWA T4 (2012), Leitfaden zur strategischen Sanierungsplanung von Entwässerungssystemen außerhalb von Gebäuden. DWA T4/2012 (de).
EPA (2008), Clean watersheds needs survey. Report to Congress 2008, USA.
Ens, A (2012), Development of a flexible framework for deterioration modeling in infrastructure asset management. Master of applied science, Department of Civil Engineering, University of Toronto, Canada.
Hochstrate, K (1999). Substanzwertorientierte Zustandsklassifizierung von Kanälen – Das Bietigheimer Modell. Korrespondenz Abwasser - Wasserwirtschaft, Abwasser, Abfall, 46 (2).
Khan, Z, Zayed, T, Moselhi, O. (2010), Structural condition assessment of sewer pipelines. Journal of Performance of Constructed Facilities 24 pp170-179.
Kley, G, and Caradot, N (2013), Review of sewer deterioration models. Report KWB project SEMA. Available under: www.kompetenz-wasser.de/SEMA.557.0.html?&L=1.
Le Gat, Y (2008), Modeling the deterioration process of drainage pipelines. Urban Water Journal 5, pp97-106.
Le Gauffre, P, Joannis, C, Breyssee, D, Gibello, C and Desmulliez, JJ (2004), Gestion patrimoniale des réseaux d'assainissement urbains. Guide méthodologique. Lavoisier Tec&Doc.
Marlow, D, Davis, P, Trans, D, Beale, D and Burn, S (2009), Remaining asset life: a state of the art review. In Final Report, Water Environment Research Fundation (WERF), Alexandria, VA, US.
Mehle, J, O'Keefe and Wrase, P (2001), An examination of methods for condition rating of sewer pipelines. Center for development of technical leadership, University of Minnesota.
Müller, K (2006), Strategien zur Zustandserfassung von Kanalisationen. Dissertation, Aachener Schriften zur Stadtentwässerung, Institut für Siedlungswasserwirtschaft der RWTH Aachen. Aachen, 2006.
Omlin, M, and Reichert, P (1999), A comparison of techniques for the estimation of model prediction uncertainty. Ecological Modelling, 115, pp45–59.
O'Reilly, MP, Prosbrook, RB, Cox, GC and McCloskey, A (1989), Analysis of defects in 180km of pipe sewers in southern water authority. TRRL Research Report 172.
Salman, B (2010), Infrastructure management and deterioration risk assessment of wastewater collection systems. University of Cincinnati, Doctor in Engineering, Division of Research and Advanced Studies of the University of Cincinnati.
Sargent, RG (1999), Validation and verification of simulation models. In Proceedings of the 1999 Winter Simulation, eds, pp39-48.
Scheidegger, A and Maurer, M (2012), Identifying biases in deterioration models using synthetic sewer data. Water Science and Technology, 2012, 66(11) pp2363-9.
Schmidt, T (2009), Modellierung von Kanalalterungsprozessen auf der Basis von Zustandsdaten. Doctoral thesis, Insitut für Stadtbauwesen und Straßenbau, Technical University Dresden, Germany.
Thornhill, R (2008), Know your limitations with PACP condition grading, NASSCO Times, 12.
Tran, D (2007), Investigation of deterioration models for stormwater pipe systems. Doctor of Philosophy, School of Architectural, Civil and Mechanical Engineering, Victoria University.
Tuccillo, ME, Jolley, J, Martel, K and Boyd, G (2010), Report on condition assessment of wastewater collection systems. EPA, United States Environmental Protection Agency, Cincinnati, Ohio.
WRc (1986), Sewerage rehabilitation manual. Water Research Centre, UK.
WRc (2004), Manual of Sewer Condition Classification – 4th Edition. Water Research Centre, UK.

This paper was presented at LESAM 2013 – the IWA Leading-Edge Strategic Asset Management conference, held 10-12 September 2013 in Sydney, Australia.

Factors contributing to large diameter water pipe failure

P Rajeev, Jayantha Kodikara, Dilan Robert, Peter Zeman and Balvant Rajani look at a case study in which failure inspection data from five Australian utilities was analysed to determine the factors contributing to failures in large diameter pipes.

P Rajeev and Jayantha Kodikara
Department of Civil Engineering, Monash University, Australia. Email: prajeev@swin.edu.au; jayantha.kodikara@monash.edu;

Dilan Robert
RMIT University, Melbourne, Victoria, Australia.
Email: dilan.robert@rmit.edu.au

Peter Zeman
Sydney Water, Parramatta, NSW, Australia.
Email: peter.zeman@sydneywater.com.au

Balvant Rajani
Rajani Consultants, Ottawa, Canada.
Email: Balvant.Rajani@gmail.com

Water utilities in Australia operate supply and distribution networks consisting mainly of ageing cast iron and steel mains. The failure of large diameter pipes (of diameters >300mm) can be highly disruptive to both water utilities and the public they serve. Failures can have major consequences in terms of economic loss to water utilities, public safety and damage to property, and also have an adverse affect on the overall performance of their assets.

Structural failures of large diameter metallic water mains are usually caused by a combination of factors, but predominantly occur when pipes affected by corrosion are subjected to excessive internal and / or external loadings. Identifying the relative contributions of each factor in a specific failure (that is, physical factors and corrosion) is often a difficult task that has not yet been resolved satisfactorily.

The factors that contribute to a specific pipe failure can be categorised into three principal groups:

- Pipe geometry, material type, pipe-soil interaction and quality of installation
- Internal loads due to operational and transient pressure and external loads due to soil overburden, traffic loads, frost loads (in cold climates) and third party interference (catastrophic loads)
- Material deterioration due largely to external and internal chemical factors; this includes biochemical microbiological and electro-chemical activities that lead to corrosion (Rajani and Kleiner, 2001).

To understand in-service pipe failures, it is necessary to understand the stresses to which pipes are subjected and any degradation of the pipe's mechanical performance with time that might contribute to failure. Although there may be a range of (sometimes unknown) variables involved, the pipe failure is the result of a deterministic process governed by physical conditions.

Regardless of the source of loading, a pipe may fail when the generated stress exceeds the nominal material strength, or when the stress intensity generated at a critical defect (for instance, as a result of pitting corrosion) exceeds the material toughness, or possibly as a combination of both. Thus, pipelines reach failure states when the pipe at a particular location loses its structural

Table 1 Summary of collected past pipe failure data

Water utilities	Period	Pipe material	Total length of asset (km)	Total number of failures
A	2000-2012	CICL, SCL, DI, PVC & AC	3061	2871
B	1973-2010	CICL, DI, S, & PVC	779	1052
D	1998-2012	CI, DI, S, & PVC	862	1023
E	1996-2009	S, AC, CI, & PVC	854	426
F	1997-2012	CI, DI, S, & PVC	426	809

CI: Cast iron; CICL: Cast iron cement lined; S: Steel; SCL: Steel cement lined; DI: Ductile iron; AC: Asbestos cement; PVC: Polyvinyl chloride

Table 2 Asset length data on the basis of pipe material

Water utility	A	B	D	E	F
Pipe material			% of pipe asset length		
CI/ CICL	- / 56.65	3.46/ -	- / 48.89	276/847	638/929
S/ SCL	- / 19.64	- / 60.08	- / 24.19	17/644	5/469
DICL	23.69	9.31	26.91	18.56	25.14
AC	0.03	27.15	-	23.93	-

Table 3 Summary of pipe failure rates (# no. of failure/km/year)

Water utility	Period (# years)	CI	CICL	S	SCL	DICL	AC
A	2000-2012 (13)	-	7.2	-	4.2		2.8
B	1973-2010 (38)	34.5	-	-	3.1	0.1	2.2
D	1998-2012 (15)	-	14.0	-	5.1	0.80	-
E	1996-2009 (14)	7.8	8.9	6	2.4	1.85	4.2
F	1997-2012 (16)	29.5	21.5	42	8.0	8.00	-

Note: These failures rates do not differentiate for the fact that some of the pipes were not cement lined for a period of time since installation.

Table 4 Commonly observed failure modes in large diameter pipe and corresponding driving factors

Failure mode	Driving factors
Longitudinal split	Internal pressure and corrosion
Piece blown out	Internal pressure and corrosion
Pinhole	Corrosion
Circumferential break	External loadings and ground movement*
Joint leakage	External / internal loads, thermal loadings and construction defects

* Note: Not common in large diameter pipes

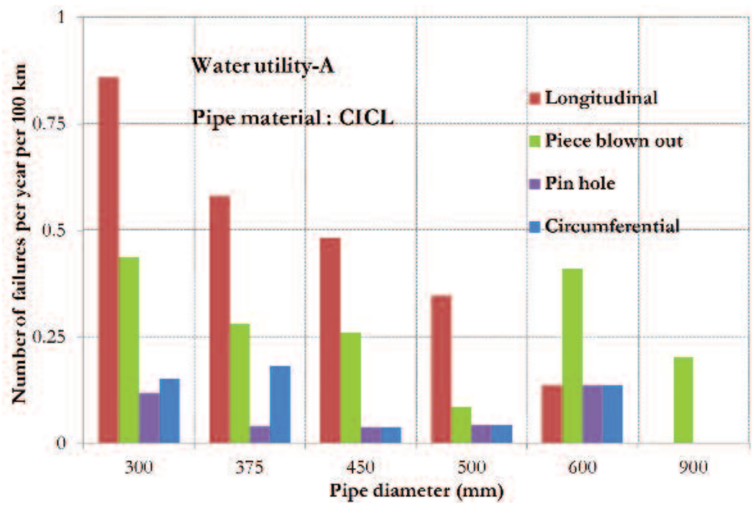
capacity sufficiently with time, due to corrosion or damage.

In order to understand the pipe failure mechanisms, it is therefore necessary to establish the long-term corrosion characteristics of pipes in their buried environment. There are instances, however, where pipes have failed without significant corrosion, and in these instances accumulation of damage due to repetitive loading may be to blame (Rajani and Kleiner, 2010).

Existing physical and statistical models for predicting failures in individual water mains address only one or a few factors. Neglecting to account for the important factors can lead to inaccurate conclusions, which result in sub-optimal failure prediction and pipe renewal strategies.

Statistical analysis of past pipe failure data, which uses available historical data on past failures to identify the possible factors leading to pipe failure, is one of the effective ways of studying the pipe failure mechanism, causes of failure and deterioration and so on. Unfortunately, however, in contrast to small diameter pipe failures, the failure data for large diameter pipes are significantly limited. Despite this, and paying attention to any inconsistencies that may be present in the field data collection, extracting any information that can help pipe failure prediction and asset management is valuable.

In this study, information (such as installation and failure data) on buried large diameter pipes collected from five Australian water utilities was analysed to understand the physical and environmental factors that led to failure. The failure data were analysed to classify commonly observed pipe failure modes and causes of failure. Corrosion patterns observed in the failed pipe sections were classified into three major groups, and then visualised to facilitate pipe failure prediction analysis. Further, on the basis of failure inspection reports, the level of corrosion at the time of pipe failure (using the average corrosion rate) was used to examine the likely corrosion levels that had led to pipe failures.



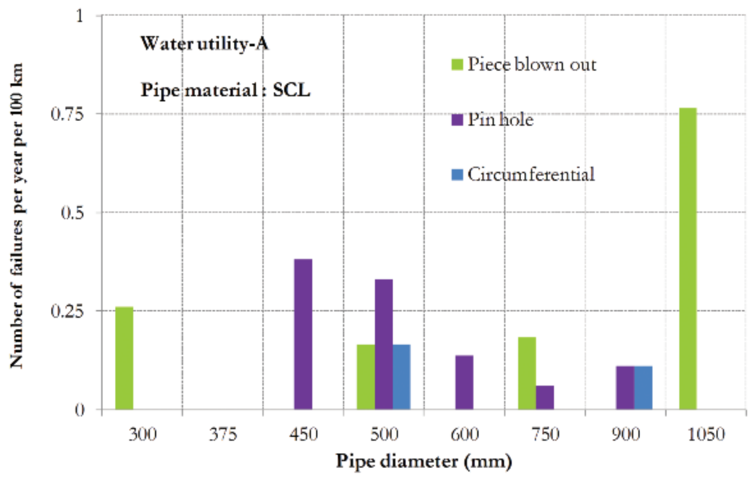


Figure 1 Histogram of failure rate based on failure mode for: (a) CICL main and (b) SCL main using past failure data obtained from water utility A

Failure statistics

As stated above, the past pipe failure data on buried large diameter pipe were collected from five Australian water utilities and analysed to understand the physical and environmental factors that could have contributed to their failure. In general, the collected data provided information on pipe diameter, pipe material, location of failure, cause of failure, failure mode, year the pipe was laid, and year of failure, though all the information was not always available.

It is also important to note that not

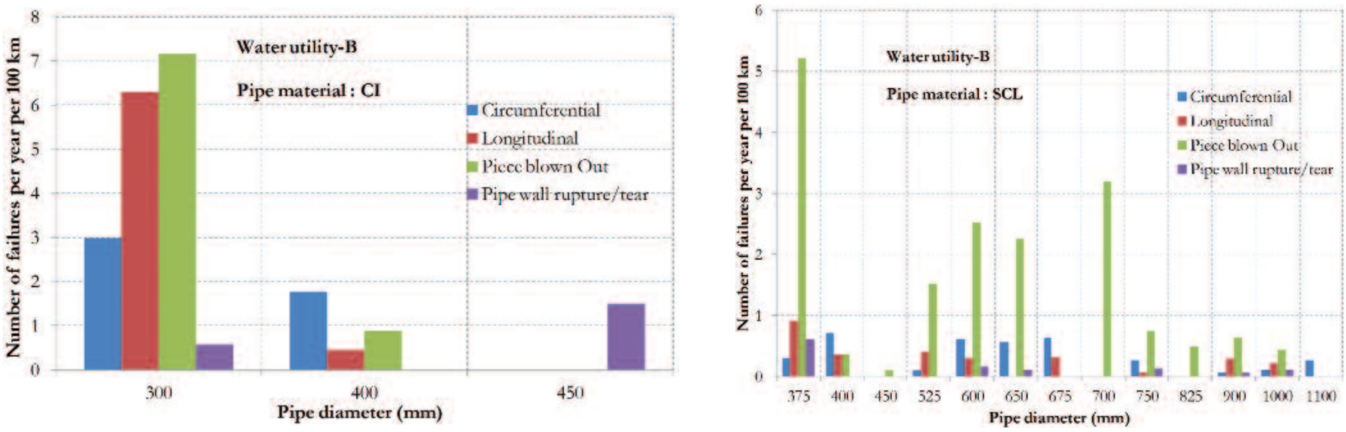


Figure 2
Histogram of failure rate based on failure mode for: (a) CI main and (b) MSCL using past failure data obtained from water utility B

all data had the same level of detail because of the differences in data collection procedures followed by different water utilities, so direct comparison of results was not always possible. Table 1 provides a summary of failure data collected from the five water utilities (referred to here by generic names, utility A to utility F). It also shows the average failure per year (that is, the total number of observed failures per period).

In this study, analyses were performed on the data for cast iron (CI), steel (S), ductile iron (DI) and asbestos cement (AC) pipes that are considered to be affected by corrosion or similar deterioration mechanisms. Table 2 provides the asset length data based on the pipe material.

The collected failure data for each water utility were analysed separately and conclusions drawn on the basis of identified common trends. The following sections discuss the results of the statistical analyses of failure data on the basis of pipe materials, failure modes and causes of failure. The pipe failure inspection reports were further analysed to understand the contribution of corrosion to the pipe failures on the basis of observed corrosion pit depth in a failed pipe section, and identified failure mode.

Pipe materials

The failure data were analysed on the basis of pipe material. Failure rate per year per km for a specific pipe material was determined using the total number of failures divided by the number of years in the observation period and the total asset length of that pipe material. Unlined and cement lined (CL) pipes were treated separately. The pipe failure rate related to pipe material is provided in Table 3. Based on the analysis, the higher failure rates were observed for both unlined and cement lined or cast iron pipes in comparison to other pipe materials for water utilities A, B, D and E. However, a higher failure rate was observed in steel pipes for water utility F. The lowest failure rate for all water utilities on a relative basis is for ductile iron pipes.

Failure modes

The actual manner in which the pipes fail is called the failure mode rather than the mechanism that causes the failure. These modes vary depending on the diameter of the pipe and the pipe material. For example, longitudinal bending-induced circumferential ('broken back') failures are more common in smaller diameter pipes that have relatively low water pressure and smaller moments of inertia. On the other hand, larger diameter pipes experience mainly longitudinal cracking and shearing at the bell due to relatively higher water pressure and moments of inertia. More details of different failure modes observed in pipelines can be found in Makar et al, (2001). The commonly observed failure modes in large diameter pipes and the identified driving factors are summarised in Table 4.

In this study, the observed failure modes were analysed in accordance with pipe material (mainly cast iron and steel) and diameter. The results of the analyses in this paper are limited to water utilities A and B only. A detailed presentation of the results for other water utilities can be found in Kodikara et al, (2012).

Figure 1 shows histograms of failure rate versus pipe diameter based on the

Figure 3
General corrosion: (a) field observation and (b) visualisation of general corrosion.

Figure 4
Patch corrosion (a) field observation and (b) visualisation of patch corrosion

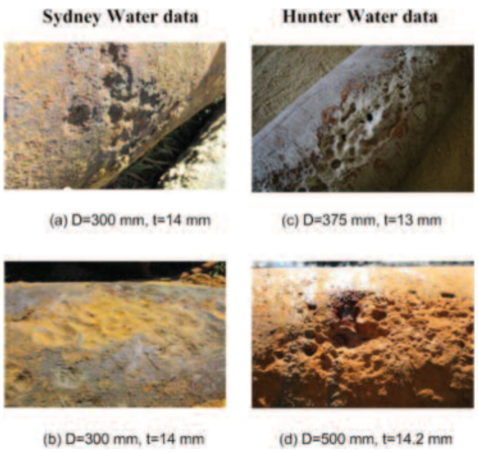


Figure 5
Observed pitting corrosion patterns

failure mode data obtained from water utility A for cast iron and steel pipes. Failures due to pieces blown out and pinholes are observed across the entire diameter range in cast iron and steel pipes. There is, however, some doubt as to how common piece blown failure in steel pipes is, since the material is more ductile. Longitudinal split, which is one of the dominant failure modes, is observed in cast iron concrete lined (CICL) pipes up to 600mm diameter.

The circumferential failures are also observed in steel pipes even at 600mm diameter, and in cast iron pipes of 900mm diameter. Usually, circumferential failures are not common in large diameter pipes due to the high moment of inertia, which restrains bending, so more attention may need to be paid to such information in future.

Figure 2 shows a histogram of failure rates based on failure type using data obtained from water utility B for CI and steel cement lined (SCL) pipes. As observed for water utility A, a large number of pieces blown out and longitudinal split failures were observed in cast iron pipes. For steel pipes, a large number of failures were in the piece blown out mode across the whole diameter range. Such data may need further attention in future for the reasons noted above. Also, failures were observed due to longitudinal split and circumferential failure across the whole diameter range.

Causes of failure

Buried pipes are subjected to internal water pressure, consisting of static water pressure and pressure transients due to surges, external loads, self-weight and pipe contents, heaving or movement in the surrounding soils, and potential inertial seismic forces. External loads typically consist of earth load and traffic load.

Unlike the uniform stress condition developed by internal pressures if no other external loads are acting, external loads develop non-uniform stress conditions (bending) around the pipe circumference. A pipe affected by corrosion or some other similar defect can fail if the stresses induced by a combination of the sum of all of these loads are a sufficient amount higher than the pipe capacity.

The failure data collected were not sufficiently extensive to make conclusive statements about the causes of failure. However, a general evaluation of the data highlighted corrosion as the main cause of failure. In addition, pressure transients and ground movement were indicated as further causes. It is, however, not clear how ground movement could affect large diameter pipes, because they have much higher rigidity due to their higher moment of inertia. This would be another aspect where more clarity would be needed in data collection.

Pipe corrosion

Utilities in Australia operate a supply and distribution network consisting of predominantly cast iron and steel pipes, with ages on average greater than 60 years. As shown above, pipe corrosion is one of the major factors controlling pipe failure.

It is envisaged that pipe failure analysis should take into account actual deterioration and defects identified either through condition assessments or as they are expected to occur in pipes on the basis of the empirical evidence. On the basis of the information collected from utilities A and D, corrosion patterns and the rate of corrosion, as evident from failed pipes, were studied. The corrosion in the pipes was mainly classified as general corrosion, patch corrosion and pitting corrosion.

General corrosion refers to reasonably uniform reduction of thickness over the surface of the pipeline wall. An example of this is shown in Figure 3a. This form of corrosion may be visualised as a reduction of thickness as in Figure 3b.

Patch corrosion is identified by graphitisation or a cluster of geometrically interacting pits, which can be approximated as a patch of corrosion as shown in Figure 4a. Pitting is defined as localised regions of metal loss that can be characterised by a pit diameter (API, 2007). On the basis of the corrosion data obtained from the utilities there were three different corrosion pit patterns: single pit, multiple non-interacting pit and multiple non-interacting pit, which were commonly observed as shown in Figure 5. The diameter and thickness of the failed pipelines are shown along with the figures. The clusters of single pits that do not geometrically interact with each other are called non-interacting multiple pits, otherwise they are called interacting pits.

The single pit can be visualised

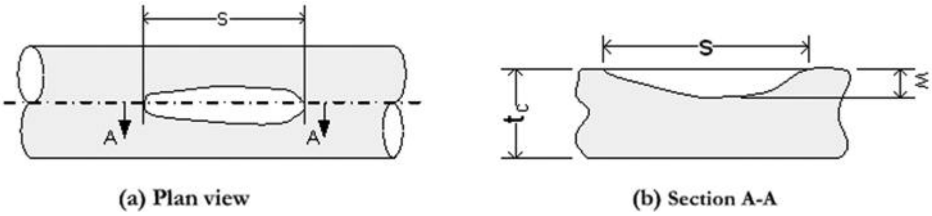


Figure 6
Single pit (s = length of the pit, w = depth of the pit, tc = pipe wall thickness)

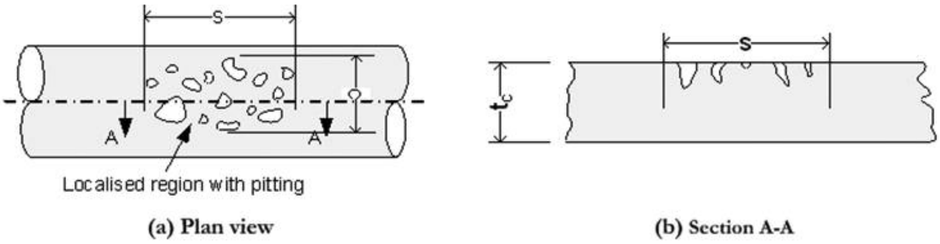


Figure 7
Schematic multiple non-interacting pit cluster (s = length of the pit)

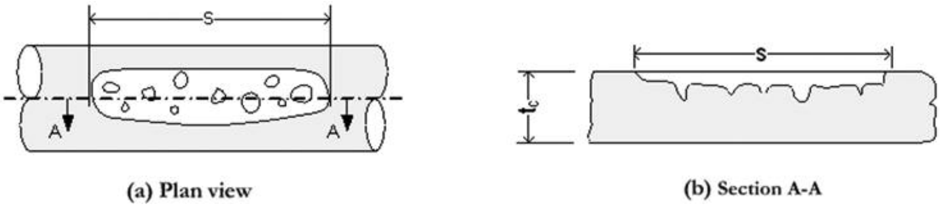


Figure 8
Schematic multiple interacting pit cluster (s = length of the pit, tc = pipe wall thickness)

as shown in Figure 6 for analysis. Drawing from API (2007), the non-interacting and interacting multiple pit can be visualised as shown in Figure 7 and Figure 8.

Corrosion rate

The inspection reports collected from the water utilities provided information on pipe laid year, the year of failure and the maximum corrosion pit depth observed in the failed section. The depth of the corrosion pit was determined during the forensic investigations of the failed section. These data were available only from water utilities A and D.

An analysis was conducted on the average rate of corrosion experienced by the failed pipes over the period when they were in operation. The methods used to estimate normalised corrosion rates were as follows:

- Average Corrosion Rate (ACR). The maximum pit depths determined during the forensic investigation of the failed section are divided by the pipe lifetime (defined as the difference between the year of failure minus the year of installation) to determine the average corrosion rates over the life of the pipelines (see Figure 9a for water utility A). It should be noted that this is an average corrosion rate over the entire pipe life, and is not reflective of actual corrosion rates the pipe was experiencing at various times in its life. For more information on actual corrosion rates, influencing parameters and mechanisms related to buried cast iron pipes, see Peterson and Melchers (2012).
- Normalised Pit Depth at Failure (NPD). The normalised pit depth was calculated by dividing the pit depth measured at failure by the original nominal pipe wall thickness, and multiplying by 100 to give a percentage.

Figure 9 shows ACR calculated using failure inspection reports for cast iron pipes obtained from water utilities A and D. The results are shown for various pipe diameters. There is significant scatter in the data, and there are some pipe failures even below 40 years featuring lower average corrosion rates at failure.

In order to examine the likely pit depths at failure, NPD is plotted against the pipe lifetime in Figure 11. As can be seen, NPD = 100% means that the pipes have failed with through wall corrosion, and values less than 100% reflects the percentage of pit corrosion with respect to the original thickness. It can be seen that quite a few data points fall on the through wall corrosion level. It is also evident that a significant number of failures have occurred with less than through wall corrosion. There are a limited number of points (three) in NPD = 75% to 100%. It may be inferred that when the

Table 5
Detailed analysis of failure data and qualitative contribution of corrosion and other factors to failure. Table must be assessed in conjunction with Figure 10.

Selected point	Cause of failure as noted in the failure inspection report	Selected point	Cause of failure as noted in the failure inspection report
R1	Corrosion and other factors	R7	Piece blown out. Failure due to corrosion.
R2	Minimal external corrosion. Failure due to other factors.	R8	Longitudinal crack seemed to follow a series of shallow pits on the external surface.
R3	Through wall corrosion. Heavy pitting corrosion.	R9	Piece blown out from collar: failure due to corrosion and other unknown factors
R4	No signs of corrosion along the point of failure, only a thin layer of surface corrosion coming off when hit. One location of deeper surface corrosion. Failure due to water hammer resulting from pumping.	R10	Failure by a piece blown out. Through wall along surface fracture but only in minimal number of locations. Surface corrosion all around fracture. Minimal surface corrosion, except for one location with up to 6mm.
R5	Longitudinal piece blown out from joint collar. Significant corrosion at collar. Failure due to corrosion and water hammer (operational changes at pumping station).	R11	Longitudinal failure with a piece blown out. Failure due to corrosion and operational change.
R6	Very minor corrosion and pitting, 2 to 3mm at most. Failure was characterised by a blown out piece of pipe caused by collar fracturing: May be due to localised corrosion. The system was operated as normal. There was no pressure transient.	R12	Piece blown out. Through wall along fracture surface but only in minimal locations. Surface corrosion all around fracture. Minimal surface corrosion, except for one location with up to 6mm.

wall thickness reduced by more than 75% of its original thickness, the pipes may have failed through wall failure.

In order to examine the possible causes and modes of failure associated with NPD, a number of data points in Figure 10 are elaborated further in Table 5. For instance, the point R3 falls on the through wall corrosion (NPD = 100%).

Summary and conclusion

In this study, the past pipe failure data and information were collected from five water utilities in Australia and analysed to identify the factors contributing to large diameter pipe failures. On the basis of the collected pipe failure data, most failures were observed in cast iron and steel pipes. Failure due to pieces blown out and pinholes are the major failure modes observed across all the utilities involved.

Corrosion is identified as a leading cause of failure, together with pressure transients and traffic load. Details of the types of corrosion observed in failed pipes were collected from the failure inspection reports. The type of corrosion observed in a failed pipe section was characterised in three main groups to facilitate pipe failure prediction for corroded pipes – namely uniform corrosion, patch corrosion and pit corrosion.

On the basis of the corrosion pit information reported in the failure inspection reports, the average rate of corrosion was calculated using the field observed maximum corrosion pit depth and the pipe lifetime. Examination of pit depths as a percentage of the original pipe thickness indicated that failures occurred at various pit depths, but there were fewer failures between 70% and 100% pit depths.

It should also be noted that some inconsistencies were found in the analysed failure data and these observations and inferences, while based on the available data, need to be further verified and checked by collecting more accurate data in the future. ●

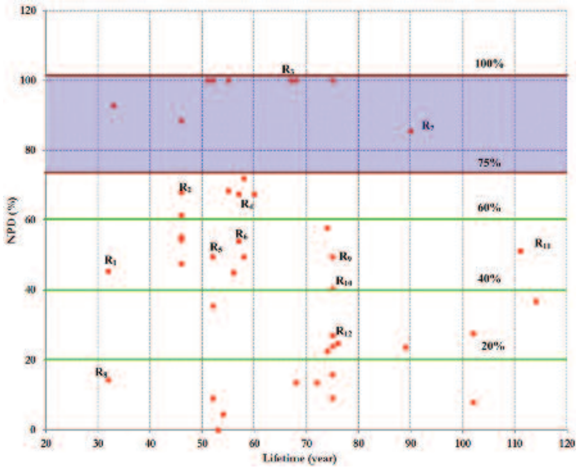
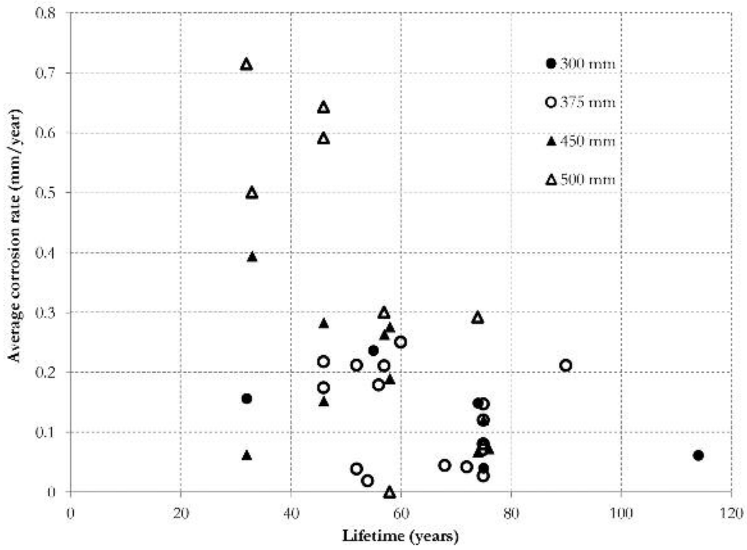


Figure 10
Normalised pit depth at failure vs age of the pipe at failure for water utility A



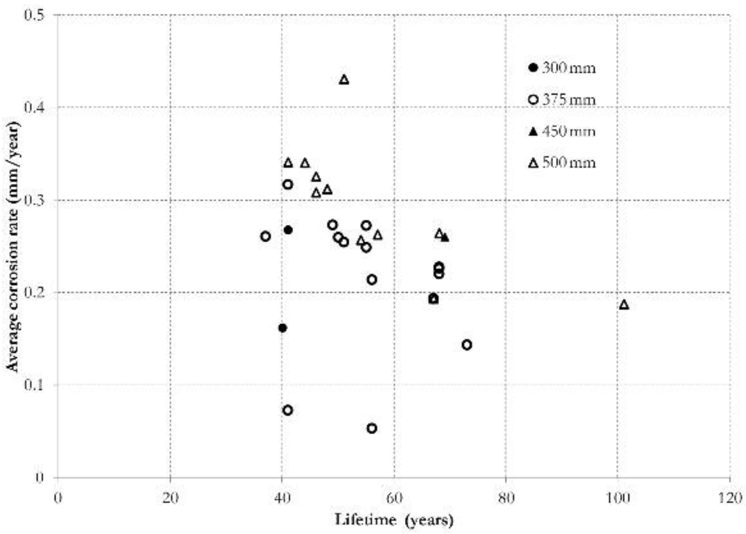


Figure 9
Average corrosion rate vs lifetime for: (a) water utility A and (b) water utility D

Acknowledgements

This publication is an outcome from the Advanced Condition Assessment and Pipe Failure Prediction project funded by Sydney Water Corporation, Water Research Foundation of the USA, Melbourne Water, Water Corporation (WA), UK Water Industry Research, South Australia Water Corporation, South East Water, Hunter Water Corporation, City West Water, Monash University, University of Technology Sydney and University of Newcastle. The research partners are Monash University (lead), University of Technology Sydney and University of Newcastle.

References

API (2007), Fitness-For-Service. The American Society of Mechanical Engineers, API 579-1/ASME FFS-1.

Atkinson, K, Whiter, JT, Smith, PA and Mulheron, M (2002), Failure of small diameter cast iron pipes. Urban Water, 4(3): pp263–271.

Makar, JM, Desnoyers, R and McDonald, SE (2001), Failure modes and mechanisms in gray cast iron pipe. Underground Infrastructure Research: Municipal, Industrial and Environmental Applications, Proceedings, Kitchener, Ontario, June 10-13, 2001, pp1-10.

Kodikara, J, Rajeev, P, Robert, D and Zeman P (2012), Critical review of historical information on large diameter pipe failure. Research report, Monash University, Australia.

Peterson, R and Melchers, R (2012), Long-term corrosion of cast iron cement lined pipes. Corrosion and Prevention, Paper 23.

Rajani, B and Kleiner, Y (2001), Comprehensive review of structural deterioration of water main: physically based modes. Urban Water, Vol 3, pp151-164.

Rajani, B and Kleiner, Y (2010), Fatigue failure of large-diameter cast iron mains. Water distribution system analysis (WDSA) 2010, Tucson, AZ, USA.

This paper was presented at LESAM 2013 – the IWA Leading-Edge Strategic Asset Management conference, held 10-12 September 2013 in Sydney, Australia.

Collaborative research on condition assessment and pipe failure prediction for critical water mains

Most major urban water utilities in Australia have extensive critical pressure main systems, parts of which have been in service for a century or more. As pipe breaks can have severe impacts on customers and safety, an international team of utilities, research organisations and technology providers initiated a global collaborative project developed to undertake research in partnership with local water utilities, local universities, international water bodies and pipe condition service providers. Dammika Vitanage, Jayantha Kodikara and Greg Allen discuss the project and its outcomes.

Dammika C Vitanage and Greg Allen
Sydney Water, Parramatta, NSW, Australia. Email: Dammika.Vitanage@sydneywater.com.au, Greg.Allen@sydneywater.com.au

Jayantha Kodikara
Department of Civil Engineering, Monash University, Victoria, Australia. Email: Jayantha.Kodikara@monash.edu

It is generally recognised worldwide that about 70% of the total asset base of urban water utilities consists of buried pipes. Sydney Water has buried systems valued at over AUS$15 billion (US$13.6 billion), and this is typical of large utilities.

Most major urban water utilities in Australia have extensive large, critical pressure main systems, parts of which have been in service up to a century or more. Failure of critical mains has significant impacts in terms of maintaining service levels to customers, loss of fire fighting supply, safety, transport disruption and other social costs, as well as significant financial and reputational implications.

With further ageing of this vital infrastructure, supply main failures will continue to occur. This will have very high and growing cost implications for the sustainability and effectiveness of water and wastewater services. This is a worldwide issue, with potential impacts of climate change on soil properties and moisture, which lead to higher costs.

In Australia, the total replacement costs of pipe network have been estimated to exceed AUS$100 billion (US$93.1 billion) (Nicholas and Moore, 2009). Over the next five years, the costs of urgently needed asset replacement are around AUS$5 billion (US$4.7 billion). Maintenance costs over the same period are estimated at some AUS$2.5 billion (US$2.3 billion) (WSAA, 2009). Elsewhere, the USEPA estimates that the US public water sector will require $335 billion of capital investment over the next 20 years to sustain essential service levels. US studies also indicate that the average cost per failure for large diameter pipes exceeds $500,000 (Nicholas and Moore, 2009).

In response to these cost drivers, and to meet demands for reliable water supply services, water utilities have already made considerable efforts to control potential failures by applying existing, state-of-the-art methods for failure prediction, condition assessment and proactive pipe asset management technologies. The methods used have limited level of confidence, which limits the ability to target renewal programmes.

It has been conservatively estimated that even a 30% improvement in the present state of the art would reduce the high consequence events by 50% and total failure events by 30%, resulting in potential savings of over AUS$160 million (US$149 million) over a 20 year period to the Australian water industry. With better prediction from condition assessment, expenditure can be delayed by five years and replacement costs reduced up to 20%, so the projected savings over a 20 year period will exceed a further AUS$300 million (US$279.3 million).

Water utilities urgently need better techniques for estimating the probability of failure of critical pipelines and for estimating their remaining life. The unavailability of such tools increases the risk of substantial funds being potentially misdirected through premature replacements. This could impact on future water service pricing. On the other hand, not undertaking timely replacement of pipes could lead to an increasing number and frequency of failures, with associated costs and disruption.

In August 2011 an international project led by the Australian water industry with Monash University leading the research (www.criticalpipes.com) started pipe failure prediction, interpretation of advanced condition assessment using machine learning, and corrosion modelling.

The University of Technology Sydney and the University of Newcastle are the other two research partners. The Australian Utility partners are Melbourne Water, South East Water, Hunter Water, South Australia Water, and Water Corporation WA. Water Research Foundation (US), (WaterRF) and United Kingdom Water Industry Research (UKWIR) are the international research partners.

Scope of the collaboration

The international team developed a scope of research to improve the reliability of predicting large pipe failure. This included addressing the following research questions:

- How, when and where will pipes fail within the network?
- How do we assess the condition of the pipe cost-effectively?
- How do we estimate pipe deterioration rates accurately with respect to the pipe environment?
- What is the time-dependent probability of the pipe failure along the pipeline?
- How do we transfer the new knowledge to the industry for optimal pipe management?

Collaboration and its success

The current success of the research programme is due to the active collaboration and participation of the international team. Recently the project completed a technology transfer tour of the UK and US that was very well received by participating water utilities and the international

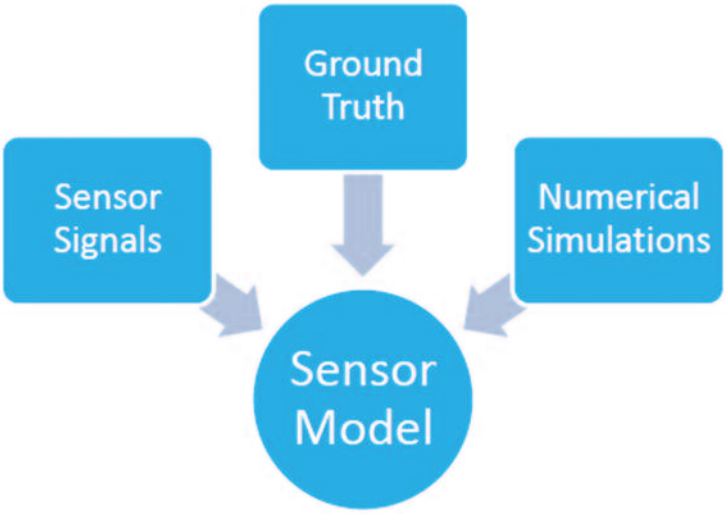


Figure 1
Governance structure of the advanced condition assessment and pipe failure prediction project

research organisations. The following demonstrates the collaborative success of the research project.

Industry partner initiation of and contribution to the project
The present research project was initiated by Australian water utilities. They sought the support of leading Australian and other researchers, and of key international partners. All were directly and actively involved in one local and one international workshop aimed at ensuring the viability and water industry relevance of the planned research. The active engagement of all parties proved that the research meets core industry needs and had considerable industry support. This was demonstrated by the industry partners' cash, in-kind and nominated expertise contributions, the access to critical water pipes, and engagement in case studies. Moreover, all partners have agreed to collaborate with each other for the benefit of the research, further demonstrating their commitment.

The involvement of collaborating partners
The industry partners involved in the project comprise the key major and some medium and small water utilities in Australia. They will contribute some AUS$4.15 million (US$3.9 million) in cash and around AUS$10 million (US$9.3 million) in kind. Their in-kind involvement covers much (>60%) of the non-labour in-kind support, to provide access to pipes and to cut out and replace pipes for research and investigation purposes. These activities have high enabling and contractor services costs. Further, the industry partners will contribute partner investigators, personnel time, sampling sites and participation in case studies. The three universities also provide significant cash and in-kind contributions to the research project.

There are five technology partners (or condition assessment service providers, as noted later) that will collaborate as partner organisations, with both cash and in-kind support. Acknowledging the uniqueness and importance of the project, WaterRF and UKWIR will provide AUS$1.2 million (US$1.1 million) in cash, and will provide substantial in-kind support to the project.

Relationship to the strategic plan of collaborating organisations
As noted earlier, in many cities large pressurised pipes are ageing and increasingly prone to failure. They are mostly located in built up areas, are under high pressure (50 to 80m head) and have very little or no redundancy. When these pipes fail, the consequences are 'catastrophic' – providing no services to customers and creating significant disruptions and safety hazards to the community. Evidently, reducing such failures is a major business and strategic priority for the utility partners. All have strategies for management of critical mains, but to date their success has been limited by the lack of knowledge and effective tools for optimal management of these assets.

Further collaboration and long-term alliances
An international planning workshop was held in Sydney (July 2009) for this project, and this was a critical catalyst in developing a proposal that met the core needs of all the partners. It established an international network that attracted the best expertise in the water industry and key university partners. Since the water and wastewater industry accounts for about 1% to 2% of GDP, international and industry-university cooperation and collaboration is essential.

To date the Australian industry partners have provided outstanding leadership in this area. Both this and international collaboration can be expected to continue and be enhanced as a result of the activities and research outcomes. A follow up planning session took place in October 2012 in Sydney that demonstrated the continuous engagement of the partners to review the progress and plan ahead to improve the research plan.

Partnership with technology providers to enhance condition assessment
Four technology providers have agreed through University of Technology Sydney to improve the data interpretation of their technologies with the project. Three research runs of two of their technologies have been completed with validation using the Sydney Water test bed site. One research run has been completed on one of the intrusive techniques and another is planned. The technology partners take part in the technical advisory committee special session every quarter, or as required. This direct engagement in improving the available technology is considered to be a successful collaboration, and is thought to be a world first in a large project of this nature.

Governance
A governance structure has been established to foster strong partnerships between industry partners and the research team, maintain rigorous probity in the expenditure or research funds, and disseminate research findings. Every three months the research project holds a management committee and technical advisory committee meetings to engage with water industry partners and international research organisations to ensure that the research is on track to deliver benefits to the water industry. Figure 1 is the outline of the governance structure.

Current results
The project was 20 months complete in June 2013, and substantial progress has been made in all three main activities. Pipe failure data has been collected to understand the status of the network performance of partners' critical pipes. These included past failure data, forensic or pipe failure inspection reports, condition assessment reports, and anecdotal evidence gathered through discussions with utility technical personnel.

Along with this, a major literature review has been completed in all three activities. The collected data and information were archived in a central server location so that all partners could access them. A report summarising the findings has been published

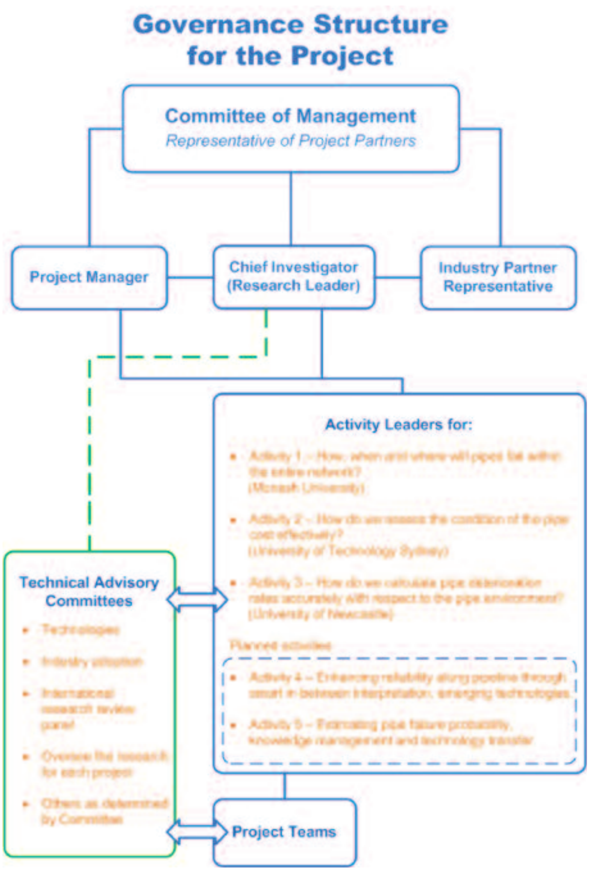
(Kodikara et al, 2012) and a companion paper is included in these conference proceedings (Rajeev et al, 2013).

One of the key field developments was the establishment of a dedicated test bed for pipe research. The test bed is a 1.5km-long decommissioned buried water pipeline laid in 1922 and located in Strathfield, NSW. It is a 600mm diameter, cement lined cast iron pipe with nominal wall thickness of 30mm and lead joints at approximately 3.6m intervals. The pipeline was made chargeable with potable water and was fitted with entry points for condition assessment tool insertion. A brief description of progress made in individual activity areas is provided below.

Failure prediction

The data analysis revealed that the majority of the critical pipe assets (>300mm) are cast iron and steel pipes, so the primary research focus is on these pipe cohorts. On the basis of the data and information collected, pipe corrosion was classified into three main classes for further analyses. These are: general corrosion, where corrosion is prevalent all around the pipe and could be idealised as a reduction in wall thickness; patch corrosion or graphitisation, where a patch of pipe is corroded; or pit corrosion, where a single pit or a cluster of pits have developed on the pipe wall. Analytical tools to compute pipe stress were developed for all three corrosion categories.

Figure 2 Approach for condition assessment sensor modelling



Of the external and internal factors that contribute to the pipe failure, traffic loads (a majority of the critical pipes are laid under roads), as well as water pressure and likely pressure surges were considered in more detail. In March 2013, a section of the test bed that crosses an arterial road to the Hume highway was fully instrumented to measure pipe response under live traffic conditions. It is expected that a useful data set, not only for pipe static analysis but also for analysis of pipe response to transient traffic loads, could be collected through this instrumentation.

Through the data analysis, the project identified that there is limited data on the pressure transients although they were considered to contribute to pipe failures. A pressure monitoring programme was initiated at selected partner networks, including the Hunter Water network. This was accompanied by hydraulic surge modelling to develop calibrated models that can be used to generate data across the network for pipe failure prediction. Another aspect of research is the development of a concept for 'smart' pipe monitoring, and the use of various sensor arrangements including distributed optical fibre sensors is being investigated (Rajeev et al, 2013).

Interpretation of condition assessment

Numerous sensor techniques such as ultrasonics, magnetic flux leakage (MFL), broadband electromagnetics (BEM), remote field eddy current technology (RFT) and acoustics are used in 'direct' pipe condition assessment. The main focus of the current research is developing new and improved automatic interpretation of sensor data using machine learning technology that is commonly used in robotics. The University of Technology Sydney (UTS) has developed collaboration with a number of external service providers (Rock Solid Group – BEM, Assed Integrity Australia with Advanced Engineering Solutions – MFL, Russel NDT Technologies / PICA – RFT SeaSnake, and Pure Technologies / Aqua Environmental – Sahara@PWA).

One of the key requirements of sensor interpretation is the availability of data and associated ground truth for data training or calibration. To date, a number of test runs have been undertaken in the test bed and ground truth was sourced by exhuming the pipe and undertaking measurements after grit blasting. A laser scanner has been used to collect ground truth data, which can produce a three-dimensional picture of the pipe surface to required accuracy. In addition, UTS has developed an automated ultrasonics (immersion probe) scanner for obtaining ground truth data. The overall process of sensor modelling is shown in Figure 2. More details of this research are presented in a companion paper at this conference (Valls Miro et al, 2013).

Prediction of corrosion

Corrosion is identified as the primary deterioration mechanism for cast iron and steel pipelines (Petersen and Melchers, 2012). To predict the remaining service life of buried critical pipes, a realistic predictive model of corrosion versus exposure time is required. Such a model should consider the main contributing factors in the buried pipe environment and be based on mechanistic approaches to be more generally applicable.

Petersen and Melchers (2012) have highlighted that such a model does not exist, although several quasi-empirical and empirical models have been proposed. In particular, they highlighted that current models use either power law or exponential curves to fit data, whereas it is more likely that a bi-model trend would better represent the corrosion process in buried pipes. The approach adopted is to develop field calibrated models that are based on fundamental corrosion science and physics.

Identifying that the past data on corrosion measurements are not fully amenable to mechanistic corrosion model development, a new protocol for data collection has been developed. The protocol involves a detailed procedure to be followed after exhuming a pipe for inspection. It involves collecting soil samples, pipe and burial details with photographic records, and scanning pipes using a 3D laser scanner before and after grit blasting. Currently, this protocol is being used in the Hunter Water network and more details are available (Petersen et al, 2013; Dafter and Petersen, 2013).

Uptake by the water industry

There are a number of strategies in place to facilitate technology transfer and uptake by the water industry to achieve early benefits of the research. They have all been designed to achieve active engagement through 'champions' and user groups from industry partners. The technical advisory committees sit every three months and comprise the industry partners from Australian Utilities, WaterRF and UKWIR. Industry partners are also engaged through planned and historical review of case studies to validate the research outcomes.

The 600mm cast iron test bed is a significant outcome of the project, for conducting research within a pipe environment. The world's first research test bed where the interpretation of the condition, failure and corrosion of the pipe is being actively researched has provided a significant opportunity for Sydney Water and other industry partners to provide more insights into pipe failure. In addition to its current use, it is expected that the current test bed could be a global facility that can be used to test pipe related research in future, including pipe rehabilitation technologies.

Case studies on pressure transients in Hunter Water and the collation of the environmental information around the pipe for calibrating the corrosion model has resulted in sampling protocols for mains break data collation and planning renewal programmes. Hunter Water, Sydney Water and Water Corporation WA have incorporated the sampling protocols into their normal business processes.

With new knowledge on failure prediction, utilities have the ability to review conservative decisions on renewal planning and have the opportunity now to better understand the risks to take more realistic decisions.

With the demonstration of the improved data interpretation ability on condition assessment the industry partners have the ability to better understand the need to define the uncertainty based on a scientific approach. This has enabled new thinking in defining specifications for condition assessment technology providers. Already these benefits provide considerable potential to save 10% of the renewal costs of critical mains, with improved targeting of the high risk mains.

Expected benefits to the collaborating organisations

The Australian industry partners participate in various research components, including pipe monitoring, pipe deterioration, condition assessment, pipe failure analyses, database management, economic analysis, validation and targeted case studies. The benefits of this participation flow directly to the industry partners, providing an improved skills base that will allow more effective future pipe asset management. This could also bring them significant financial benefits.

Benefits of the research to the wider Australian water industry

The benefits to the wider Australian water industry and also to the international water industry include: more rational methods to determine how, when and where pipes are likely to fail in the network; prioritisation of factors that affect pipe failure, with guidance on what to look for in condition assessment and on possible methods to reduce pipe failures; innovation in cost-effective condition assessment techniques and guidance to choose them; improved knowledge guidance, decision support and education workshops for optimal pipe management; and tools, methods and strategies with a defined level of low uncertainty, and an increased level of confidence in predicting the probability of failure, to target critical main replacement.

Expected economic and social returns to the broader Australian community

As noted, the project outcomes will contribute to the continuation of reliable, undisrupted and safe water supply to Australian communities. It will reduce social, economic and environmental impacts associated with critical pipes failure. There also will be substantial cost savings. As highlighted earlier, as a conservative estimate, a 30% improvement in present state-of-the-art can deliver AUS$160 million ($US149 million) over 20 years and if this result in delay of current expenditure in pipe replacement for five years, a further AUS$300 million (US$280 million) can be saved over this period (Nicholas & Moore, 2009). In turn, these cost savings will help sustain lower water prices, benefiting the community at large. This does not include the very significant intangible benefits to the community of avoiding major disruptive events that lead to losses of homes, closures of roads, parklands, shops, and so on, and, of course, loss of water. Internationally, even larger benefits apply.

Concluding remarks

This article has summarised some details of a global collaborative project developed to address the management of critical water mains. The strength of the project is achieved through partnership between local water utilities, global water bodies, condition assessment service providers and local universities as research providers.

In contrast to pure academic activity, the research is focused through real industry needs and active industry participation. Nonetheless, bottom-up scientific research is being pursued, seeking to fill knowledge gaps and produce solutions that present a significant advance from the current state-of-play, yet can be directly used by the utilities. The approach adopted by the collaborators is geared to produce benefits for all parties involved, representing win-win conditions. ●

Acknowledgements

This publication is an outcome from the Advanced Condition Assessment and Pipe Failure Prediction Project funded by Sydney Water, US Water Research Foundation, Melbourne Water, Water Corporation (WA), UK Water Industry Research, South Australia Water Corporation, South East Water, Hunter Water Corporation, City West Water, Monash University, University of Technology Sydney and University of Newcastle. The research partners are Monash University (lead), University of Technology Sydney and University of Newcastle.

References

Dafter, M and Petersen, R (2013), Advanced condition assessment of Hunter Water's cast iron watermain. Corrosion and Materials, Australian Corrosion Association, Vol 38, No 3, pp42-45.

Kodikara, J, Rajeev, P, Robert, D and Zeman P (2012), Critical review of historical information on large diameter pipe failure. Report of Monash University, Monash University, Melbourne.

Nicholas, D and Moore G (2009), Condition assessment and failure prediction of pressure pipelines: scoping study for ARC Proposal. Report prepared for Water Services Association of Australia. Water Services Association of Australia, Melbourne.

Petersen, RB, Dafter, M and Melchers, RE (2013), Long-term corrosion of buried cast iron water mains: Field data collection and model calibration. LESAM 2013, 10-12 September, Sydney.

Petersen, RB and Melchers, RE (2012), Long-term corrosion of cast iron cement-lined pipes, Corrosion and Prevention 2012, Australian Corrosion Association, 11-14 November, CDRom Proceedings, Melbourne.

Rajeev, P, Kodikara, J, Robert, D, Zeman, P and Rajani, B (2013), Factors contributing to large diameter water pipe failures as evident from failure inspection. LESAM 2013, September 10-12, Sydney.

Rajeev, P, Kodikara, J, Chiu, WK and Kuen, T (2013), Distributed optical fibre sensors and their applications in pipeline monitoring. Key Engineering Materials, Vol 558, pp424-434.

Valls Miro, J, Rajalingam, J, Vidal-Calleja, T, de Bruijn, F, Wood, R, Vitanage, D, Ulapane, N, Wijerathna, B and Su, D (2013), A live test-bed for the advancement of condition assessment and failure prediction research on critical pipes. LESAM 2013, 10-12 September, Sydney.

WSAA (2009) National Performance Report 2007/2008. Report of Water Services Association of Australia. Water Services Association of Australia, Melbourne.

This paper was presented at LESAM 2013 – the IWA Leading-Edge Strategic Asset Management conference, held 10-12 September 2013 in Sydney, Australia.

Wastewater pipes in Oslo: from condition monitoring to rehabilitation planning

Oslo VAV is undertaking a project that will ensure improved condition monitoring and rehabilitation planning in the Norwegian capital. Rita Ugarelli, Yves Le Gat, Ingrid Selseth and Jon Rostum introduce a condition monitoring and assessment work package.

Rita M Ugarelli
SINTEF Building and Infrastructure, Oslo, Norway. Email: rita.ugarelli@sintef.no

Yves Le Gat
Irstea Bordeaux – REBX, Cestas, France. Email: yves.legat@irstea.fr

Ingrid Selseth
SINTEF Building and Infrastructure, Trondheim, Norway. Email: ingrid.selseth@sintef.no

Jon Rostum
SINTEF Building and Infrastructure, Trondheim, Norway. Email: jon.rostum@sintef.no

The Norwegian capital of Oslo's water and sewerage utility Oslo Vann og Avløp (Oslo VAV) has been undertaking a Secure and Monitored Service (SMS) project, which aims to improve the efficiency and security of monitoring and control in Oslo VAV's urban water and wastewater system. This article presents the results of work package 1 (WP1), which deals with condition monitoring and assessment of the wastewater pipes.

The project is co-financed by the Norwegian research centre (RFF Hovedstaden) and Oslo VAV. WP1 aims to provide the utility with an analysis of the current and future level of deterioration in its wastewater pipes and an estimate of the resources required to improve the system's condition through rehabilitation (both are important for master planning (the hovedplan) and for rehabilitation schemes (the saneringsplan)).

The model applied for the deterioration analysis is called GompitZ and it defines the relationship between the current state and the expected service time of sewer pipes using CCTV data as the classification input. The GompitZ deterioration modelling tool was delivered by IRSTEA (Le Gat, 2008) within the framework of the CARE-S FP5 project (Sægrov, 2006). The model has been further developed over the past few years thanks to testing and validation undertaken in Oslo. The GompitZ tool probabilistically models pipe deterioration at the single pipeline level – the network segment between two manholes. These are modelled as a succession of a few discrete condition grades (four to six are usually considered), within the Non-Homogenous Markov Chains (NHMC) framework. The probability that a pipeline will be in a given condition or better is formalised as a survival function of the pipe age, derived from the Gompertz distribution (see Willemse and Koppelaar, 2000). The survival function depends on covariates (characteristics of the pipeline and of its environment) influencing either the initial condition state at pipe installation or the deterioration speed, which is also influenced by an additional individual frailty factor.

Table 1
Number of pipes in each condition class

Condition class	No of pipes	%
1	3936	47%
2	770	9%
3	1276	15%
4	894	11%
5	1457	17%
Grand Total	8333	

As well as a model parameter calibration module based on maximum likelihood, the GompitZ tool contains a module devoted to long-term simulation of rehabilitation programmes. Four rehabilitation strategies can be performed and therefore compared: a 'do-nothing' option that simulates the natural evolution of the pipes in the absence of rehabilitation; 'length-driven' and 'budget-driven' options that simulate the annual rehabilitation of the most deteriorated pipes up to a total length or budget fixed by the user for each year in the simulation period; and an 'optimisation' option that estimates the optimal mean annual rehabilitation length of most deteriorated pipes to be implemented in order to bring the network to just below a given global deterioration condition at a user-given time horizon.

Comparing different strategies allows users to see and calculate the benefits in terms of the network condition improvement obtained by applying a given rehabilitation strategy instead of doing nothing. Costs versus benefits can therefore be balanced in order to choose the best and more feasible solution.

The process of investigating the quality of the data, selecting the final dataset for model calibration and its improvements, and finally comparing rehabilitation scenarios is presented below. The article is supported by results and comments explaining the practical value of the results to support infrastructure asset management at tactical level.

Data requirements and analysis of input data for calibration and prediction

The GompitZ programme needs pipe data and inspection data, which are both available at pipe level. The data are used to calibrate the model parameter module to identify which factors (covariates) influence the deterioration process. Length, diameter and age at inspection are default covariates in the GompitZ interface, and each has a

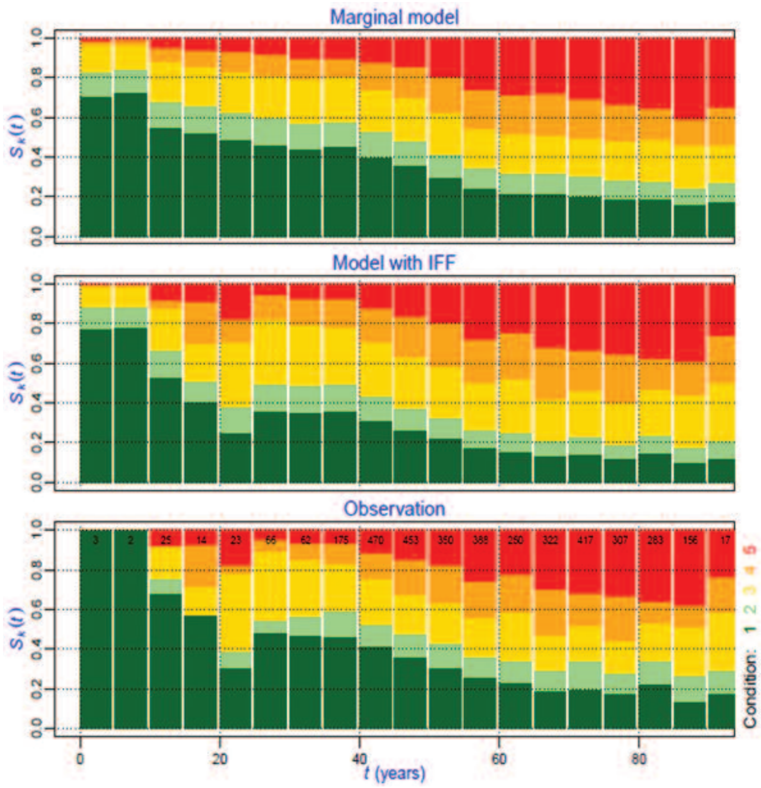


Figure 1
Graphical comparison of mean observed and modelled condition distributions versus age at time of inspection for the BET model)

column in the pipe data input file. Further, the user can choose other 'free' covariates as input for the model. The inspection data requires three type of information: the pipe identification, the year of inspection and the pipe condition class.

The Oslo VAV drainage network

Oslo VAV's database contains data from 53,264 pipe lengths that are owned and managed by the Oslo municipality. Out of these lengths, 31% were registered as combined sewers, 34% as stormwater sewers, and 31% as foul sewers (Ugarelli et al, 2010). The total length of the sewer system is estimated to be approximately 1960km. In total, 80% of the pipes are made from concrete.

Descriptive analysis of the inspected pipes used for calibration

Data relating to a total of 8333 inspected pipes was provided during summer 2012. Due to a change in the information system in 2008, the data that was initially provided lacked some data collected before 2007, so that was included in the project in January 2013. Oslo VAV inspected the sewer network area by area following a river basin strategy. The inspections were carried out from 2002 to 2012, but mainly concentrated in 2008 to 2012. These inspections were used to calibrate the models, while updated inspection data from January 2013 have been used for the predictions.

Classification of pipes conditions

Data from inspections are inputs for calculating damage scores for each inspected pipe based on definitions used in the Norwegian Standard (Norvar, 150/2000). According to these standards, pipes are grouped in five classes according to their level of deterioration, where 1 stands for pipe as good as new and 5 for pipe close to collapse. This work has highlighted a major issue in the Norwegian guidelines used to classify pipes from visual inspection: the standard leads to a much more negative figure for the overall network's need for rehabilitation than in reality. The experience gained led VAV to modify the thresholds for pipe classifications proposed by the standard into ranges better calibrated to its experience. In all, 19,525 observations are connected to 8333 pipes and the condition class distribution is shown in Table 1.

Description of input data used in the predictions

Calibration of the models was carried out in 2012 with the inspection data available at that time (data from 2001 to 2007 and from 2012). In 2013 more digital inspection data became available, but this has not been used for recalibrating the models due to time constraints and the fact that the established models are representative enough.

The new inspection data appeared to be similar to that used to calibrate the models: the proportion of pipes belonging to each condition class is almost the same in both new and old datasets. In summary, the calibration of the models is based on the inspected data available at the beginning of 2012, while the prediction of the ageing process, for 2015 to 2040, includes all the available data.

Data to analyse the criticality of pipes

To select pipes for rehabilitation, including the vulnerability of the surroundings in case of a break as recommended by Ugarelli et al (2010) and Røstum 2011, it was decided to run a preliminary and simple criticality analysis at this stage. Oslo VAV has defined criteria that take into account possible impact in case of pipe collapse or break (Table 2). In total, seven criteria have been identified, relating to water quality, customers and infrastructure. The 'consequence number' (CN) refers to how many criteria a given pipe fulfils. The classification of the pipes was performed based on GIS shape thematic maps.

The list of criteria is currently under review: in WP2 of the project the aim is to develop a risk framework for rehabilitation planning. When the risk approach was implemented in spring 2014, the choice of pipes to be prioritised for annual rehabilitation was based on a trade-off between costs, condition and risk, and not just costs and condition as applied in WP1 for long-term planning. The annual long-term rehabilitation rate is calculated by WP1, whereas the specific pipes to be prioritised each year are ranked by WP2.

Calibration of models of deterioration

The data allowed four calibrated models to be produced, one for each defined category of pipes (for more information see Ugarelli et al, 2013). An initial set of 8333 inspections was available, 7656 of which could be used to calibrate the deterioration models –

Table 2
Criteria for defining consequences

Location / type of pipe

1	Water quality	Interceptor close to river
2	Water quality	Main sewer from a hospital
3	Customers	Pipes from vulnerable customers (hospital, nursing home, museum, city hall)
4	Customers	Big pipes; storm water from 1000mm and sewer pipes from 600mm
5	Infrastructure	Pipes close to buildings (2m)
6	Infrastructure	Pipes close to roads with high traffic levels
7	Infrastructure	Pipes below granite paved streets

that is, there was no missing data or inconsistencies (such as an inspection year earlier than the segment installation year). It must be mentioned that among the 7656 data retained, 2113 relate to an unknown pipe material. Several combinations of covariates were tested and compared with respect to log-likelihood and number of significant covariates.

The following explanatory factors have been tested as covariates in the deterioration model:

- Pipe diameter (mm)
- Effluent type (combined versus wastewater)
- Tramway proximity (yes/no)
- Presence of trees close to the sewer (yes/no)
- Construction period (1850 to 1929, 1930 to 1945, 1946 to 1969, or 1970 to 2011)
- Road traffic (0, 1 to 500, 501 to 5000, 5001 to 15,000 vehicles/day)
- Type of bedding soil (marine deposits, detritus material, fillers or rock)

The network deterioration is modelled by calibrating separate models for the categories of pipes defined in Table 3. These four groups cover 93% of the wastewater network. The remaining pipes are pipes that are missing required data such as construction year, material or length. An example of calibration for small pipes is proposed below.

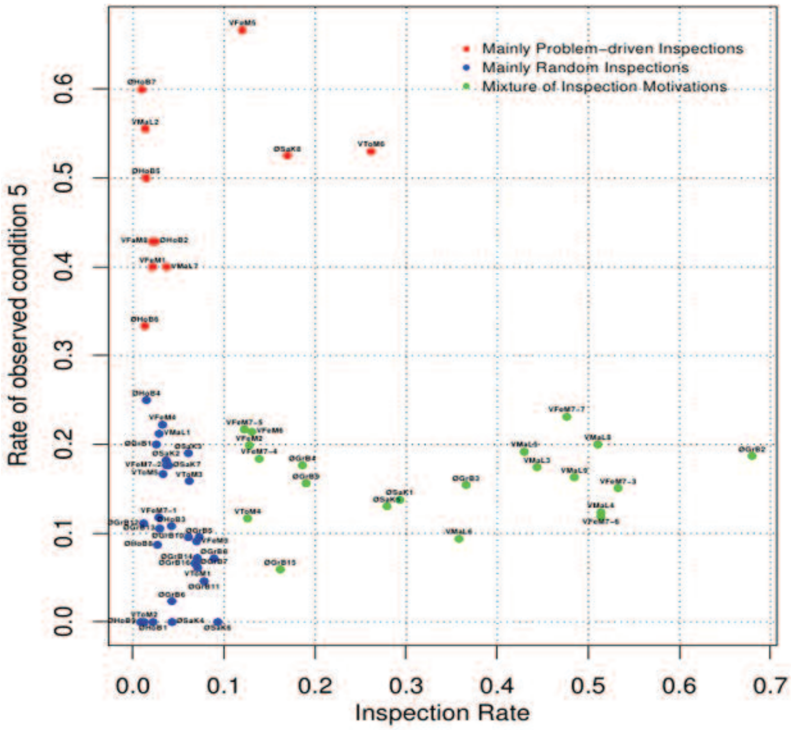
Example of a calibrated model: model for small concrete pipes (BET)

The BET model is calibrated with 3783 inspections. No relevant covariate was found to influence the initial deterioration state. The deterioration speed is found to significantly decrease with the pipe diameter, which is considered as a continuous covariate, and with the interaction of flow type AF (combined flow) and OV (stormwater) in the presence of trees (covariate labelled 'Trees') in the vicinity of the pipe (covariates labelled 'AFTrees' and 'OVTrees').

The deterioration speed was conversely found to increase with the combined flow (AF) main effect, with an installation year between 1946 and 1969, with the soil types 'marine' and 'rock', and in the presence of trees.

Figure 1 illustrates the good quality of the models' goodness-of-fit. The model with IFF (accounting for individual frailty) and the 'Marginal Model' (showing the average speed of deterioration) predict the condition probabilities for each inspection. The x-axis is the age at inspection, grouped by five-year time steps, and the numbers on the observations plot are the number of pipes in each of the five-year groups.

Figure 2
GIS zones in Oslo plotted according to their inspection rate versus their rate of observed condition 5)



Improving the calibrations with a weighting method

It is important to analyse whether inspection data are representative of the whole wastewater network: that is, to understand whether pipes are randomly inspected in accordance with a zone inspection plan regardless of their condition, or inspected to investigate an obvious dysfunction. In the first case the inspected sample can be assumed to be representative. In the second case it can be suspected that the worst condition classes will be over-represented, the calibrated models may be biased toward worse condition states, and the need for rehabilitation may therefore be overestimated.

A weighting method for evaluating the distinction between systematic area and problem-driven inspections is described below. Analysis of the deterioration data for the concrete pipes in the Oslo drainage system, when carried out without weighting – that is, with equal weights (with a value of 1) allocated to all pipes – shows an evident excess of pipes in bad condition (pipe conditions 4 and 5). It can therefore be hypothesised that the available sample of CCTV inspected pipes is not representative of the whole target population, but is subject to a selection bias (sometimes also called 'recruitment' bias). Selection bias is a common issue in epidemiological studies, due to the preferential sampling of individuals in poor condition.

A practical way to correct model parameter estimates to prevent selection bias is to weight the observations. Response-dependent weights are suggested by the theoretical investigations of Wang and Carroll (1995), which were particularly devoted to the logistic regression model from which the GompitZ estimation procedure is derived. The term 'response' refers to the variable whose probability is to be modelled, so the condition state in the present context. Response-dependent weights are then designed to give less influence in the parameter estimation process to condition states that are supposed to be over-represented in the sample.

Theoretical background of the weight calculation

In order to be able to calculate a relevant set of weights, it is necessary to make hypotheses about the bias mechanism, that is, to model the bias. Some notations must be stated first. The available calibration sample has a size denoted as s, which is distributed

Table 3
Grouping of pipes

Group	# of pipes	Length [m]	Comment
BET	22,416	884,489	Concrete pipes up to 600mm
cBET	4286	163,530	Concrete culverts from 600mm
CULV	1189	47,766	Other culverts from 600mm
PIPE	19,416	733,111	All other pipes materials up to 600mm
Sum	47,307	1,828,896	

Scenario	Consequence	Max portion of pipes in condition class CC1	CC2	CC3	CC4	CC5
A1	Low	1.0	0.8	0.4	0.2	0.01
	High	1.0	0.8	0.4	0.01	0.01
A2	Low	1.0	0.8	0.4	0.2	0.05
	High	1.0	0.8	0.4	0.025	0.025
A3	Low	1.0	0.8	0.4	0.2	0.075
	High	1.0	0.8	0.4	0.025	0.025
A4	Low	1.0	0.8	0.4	0.2	0.1
	High	1.0	0.8	0.4	0.05	0.05

Table 4
Description of different rehabilitation scenarios

among the condition states in sub-samples of sizes ($s_j, j \in \{1,2,3,4,5\}$), where j indexes the condition states: $\Sigma_j s_j = s$.

The 'true', but unknown, condition proportions in the target population are denoted as p_j, with:
$\Sigma_j p_j = 1$

The proposed bias model is based on two hypotheses:

- The total sample size s is assumed to be the sum of n random inspections and m problem-driven inspections: $s = n + m$
- A problem-driven inspection will statistically result in the condition proportions:
  $q = (q_j, j \in \{1,2,3,4,5\})$

The unknown, condition proportions (p_j) in the target population, can therefore be estimated by:

$$\hat{p}_j = \frac{s_j - mq_j}{n} \qquad (1)$$

The key idea is then to weight each individual observation according to the observed condition state. The set of weights denoted ($w_j, j \in \{1,2,3,4,5\}$) are calculated to match the following requirements:

$$\begin{cases} \dfrac{s_j w_j}{\sum_{k=1}^{5} s_k w_k} = \dfrac{s_j - mq_j}{n}, j \in \{1,2,3,4,5\} \\ \sum_{k=1}^{5} s_k w_k = s \end{cases} \qquad (2)$$

Equation (2) expresses that the weighted condition proportions estimate the true condition proportions in the population, and that the total sum of weights in the sample equals the sample size.

The requirements of Equation (2) can be now turned into a non-singular system of five linear equations in the five unknowns w_j. The square 5 x 5-matrix A is defined to that end by the following components (A_{ij}):

$$\begin{cases} A_{ij} = s_j(s_i - mq_i) i \neq j, i \in \{1,2,3,4\}, j \in \{1,2,3,4,5\} \\ A_{ii} = s_i(s_i - mq_i - n), i \in \{1,2,3,4\} \\ A_{5j} = s_j, j \in \{1,2,3,4,5\} \end{cases} \qquad (3)$$

The first four rows of matrix A directly derive from the first equation in Equation (2), but the fifth condition, that is for i = 5, is co-linear to the first four previous ones, and is replaced by the condition on the sum of weights expressed by the second equation in Equation (2).

The vector B is defined as $B^T = (0\ 0\ 0\ 0\ s)$. The vector of unknowns $W = (w_j)$ is the solution of the linear equation $AW = B$.

An example of weighted regression: small diameter concrete pipes in the Oslo case study

Computation of the bias-correcting weights for the Oslo case study has been completed for the subset of inspections related to small concrete pipes. The un-weighted model, BET, was presented above.

To obtain rough estimates of the quantities m/s and (q_j), a geographical analysis has been carried out based on the inspection data aggregated by GIS zone. The Oslo drainage network is subdivided into 62 GIS zones, for which the total number of sewer segments, the number of segments inspected between 2002 and 2011, and the proportions of the five condition classes observed in these inspections are known. These data are summarised in Figure 2, which plots one dot per zone according to its inspection rate, known as rsn in the sequel, and the rate of occurrence of condition class 5, called rc5 in the sequel. Three clusters can be distinguished in Figure 2:

- 11 zones with rc5 > 0.3 and rsn < 0.3 (< 0.5 for eight of them), which are suspected to have been mostly inspected because of problems
- 30 zones with rc5 < 0.3 and rsn < 0.1, which are likely to have been randomly inspected
- 21 zones with rc5 < 0.3 and rsn > 0.1, which are likely to have been inspected for both problems and random assessments

The first cluster allows an estimate of a global rate of problem-driven inspections, the value of which is around 0.066. This cluster also makes it possible to estimate the condition proportions in problem-driven inspections, which was found to be:

$q = (0.146, 0.068, 0.108, 0.130, 0.548)$

This enabled an estimate of the number of random and problem-driven inspections per zone, and then to estimate the set of weights:

$w = (1.121\ 1.046\ 1.052\ 0.959\ 0.629)$

Using these weights, the GompitZ BET model has been re-estimated. Some factors were found to be less significant, due to the smaller weight of severely deteriorated pipes in the

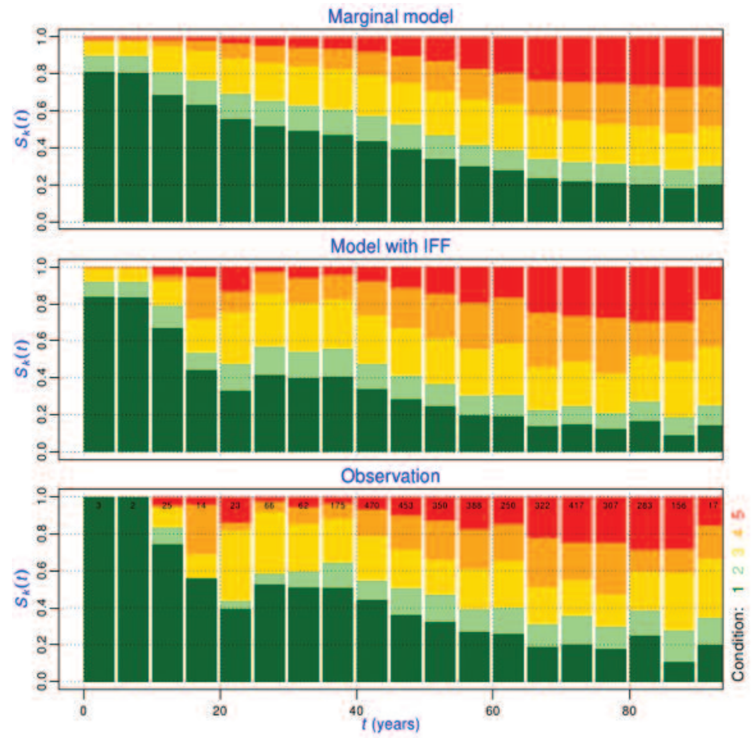


Figure 3
GOF-IFF-W-BET – Weighted condition state probabilities versus pipe age on observation

analysis; covariates L1946_69, s_marin and AFTrees are no longer significant, although the remaining significant factors maintain the same influence as in the un-weighted model. Figure 3 shows the accuracy of the weighted model; the comparison with the previous Figure 3 shows some decrease in the importance of condition class 5 in the deterioration process because of the bias correction.

Analysis of rehabilitation needs for the whole wastewater network

Given the calibrated models, the next step has been to use them to predict the future amount of pipes in each condition class if no rehabilitation were undertaken (the 'do nothing' scenario) and to analyse how different rehabilitation scenarios can impact on system condition.

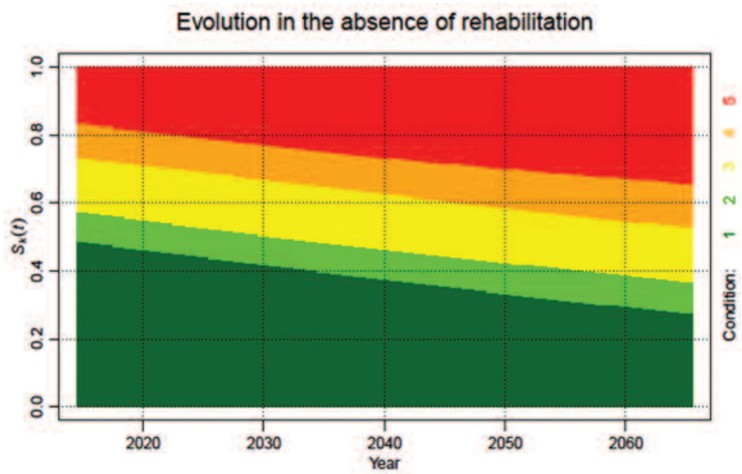
As described in the introduction, three rehabilitation strategies can be simulated. In Oslo the 'optimisation' option was chosen. The results for the 'do nothing' scenario can be then compared with the results of different rehabilitation strategies: for a given period of time, a particular deficiency (for instance, pipes in worst condition) will be reduced to achieve a particular level of service that will be maintained in the long-term.

The choice of rehabilitation scenarios to be tested was defined in close collaboration with Oslo VAV. The winning scenario was selected based on a trade-off between the costs of a given rehabilitation option and the benefit achievable in terms of improved conditions in the system over a period of 15 years. The winning scenario has been implemented by Oslo VAV to calculate the investment requirement in the Master plan for 2015 to 2030.

Preparing input data for the prediction

The process of predicting future deterioration has been performed for each group of pipes defined for the calibration (Table 3). Oslo VAV has introduced some consequence criteria for vulnerability analysis. The consequence number (CN) is the number of criteria fulfilled by each pipe. Pipes with high consequences in case of failure should be prioritised compared to pipes with a similar probability of being in a given condition class, but which have a lower impact. VAV has suggested that a CN=3 or higher should be considered as an indicator of a pipe with high failure consequences. The input files have been divided in two based on the CN value.

Figure 4 Simulation of condition distribution evolution in the absence of rehabilitation (the 'do nothing' scenario



Costs for rehabilitation

To choose between different rehabilitation strategies, it is necessary to know the costs of the alternatives compared with the benefit, which is estimated as improvement of the network condition.

A list of prices in use in Oslo VAV for pipe rehabilitation has been created based on data retrieved from past projects. Several Oslo VAV projects have been reviewed to estimate the unit costs (NOK/Meter or NOK/intervention, at 2012 values) to be applied to estimate the total cost of the various rehabilitation options. The result of this survey is an assessment of the unit costs of interventions to be performed to bring pipes in class 2, 3, 4 or 5 back to class 1. The unit costs include all the costs that will be incurred from beginning to end of a project and are provided as a function of the diameter of the pipe. The cost components have a different weight in the project cost functions depending on the rehabilitation technology applied.

The do-nothing scenario

Figure 4 displays the 'natural' evolution of the network condition distribution in the absence of rehabilitation (the 'do nothing' scenario) for 2012 to 2060. The clear worsening of the network is visualised by the increase in the pipe stock in condition classes 4 and 5 and the decrease in the size of the pipe stock in condition classes 1 and 2. Figure 4 shows the deterioration process for the whole network, but the results are different for each group of pipes.

Optimised scenarios

To identify the correct long-term rehabilitation rate to be applied, four scenarios have been tested, and for each of these two strategies have been applied to pipes with low and high consequences in case of failure. The predictions are made by setting stronger objectives for pipes with high expected consequences (CN>=3) than for pipes with lower or no consequences (CN<3).

The objective function, for example {1.0 – 0.8 – 0.4 – 0.2 – 0.01}, means having less than 100% of the network length in condition class 1, less than 80% in class 2, and less than 40% in class 3. Class 4 should be less than 20% of the network and class 5 less than 1% at the given time horizon. The functions used for the different scenarios are shown in Table 4.

To estimate the effect of classifying all large diameter pipes (>600mm) as pipes with high consequences, a modified version of scenario A4 has been analysed (A4b). The results show a small increase in rehabilitation rate and rehabilitation cost in the planning period. The costs of the different rehabilitation scenarios are calculated

Table 5 Summary of rehabilitation strategies

Scenario	Sum rehab length in 2015-2030	Average annual rehab rate (NET) 2015-2030	Sum rehab rate in period 2015- 2030	Sum costs (MNOK, 2012 value) 2015- 2030
A1	1327.4	4.5%	73%	8075.7
A2	853.3	2.9%	47%	6566.8
A3	642.0	2.2%	35%	5639.3
A4	425.8	1.5%	23%	4663.9
A4b	466.6	1.6%	26%	4875.0

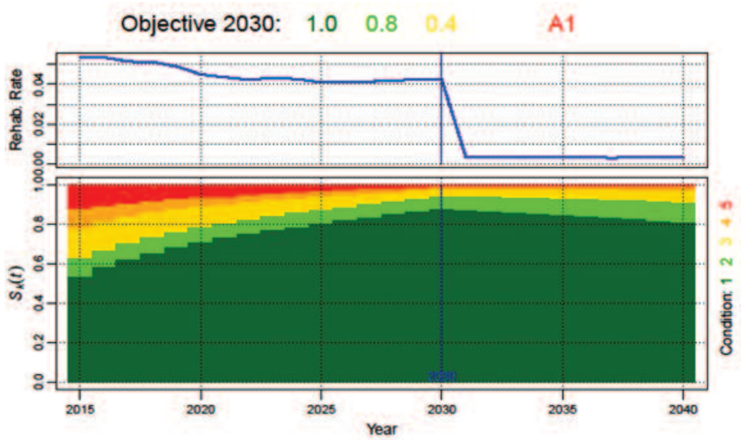


Figure 5

The predicted rehabilitation rate and predicted proportion of pipes in each condition, using rehabilitation strategy A1

applying the unit costs assessed for Oslo VAV (in 2012 NOK).

As an example, Figure 5 shows the evolution of the network condition applying the optimised strategy A1. By comparing Figure 4 and Figure 5 it is possible to see (and calculate) the benefit in terms of improvement of the network conditions obtained by applying a given rehabilitation strategy, instead of 'doing nothing'.

Table 5 presents the results obtained for each scenario. The study also produced an annual value of rehabilitation rate to be applied each year to achieve the set goal.

Conclusions

The OSLOVAV SMS project aims to improve monitoring and control efficiency and security for the utility's urban water and wastewater system. WP1 deals with condition monitoring and assessment of the wastewater pipes. The results achieve in WP1, which concluded in May 2013, are presented in this paper.

WP1 aimed to provide Oslo VAV with analysis of the current and future level of deterioration of its wastewater pipes and an estimate of the resources required to improve the system's condition through rehabilitation. The results have been used by Oslo VAV to calculate the rehabilitation rate to be used for investment planning in the Master plan. The selection of pipes to be included in the annual rehabilitation plan is now being studied, and will be established using a risk-based approach (WP2).

The main outcomes of WP1 consists of the selection of the dataset, calibration of four deterioration models, and prediction of four (five) rehabilitation strategy scenarios. However, the recommendations also provided data quality improvements, and the findings from data screening represent valuable project results that Oslo VAV will use. WP1 has also highlighted a major issue in the Norwegian guidelines (Norsk Vann, 2007) used to classify pipes from visual inspections. ●

References

Le Gat, Y (2008), Modelling the deterioration process of drainage pipelines. Urban Water Journal, Vol 5, No 10.

NORVAR-rapport 150/2007: Dataflyt - Klassifisering av avløpsledninger (Dataflow. Classification of sewer pipes).

Røstum, J, Ugarelli, R and Selseth I (2011), Risikovurdering av vanndistribusjon som en del av ROS VAV prosjektet. SINTEF rapport SBF 2011 0052.

Sægrov S (2006), CARE-S, Computer Aided Rehabilitation of Sewer Networks, IWA Publishing, ISBN1843391155, 2006.

Ugarelli, R, Venkatesh G, Brattebo H, Saegrov S and Di Federico V (2010), Asset management for urban wastewater pipeline networks. Journal of Infrastructure Systems, ASCE Vol1 6 No 2, pp112–121.

Ugarelli R, Selseth I, Le Gat Y (2013), SMS from Oslo VAV – Secure and Monitored Service from Oslo VAV, RRF -project report (SBF2013F0049).

Willemse, WJ, Koppelaar, H, (2000), Knowledge elicitation of Gompertz' law of mortality. Scandinavian Actuarial Journal Vol 2, pp168–179.

Wang, CY and Carroll, RJ (1995), On robust logistic case-control studies with response-dependent weights. Journal of Statistical Planning and Inference Vol 43 No 3 pp331-340.

This paper was presented at LESAM 2013 – the IWA Leading-Edge Strategic Asset Management conference, held 10-12 September 2013 in Sydney, Australia.

AM DIARY

A listing of upcoming asset management-related events and conferences. Send event details to WAMI for inclusion.

Smart Water Programme at the European Utility Week
4-6 November 2014, Amsterdam, The Netherlands
Web: www.european-utility-week.com

Water Loss Reduction in Water Supply Systems
10-11 November 2014, Sofia, Bulgaria
Web: www.bwa-bg.com

New Developments in IT and Water
8-10 February 2015, The Hague, The Netherlands
Web: www.iwcconferences.com

7th Global Leakage Summit
17-18 March 2015, London, UK
The aim of this summit is to help water utilities develop faster and more efficient leakage management systems, integrated with whole network management and optimisation, smart asset management and integrated sensor management, that take into account economic levels of leakage, but also reflect the true value of water and supply delivery targets. The event includes pre and post workshops alongside the two-day summit on the latest developments and insight in the industry.
Web: www.global-leakage-summit-2015.com

9th Water Tech Funding Forum
16-17 April 2015, New York, US
Web: www.watervent.com

Cities of the Future - Transitions to the Urban Water Service of Tomorrow
28-30 April 2015, Mulheim an der Ruhr, Germany
Web: https://conference.trust-i.net

Regional Utility Management Conference Improving Performance in Emerging Economies
13-15 May 2015, Tirana, Albania
Web: http://utilityconf.al

LESAM 2015
17-19 November 2015, Yokohama, Japan

For a full list of water sector events taking place in 2014, visit: www.iwapublishing.com