A Markov Model for Stormwater Pipe Deterioration

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Abstract: Effective management of stormwater pipe networks requires accurate assessment of the structural condition of the pipes. Indeed, the recent introduction of Australian accounting standard AAS27 compels Local Government to prepare annual financial statements including, amongst other things, the depreciated value of their stormwater network. A rational approach to assessing depreciation is to base it on structural deterioration. This study presents a Markov model for the structural deterioration of stormwater pipes. The model is calibrated, using Bayesian techniques, to structural condition data from the stormwater asset database of Newcastle City Council (Australia). It is shown that the Markov model is consistent with the data. The pipe characteristics of diameter, construction material, soil type, and exposure classification were found to influence the deterioration process. It is also shown that the depreciation methods required by AAS27 significantly overestimate the structural deterioration.

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Keywords: stormwater, storm sewers, pipes, deterioration, Markov process,
Bayesian analysis, accounting, Australia

INTRODUCTION

The aging of stormwater pipes adversely affects their performance. These adverse effects can be classified into two broad categories, structural deterioration and loss of serviceability. Structural deterioration normally involves some form of breakage or deformation of the stormwater pipe, whilst a loss of serviceability is usually caused by blockages or intrusions that result in a reduction of the stormwater pipe's hydraulic efficiency.

Current Australian accounting standards (AASs), namely AAS27 (AARF 1996), require that Local Government prepare annual financial statements. These statements must include, amongst other things, the depreciated amount for the stormwater pipes that are under their control. AAS27 calls upon AAS4 (AARF 1997) which describes various depreciation methods. Both of these accounting standards rely on the Local Government Asset Accounting Manual (LGAAM) (DLGC 1995) to define the depreciation method. The LGAAM does not give a useful life for stormwater pipes; however, useful lives for sewerage and water supply pipes are provided. These useful lives are 80 years for water mains, while sewerage pipes range from 40-70 years. The currently accepted industry practice is to use linear depreciation over a useful life of either 70 or 100 years for stormwater pipes.

A more rational approach to assessing depreciation is to base it on structural deterioration. This is the motivation for this study.

The structural deterioration of stormwater pipes is estimated through the use of condition ratings. The condition ratings take the form of discrete states so as to reduce the computational complexity associated with a continuous condition ratings system (Madanat et al. 1995). The structural condition of stormwater pipes is described by five states. These states are selected for consistency with the condition ratings specified within the LGAAM. State 1 represents a pipe in a near new condition, while state 5 represents a pipe in an unserviceable, i.e. failed, condition (see Table 1 for a description of these states).

Review of the literature revealed that Markov models for infrastructure deterioration are quite common, with road bridges being a frequent candidate for analysis. For example, Cesare et al. (1992) estimated the Markov transition probabilities for various bridge types and bridge components, using nonlinear programming methods, and Madanat and Wan Ibrahim (1995) determined the transition probabilities for concrete bridge decks using Poisson and negative binomial based regression techniques.

Some deterioration models for sewer pipe networks have been developed. Røstum et al. (1999) modelled the deterioration of Norwegian sewer pipes

using a cohort survival model based on the Herz (1996) distribution. Mailhot et al. (2000) estimated the structural deterioration of a Canadian sewer network using a model based on the Weibull distribution. Wirahadikusumah et al. (2001) modelled the deterioration of American combined sewer pipes using a Markov model calibrated to an exponential regression curve.

However, the deterioration processes affecting sewer and stormwater pipes are considered to be different. Within Australia, stormwater and sewer systems are separate, and so are subject to different deterioration processes. Sewer pipes are subject to internal attack by acids associated with sewage, whereas stormwater is relatively clean, resulting in pipe damage being caused predominantly by external factors.

No deterioration models for stormwater pipe networks were found within the literature. However, it is noted that Jacobs et al. (1993) used chance constrained multiobjective programming to optimally schedule the rehabilitation of a stormwater drainage network. Their model assumes that pipes deteriorate linearly with time and aims to minimise the total expected costs from rehabilitation and expected losses from wear out and flooding.

The principal contribution of this study is the application of a multistate Markov model to simulate the structural deterioration of stormwater pipes.

Bayesian methods are used to calibrate the model, and statistical hypothesis tests and Monte Carlo simulation are used to validate the suitability of the model.

This paper is organised as follows. The next section provides an overview of the case study involving data from a stormwater network located in Newcastle, Australia. The Markov model is then introduced. The procedures used to calibrate and validate the Markov model, along with the theory associated with these procedures, are then discussed. The results of the case study follow.

CASE STUDY DESCRIPTION

Data Source

The data set used in the case study was obtained from the Newcastle City Council (NCC) stormwater asset database. The data set consisted of a total of 497 pipes. Information recorded for each pipe included asset identification, condition rating, survey, and general pipe information. All pipes were situated within road reservations, and so were subject to traffic loadings. No maintenance or cleaning was performed on the stormwater pipes.

The total length of pipes within the database is 17 km, whilst the length of the entire NCC stormwater network is 380 km. This provides a sample size of approx. 4.5%.

In accordance with industry practice and accounting standards, NCC uses linear depreciation over a useful life of 70 years. The replacement value of the network was estimated, in 1997, to be approx. \$145 million (Australian).

Condition Evaluation Procedure

The structural and serviceability condition ratings of the stormwater pipes were assessed using the SEWRAT computer program, which is a component of the evaluation system contained within the Australian Conduit Condition Evaluation Manual (Water Board 1991). SEWRAT provides a condition rating based on the number and severity of defects affecting a pipe. Defects are assessed using closed circuit television (CCTV) surveys of a pipe. When a defect is encountered, a score is allocated based on the type and severity of the defect. On completion of the survey, SEWRAT then calculates three scores:

- peak – maximum total score for a single metre length;
- mean – total score divided by the total length; and
- average – total score divided by the number of defects.

The pipe is then graded according to threshold values of the peak, mean, and average scores, with the worst grading of the three being used. SEWRAT uses a three state grading system. This is unsuitable for Local Government requirements, which requires a five state system in accordance with Table 1. Coombes (1997) found state 5 to be redundant for stormwater pipes. State 5 represents a pipe that cannot convey water. This is not observed in the field, where even extremely structurally damaged stormwater pipes can still convey stormwater effectively (see Fig. 1). Thus, a four state grading system was adopted using the first four structural condition states described in Table 1. The data was classified using this four state system and is summarised in Table 2.

Pipe Categories

The data set was classified according to the pipe categories present within the data set. These pipe categories were then subclassified into their constituent values. Table 3 summarises the categories used within this study.

The entire data set was randomly split into two separate data sets, labelled as split1 and split2, for use within the split sample analyses.

Pipe diameter was separated into two categories values representing small and large pipes. Small pipes ($d < 600$) have diameters of less than 600 mm while large pipes ($d \geq 600$) have diameters of 600 mm or greater. The distinction at 600 mm ensured that a sufficient number of pipes were available to permit a reliable investigation on the effects of pipe size.

The two major pipe construction materials, concrete (conc) and vitreous clay (VC), were used. There were some other materials present within the data set – brick, earthenware pipe, and stone. However, there were insufficient numbers of these to justify analysis.

Two major soil types, alluvial (all) and podzolic (pod), were used. The alluvial soil consisted of Fullerton alluvial soil only. The podzolic soil is a collection of three separate soil types, those being Duckhole podzol, grey brown podzolic, and Thornton brown podzol soils. The combination into a single grouping is acceptable because these soils are similar – all have been formed through the weathering of similar rocks.

The exposure classifications – A2, B2, and C – were derived from the AS3600 (Standards Australia 1994) exposure classifications, as summarised in Table 4. The AS3600 exposure classification system is intended for concrete members, and was considered appropriate for use here because over two thirds of the pipes are concrete.

The serviceability ratings – serviceability conditions 1, 2, and 3 (s1, s2, and s3 respectively) – were obtained directly from SEWRAT surveys of the pipes using procedures similar to those used in the structural condition evaluation. The serviceability condition provides a measure of the severity of the defects that affect the hydraulic performance of a pipe. Defects affecting the serviceability condition include debris, obstructions, and root intrusions. Serviceability conditions 1 and 3 respectively represent the pipes that are the least and most affected by serviceability defects.

MARKOV MODEL

The Markov model describes a stochastic process where the probability of jumping into a state at time t+1 only depends upon the state occupied at time t. The transition probability matrix **P** describes the probability of changing states within each time interval. The **P** matrix used in this study is based on a four state model with permissible annual state transitions displayed in Fig. 2.

Thus:

$$\mathbf{P} = \begin{bmatrix} 1 - (P_{12} + P_{13} + P_{14}) & P_{12} & P_{13} & P_{14} \\ 0 & 1 - (P_{23} + P_{24}) & P_{23} & P_{24} \\ 0 & 0 & 1 - P_{34} & P_{34} \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (1)$$

where P_{ij} is the transition probability from state i in year t to state j in year $t+1$.

Note that $P_{ij} = 0$ for $i > j$. This imposes the constraint that pipes cannot

improve in condition. Also, $P_{44} = 1$ because state 4 is the worst possible state. This is an absorbing state, i.e. once entered it cannot be left. It is further noted that P_{ij} are independent of pipe age. This represents a homogeneous Markov model.

The probability of being in state j , in year $t+1$, can be determined through the application of the total probability theorem:

$$p_j^{t+1} = \sum_{i=1}^j P_{ij} \times p_i^t \quad (2)$$

where p_i^t is the probability of being in state i in year t .

The Markov model provides a conceptually sound model for the deterioration process. The Herz and Weibull models, as used in sewer deterioration models, were considered inappropriate models for stormwater deterioration. These models assume that a pipe can be in one of two possible states – either a functioning or a failed state (Høyland and Rausand 1994, p. 214). However, when a pipe fails, we only know that it has left its current state – we do not know which state it has then entered. In some circumstances it may be reasonable to assume, upon failure, that the pipe progresses to the next worst state; although, this does not seem appropriate for stormwater pipes. The structural condition of a stormwater pipe, however, does not necessarily deteriorate gradually. Gradual deterioration is more likely to occur for the serviceability condition, due to the progressive build up of siltation and debris, and through increased root intrusions. The structural condition is

most likely to deteriorate through a damage event, such as an earthquake, an overladen truck, or through mine subsidence (a relatively common occurrence within the Newcastle area). Hence, the Herz and Weibull models are not appropriate – a pipe may deteriorate into the next worst state, or may skip one or more states in accordance with the severity of the damage event. These multistate transitions are permissible within the Markov model (see Fig. 2).

MODEL CALIBRATION AND VALIDATION

This section describes the calibration of the Markov model to the data set, and the procedures used in validating that the Markov model is consistent with the deterioration process. However, before we can outline these procedures, we must first discuss some of the key ideas that will be used within the calibration and validation procedures.

The objective of the calibration is to establish the parameters, of the Markov model, which produce outcomes that are consistent with the available data. In contrast, the objective of the validation is to test the adequacy of the model, and its assumptions, using the available data.

A Bayesian approach is used to identify these parameters of the Markov model. The set of (pipe condition) observations $\mathbf{y} = \{\mathbf{y}_1, \dots, \mathbf{y}_n\}$ are

hypothesised to be a random realisation from the (Markov) probability model M , with the probability mass function $f(\mathbf{y} | \boldsymbol{\theta}, M)$, where $\boldsymbol{\theta}$ is the unknown model parameter vector. The function $f(\mathbf{y} | \boldsymbol{\theta}, M)$ is known by two names depending upon the context in which it is used – either the sampling distribution or the likelihood function. $f(\mathbf{y} | \boldsymbol{\theta}, M)$ is referred to as the sampling distribution when it is used to describe the probability model generating the sample data $\mathbf{y}$ for a given $\boldsymbol{\theta}$. Here, however, $f(\mathbf{y} | \boldsymbol{\theta}, M)$ is referred to as the likelihood function because the data $\mathbf{y}$ is known and inference is sought on the parameter $\boldsymbol{\theta}$.

The parameter vector $\boldsymbol{\theta}$ is estimated using Bayesian inference. Bayesian inference considers the parameter vector $\boldsymbol{\theta}$ to be a random vector whose probability distribution describes what is known about the true value of $\boldsymbol{\theta}$. Prior to the analysis of the data $\mathbf{y}$, knowledge about $\boldsymbol{\theta}$, given the model M , is summarised by the probability density function $p(\boldsymbol{\theta} | M)$. This is known as the prior density, and can incorporate subjective belief about $\boldsymbol{\theta}$. Bayes' Theorem is then used to revise, using the information contained in $\mathbf{y}$, what is known about the true value of $\boldsymbol{\theta}$. Thus:

$$p(\boldsymbol{\theta} | \mathbf{y}, M) = \frac{f(\mathbf{y} | \boldsymbol{\theta}, M) p(\boldsymbol{\theta} | M)}{\int f(\mathbf{y} | \boldsymbol{\theta}, M) p(\boldsymbol{\theta} | M) d\boldsymbol{\theta}} = \frac{f(\mathbf{y} | \boldsymbol{\theta}, M) p(\boldsymbol{\theta} | M)}{p(\mathbf{y} | M)} \quad (3)$$

where $p(\boldsymbol{\theta} | \mathbf{y}, M)$ is the posterior density summarising the current knowledge of the true value of $\boldsymbol{\theta}$, given the observed data $\mathbf{y}$ and the model hypothesis M ; and $p(\mathbf{y} | M)$ is the marginal likelihood function. Note that $p(\mathbf{y} | M)$ is

independent of θ . Thus, we can express the posterior density as being proportional to likelihood function $\times$ prior density.

Calibration: Metropolis-Hastings Algorithm

The calibration was implemented using the Metropolis-Hastings (M-H) algorithm. The M-H algorithm is a member of the family of Markov chain Monte Carlo (MCMC) methods [see, for example, Gelman et al. (1995) for a more detailed description]. MCMC methods provide a means to simulate from almost any probability distribution. This property is exploited in this analysis to allow the M-H algorithm to sample from the posterior distribution.

MCMC methods must first be allowed to converge to a stationary distribution, which, by design, is the posterior distribution. Once convergence has been achieved, the MCMC samples are samples from the posterior distribution.

The implementation of the M-H algorithm is straightforward. At each iteration, a trial parameter is sampled from a proposal distribution; although the proposal distribution is arbitrary, good performance requires selection of a distribution that approximates the posterior. This trial parameter is then subjected to an acceptance test based on a random draw from a uniform

distribution. If it is accepted, the Markov chain moves to this trial parameter; otherwise the chain remains at its current position. The initial starting value for the M-H algorithm was the parameter set which maximises the posterior. This was obtained using the SCE method (Duan et al. 1993), an efficient and robust optimisation technique.

In this study, a noninformative uniform prior distribution was assigned to the transition probabilities P_{ij} . It can easily be shown that the logarithm of the likelihood function is:

$$\log f(\mathbf{y} | \boldsymbol{\theta}, M) = \sum_{t=1}^N \sum_{j=1}^4 n_j^t \log(p_j^t) \quad (4)$$

where t is the pipe age in years; N is the maximum age reported in the data set; and n_j^t is the number of pipes in condition j at age t . The M-H algorithm was allowed to “warm up” for 10000 iterations, and produced 20000 samples from the posterior.

Validation: Hypothesis Testing

The validation process took the form of hypothesis testing. Hypothesis testing allows one to establish whether the proposed probability model is consistent with a set of observations. Within this analysis, there were two separate hypotheses to be tested. The first hypothesis to be tested was that the observations are distributed according to the (hypothesised) Markov model. This assesses whether the Markov model is appropriate for

stormwater pipe deterioration. This testing is performed using the entire data set and through a split sample analysis. The split sample analysis is a more rigorous test because it uses data independent of that used in the model calibration.

The second hypothesis to be tested is that pipes having different category values deteriorate according to the same Markov model. This test affords an understanding as to whether the pipe category value has an influence on the deterioration process. It is noted that these are split sample tests because the data, contained within each set of category values analysed, are independent of each other.

The hypothesis testing procedure used was the Chi squared (χ^2) test based on the Pearson X^2 statistic:

$$X^2 = \sum_i \frac{(O_i - E_i)^2}{E_i} \quad (5)$$

where O_i and E_i are respectively the observed and expected number of pipes in group i where a group refers to the pipes with a particular condition rating at a particular observed age. To ensure that the X^2 statistic approximates the χ^2 distribution accurately, the traditional rule of thumb is enforced, namely that all expected frequencies should be at least 1.0, and 80% or more of the expected frequencies should be at least 5.0 (Cochran 1954). This rule of thumb is known to be conservative (Moore 1986). Where the expected

frequencies did not meet this rule, two or more groups were combined to form a new group.

RESULTS

The M-H algorithm was implemented to estimate the Markov transition probabilities for stormwater pipes. The data set was analysed in several ways – using the entire data set, a random split sample analysis, and analysing the various pipe categories (diameter, construction material, soil type, exposure classification, and serviceability condition) within the data set. The first two analyses provided a means of determining the appropriateness of the Markov model, whilst the third set of analyses explored whether there were significant differences in structural deterioration between pipe category values.

Validation of Markov Model Assumption

Validating that the data was distributed according to the Markov model was performed in two ways – using the entire data set and through the split sample analyses (split1/split2 and split2/split1). An explanation of the doublet notation (data 1/data 2) is required. Data 1 refers to the data set to which the parameters have been calibrated (using the M-H algorithm), whereas data 2 is used to test the model hypothesis (using the χ^2 test). That is,

the transition probabilities are estimated using data 1, and then the model is compared with the observations contained within data 2.

The resultant transition probabilities and the χ^2 test results are detailed in Tables 5 and 6 respectively. The split sample tests suggest that the Markov model is consistent with the data (at the 5% significance level). Thus, the Markov model is an appropriate model for stormwater pipe deterioration. This statement can be further substantiated by examination of the plots of the observed frequencies in each condition and the (conservative) 95% probability limits derived from the Markov model. These limits were estimated through Monte Carlo simulation. The conservative nature of these limits is a result of the distribution being discrete, compounded by the small number of observed frequencies contained within the data set. These 95% probability limits encompass the vast majority of the observed data points (see Fig. 3 for the plot of split1/split2).

It is important to appreciate that considerable parameter uncertainty exists. Table 5 quantifies this by reporting the posterior 95% probability limits on the transition probabilities for the entire data set analysis. This uncertainty arises from limited sample data. It can be displayed using histograms of the transition probabilities produced by the M-H algorithm – Fig. 4 presents histograms obtained for the entire data set analysis. Note that the vertical lines indicate the mean values of each parameter. The mean values of the

transition probabilities pass near the peak value of the histogram, except for P_{13} . This is a result of the secondary peak near zero, which slightly skews the mean value towards this peak.

Category Analysis

The various pipe categories were analysed for category value differences, and the results of the χ^2 tests are summarised within Table 7. Four of the five pipe categories analysed (diameter, construction material, soil type, and exposure classification) rejected the null hypothesis. This indicates that the Markov models for the category values, contained within each of these pipe categories, are statistically different – implying that the deterioration process is different for each of these category values. This effect can be illustrated by, again, considering the plots of the observed frequencies and the model 95% probability limits – Fig. 5 shows the plot for $d < 600 / d \geq 600$. Only 5 of 60 points lie outside of the limits, which does not suggest a poor fit by the model. However, the failure of the χ^2 test arises due to a few large discrepancies between the observed values and the expected values of the model that occur where there are large amounts of data available (e.g. condition 1 at age 56 years). It is to be expected that an appropriate model will provide a good fit to these points – the model, shown in Fig. 5, does not.

Pipe diameter was found to affect deterioration. The deterioration of smaller pipes was greater than that of larger pipes. A possible explanation for this is that pipe designers are underestimating the traffic loadings or the cover requirements for these smaller pipes, resulting in increased pipe damage for smaller pipes.

Pipe construction material affects deterioration. The results show that concrete pipes are stronger and more durable than vitreous clay pipes, as one would expect.

Soil type was found to affect deterioration. Pipes in alluvial soils deteriorate more rapidly than those in podzolic soils. This might be a result of the different formational environments of the soils. The podzolic soils are formed through the weathering of rocks, whilst the alluvial soils are deposited from a saline environment. Also, the alluvial soils are much more likely to be acid sulphate soils. These factors may increase the rate of deterioration due to the increased salt (chloride) content accelerating corrosion within the predominantly concrete pipes, and also through the sulphuric acids, formed by the acid sulphate soils, attacking the pipes (Stephen Fityus 2001, pers. comm.).

The exposure classification influences deterioration. It should be noted that no statistical comparisons using the category value C were possible, due to

insufficient data being available for use in the χ^2 test. Nonetheless, an effect was still obvious with B2 pipes deteriorating at a faster rate than A2 pipes. This effect might result from B2 pipes being located near the coastline (see Table 3). This could increase the rate of corrosion, and thus deterioration, of the predominantly concrete pipes due to the increased salt (chloride) content.

The serviceability condition did not affect deterioration. The serviceability condition is based on defects that affect the hydraulic, not structural, performance of a pipe. Thus, it is not unexpected that no influence on structural deterioration was detected. The reason for the model only being calibrated to the data in serviceability condition 1 is that this category value contained almost twice the amount of data compared to the other two category values (serviceability conditions 2 and 3). Also, these two category values had the vast majority of the data clustered into the age groups of 51 and 56 years.

The difference in the deterioration rates for the various category values is illustrated in Fig. 6, which gives the expected proportion of pipes in condition 4 as a function of age. The graph shows that the deterioration rates for the category values vary significantly, confirming the results in Table 7.

Comparison to Accounting Standards

The depreciation curve derived from AAS27 depreciation requirements is significantly different to the deterioration curve estimated by the Markov model. This is illustrated in Fig. 7, which also includes the 95% probability limits and median derived from the Markov model. It shows that the AAS27 depreciation curve very significantly overestimates the deterioration of stormwater pipes. This highlights the need to derive infrastructure deterioration models from observed performance, rather than notional performance.

Discussion

The χ^2 tests are of extreme importance to this analysis. They provide an effective means of interpreting the results by allowing one to determine whether the Markov model provided a consistent fit to the data, and also whether any other pipe characteristics, besides age, had an influence on the deterioration process.

A nonhomogeneous (time varying) Markov model was not required to model the deterioration process. The hypothesis testing showed that the homogenous Markov model was adequate. While implementation of a nonhomogeneous model is appealing, there is one major drawback that must first be considered. This is the increased number of parameters that must be estimated from the data set. This leads to a greater uncertainty within the

parameters, which can diminish any advantages gained by using this type of model.

The argument proposed that a stormwater pipe deteriorates through a damage event, and that this damage event may cause a pipe to deteriorate by more than one state, in accordance with its severity, appears justifiable given the data. Table 4 shows that the transition from state 2 to state 4 is the most likely transition to occur. It also shows that the Herz and Weibull models are not appropriate because they cannot simulate the true nature of the deterioration process, which involves multistate transitions.

The findings of this study and that of Wirahadikusumah et al. (2001) have recognised various factors that affect the structural deterioration of both stormwater pipes and combined sewers. These are the pipe construction material and the soil type. It must be noted that these two factors are the only ones common to the two studies, so it is quite possible that more factors may affect the structural deterioration of both forms of pipes.

The serviceability condition is an indicator of the hydraulic performance provided by the pipe and is, thus, an important factor in stormwater pipe network management. As the hydraulic performance of a pipe decreases, the number of pipe surcharges becomes more frequent due to the associated blockages, intrusions, etc., within the pipe. When these surcharges become

too frequent, the pipe needs to be refurbished or replaced. This suggests that a combination of both structural and serviceability conditions should be considered when determining a stormwater pipe network management strategy.

CONCLUSION

This paper has presented a homogeneous Markov model for the structural deterioration of stormwater pipe infrastructure. The Markov transition probabilities were estimated using the Metropolis-Hastings algorithm. The Markov model was shown, both conceptually and through statistical analyses, to be an appropriate model for stormwater pipe deterioration. Various pipe characteristics were found to influence the deterioration process. These were pipe diameter, construction material, soil type, and exposure classification, whilst the pipe serviceability condition did not affect deterioration. The depreciation requirements of Australian accounting standards were shown to significantly overestimate the actual deterioration of stormwater pipes.

ACKNOWLEDGMENTS

We thank Newcastle City Council for providing the database used within this paper. This paper was improved through the comments and suggestions of three anonymous reviewers.

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CAPTIONS - TABLES

TABLE 1. Description of Structural Condition Ratings (DLGC 1995).

TABLE 2. Number of Pipes as a Function of Age and Structural Condition (NCC Stormwater Network).

TABLE 3. Categorisation of Data.

TABLE 4. Exposure Classifications [*AS3600* (1994)].

TABLE 5. Posterior Markov Transition Probabilities (Model Verification).

TABLE 6. Summary of χ^2 Tests (Model Verification).

TABLE 7. Summary of χ^2 Tests (Category Analysis).

CAPTIONS - FIGURES

FIG. 1. Extremely Structurally Damaged Stormwater Pipe Capable of Conveying Stormwater.

FIG. 2. Flowchart Displaying the Possible Transitions of State.

FIG. 3. 95% Probability Limits (Derived from Sample split1) and the Observed Frequencies for Sample split2, as a Function of Age.

FIG. 4. Histograms of Transition Probabilities (Entire Data Set).

FIG. 5. 95% Probability Limits (Derived from Sample $d < 600$) and the Observed Frequencies for Sample $d \geq 600$, as a Function of Age.

FIG. 6. Markov Model Deterioration Curves (Condition 4).

FIG. 7. Comparison of AAS27 Depreciation and Markov Model Deterioration Curves.

TABLE 1. Description of Structural Condition Ratings (DLGC 1993).

Structural Condition (1)	Physical Description (2)
1	Near perfect condition
2	Some superficial deterioration
3	Serious deterioration, requiring substantial maintenance
4	Level of deterioration affects the fabric of the asset, requiring major reconstruction or refurbishment
5	Level of deterioration is such to render the asset unserviceable

TABLE 2. Number of Pipes as a Function of Age and Structural Condition (NCC Stormwater Network).

Age (1)	Total number of pipes (2)	Structural Condition (See Table 1)			
		1 (3)	2 (4)	3 (5)	4 (6)
3	10	9	0	1	0
5	3	3	0	0	0
8	1	1	0	0	0
9	1	0	1	0	0
20	14	12	2	0	0
26	18	12	2	0	4
30	27	24	2	0	1
36	22	14	3	1	4
40	12	7	1	0	4
41	2	2	0	0	0
46	45	18	3	7	17
50	1	1	0	0	0
51	77	38	9	16	14
56	216	95	20	25	76
60	8	2	0	0	6
61	18	15	2	0	1
66	1	1	0	0	0
70	5	1	0	2	2
80	4	0	0	0	4
90	5	5	0	0	0
110	7	2	1	0	4
All	497	262	46	52	137

TABLE 3. Categorisation of Data.

Analysis / category (1)	Data set / category value (number of samples) (2)
Entire Data Set	Entire Data Set (497)
Split Sample	split1 (249), split2 (248)
Diameter	d<600 (376), d≥600 (121)
Material	conc (342), VC (135)
Soil Type	all (296), pod (201)
Exposure	A2 (216), B2 (238), C (43)
Serviceability	s1 (191), s2 (88), s3 (101)

TABLE 4. Exposure Classifications. (AS3600 1994)

Classification (1)	Description (2)
A2	Pipes more than 1 km from the coastline
B2	Pipes within 1 km from the coastline
C	Pipes within 1 km from the coastline and within tidal zones

TABLE 5. Posterior Markov Transition Probabilities (Model Verification).

Transition (1)	Entire data set		Mean	
	Mean (2)	95% probability limits (3)	Split1/ split2 (4)	Split2/ split1 (5)
1 to 2	0.0101	0.0061, 0.0134	0.0087	0.0071
1 to 3	0.0016	0.0000, 0.0056	0.0004	0.0039
1 to 4	0.0002	0.0000, 0.0036	0.0007	0.0004
2 to 3	0.0021	0.0000, 0.0332	0.0161	0.0005
2 to 4	0.0542	0.0299, 0.0772	0.0219	0.0237
3 to 4	0.0009	0.0000, 0.0291	0.0012	0.0048

TABLE 6. Summary of χ^2 Tests (Model Verification).

Analysis	χ^2	Degrees of freedom (df)	$\chi^2_{(0.05, df)}$
(1)	(2)	(3)	(4)
Entire Data Set	36.155	27	40.112
Split1/Split2	26.155	16	26.295
Split2/Split1	27.385	19	30.143

TABLE 7. Summary of χ^2 Tests (Category Analysis).

Analysis	χ^2	Degrees of freedom (df)	$\chi^2_{(0.05, df)}$
(1)	(2)	(3)	(4)
d<600/d≥600	32.557	8	15.507
d≥600/d<600	64.965	21	32.670
conc/VC	117.551	4	9.487
VC/conc	370.271	30	43.772
all/pod	30.480	18	28.868
pod/all	44.009	10	18.306
A2/B2	57.640	7	14.067
B2/A2	55.687	18	28.868
s1/s2	7.280	4	9.487
s1/s3	4.378	5	11.07

FIG. 1. Extremely Structurally Damaged Stormwater Pipe Capable of Conveying Stormwater.

FIG. 2. Flowchart Displaying the Possible Transitions of State.

FIG. 3. 95% Probability Limits (Derived from Sample split1) and the Observed Frequencies for Sample split2, as a Function of Age.

FIG. 4. Histograms of Transition Probabilities (Entire Data Set).

FIG. 5. 95% Probability Limits (Derived from Sample $d < 600$) and the Observed Frequencies for Sample $d \geq 600$, as a Function of Age.

FIG. 6. Markov Model Deterioration Curves (Condition 4).

FIG. 7. Comparison of AAS27 Depreciation and Markov Model Deterioration Curves.