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Markov and Neural Network Models for Prediction of Structural Deterioration of Stormwater Pipe Assets

H. D. Tran¹, B. J. C. Perera² and A.W.M. Ng³

Abstract. Stormwater pipe networks in Australia are designed to convey water from rainfall and surface runoff. They do not transport sewerage. Their structural deterioration is progressive with aging and will eventually cause pipe collapse with consequences of service interruption. Predicting structural condition of pipes provides vital information for asset management to prevent unexpected failures and to extend service life. This study focused on predicting the structural condition of stormwater pipes with two objectives. The first objective is the prediction of structural condition changes of the whole network of stormwater pipes by a Markov model at different times during their service life. This information can be used for planning annual budget and estimating the useful life of pipe assets. The second objective is the prediction of structural condition of any particular pipe by a neural network model. This knowledge is valuable in identifying pipes that are in poor condition for repair actions. A case study with CCTV inspection snapshot data was used to demonstrate the applicability of these two models.

CE Database subject headings: Stormwater management; Markov models; Probability; Neural networks; Structural failures; Deterioration

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Introduction

Stormwater pipe networks in Australia are designed to convey water from rainfall and surface runoff. They do not transport sewerage. Their age and deterioration has approached a stage where failures of pipe networks start to increase (Engineers Australia, 2001; 2005). In general, the condition of stormwater pipes is commonly divided into structural and hydraulic conditions in order to recognize the distinctive effects and consequences of two different processes of structural and hydraulic deterioration (Tran et al. 2008; 2009). Effective operation and management of the stormwater pipes is increasingly required, and thus asset managers must be well prepared to answer some critical questions as stated below:

- What is the annual budget required to maintain the performance of the pipe networks?
- If annual maintenance is deferred, when would the conditions of pipe networks become critical?
- Which pipes are in poor condition requiring repair or overhaul?

In the current management practice of stormwater pipe systems in Australia, closed circuit television (CCTV) inspection and condition grading schemes are two common tools used for assessing the condition of stormwater pipes (both structural and hydraulic conditions) at the time of inspection (WSAA 2002). Because of the large expenses involved in this process, it is not affordable to carry out CCTV inspection for all pipes in a network of hundreds of kilometers. As a result, only a fraction of the pipe network is CCTV-inspected only once, which produces one set of snapshot data. Predicting current and future condition of pipes based on this snapshot data is becoming an extremely important task in asset management as the predictive information can be used for answering the above questions and for making decisions as to when and how to maintain, overhaul or replace the pipes. Therefore, there is an increasing effort among researchers to develop mathematical models using limited samples of CCTV inspected pipes for predicting the current and future condition of stormwater pipe networks.

This study focused on predicting the structural condition of stormwater pipes with two objectives. The first objective is the prediction of structural condition changes of the whole network of stormwater pipes by a Markov model at different times during their service life. The outcome of the Markov model is the timely prediction of the structural condition changes of the whole population of stormwater pipes. This information can be used for planning annual budget and estimating the useful life of pipe assets considering the prediction. The first objective was done using the Markov model which was

successfully developed by Micevski et al. (2002) for structural deterioration and was subsequently applied by Tran et al. (2008) for hydraulic deterioration of stormwater pipes. Achieving this objective successfully will reconfirm the reliability of the Markov model in stormwater pipe deterioration modelling. The second objective is to improve the performance of the neural network model (NNM) developed by Tran et al. (2009) for predicting the structural condition of individual pipes, since the Markov model in Micevski et al. (2002) and Tran et al. (2008) had no link mechanism between pipe factors such as pipe size and age with pipe deterioration and thus failed to predict the structural condition of a particular pipe. The improved predictive performance of NNM was done in this study by using the Bayesian Markov chain Monte Carlo simulation technique which was used for calibrating the NNM for hydraulic deterioration of stormwater pipes in Tran et al. (2007). The structural condition for any particular pipe predicted by the NNM can be used for identifying pipes that are in poor condition for repair actions. In this paper, a dataset supplied by City of Greater Dandenong in Australia was used to demonstrate the applicability of these two models. The remainder of the paper is organized into six sections. The next two sections describe the Markov model and the neural network model with their theory and calibration. The methods used to assess the performance of the models are described then, followed by the case study. The next section discusses the results. Finally, the last section presents conclusions drawn for the study.

Markov Model

The Markov model for predicting the structural condition changes of the whole network of stormwater pipes in this study was initially developed in Tran et al. (2008) for modeling hydraulic deterioration. The structure of the Markov model is based on Markov chain theory (Ross 1997). The Markov chain operates in such a way that, whenever the process is in condition state i at year t , there is a probability P_{ij} that the process will move to state j at year $t+1$. The time interval of the Markov chain was chosen in this study as one-year and was indexed using non-negative integers. The important property of the Markov model is that the transition probability P_{ij} depends only on the present state (i.e. state i), which means the process is independent of historical states (Ross 1997). The transition matrix for the whole network of pipes (or pipe population) can be estimated from a sample of pipes if the sample is assumed to represent a 'homogenous' population. In this case, the effects of pipe factors are ignored.

This means that all pipes now have the same transition matrix (\mathbf{P}) and this transition matrix represents the behavior of pipe population with regard to the condition changes over time. The transition probabilities can be estimated using the posterior distribution which is related to the observed structural conditions of pipes in the sample as described in Tran et al. (2008):

$$\log(L(\mathbf{Y} | P_{ij})) = \sum_{t=1}^T \sum_{k=1}^3 n_k^t \log(s_k^t) \quad (1)$$

where $L(\mathbf{Y}|P_{ij})$ = the likelihood to observe a set \mathbf{Y} of structural conditions of pipes in the sample given the transition probabilities P_{ij} , t = the age (in years) of a pipe in the sample, T = the maximum age found in the sample and n_k^t = the number of pipes observed in condition k at year t , $k = 1..3$ since the structural condition is graded from 1 to 3 in the case study, s_k^t = the probability of pipe in condition k at year t .

The calibration of the Markov model is to estimate the model parameters (i.e. transition probabilities) by sampling from their posterior distribution shown in Eq. (1). The Metropolis-Hastings algorithm (MHA), a class of the Bayesian Markov chain Monte Carlo (MCMC) (Ross 1997) can be used to perform the sampling. The basic idea behind the Bayesian MCMC is the use of a Markov chain whose stationary probabilities are identical to the wanted posterior distribution (Ross 1997). The MHA allows sampling from most types of posterior distribution with reliable results and the ease of coding on a computer program. The Markov chain of the Bayesian MCMC is run a large number of times (called iterations) until it converges to the stationary probability, which can easily be observed in general. After discarding the warm up runs, the remaining values are the sampling data from the wanted posterior distribution (i.e. the distributions of transition probabilities). The mean values and their 95% confidence ranges can be calculated from the sampling data of the posterior distributions. Since the true values of transition probabilities are unknown, the mean values within 95% confidence ranges can be used to approximate the true values. Furthermore, the 95% confidence ranges of the transition probabilities give an indication of the uncertainty of the model parameters. Detailed implementation of MHA is described in Micevski et al. (2002) and Tran et al. (2008).

Neural Network Model (NNM)

The NNM for predicting the structural condition of individual stormwater pipes in this study was described in Tran et al. (2009). The structural deterioration of individual pipes is considered a pattern that is assumed to be characterized by a number of pipe factors such as pipe size and pipe location. The feed forward neural networks was adopted to detect or classify these patterns in a way that pipe factors are used as the input signals and pipe conditions are the target to be classified or predicted. The use of 'feed-forward' property was to ensure that the network outputs can be calculated as explicit functions of the inputs and the network weights, and thus can reduce the unnecessary complexity in determining the network topology which might affect the predictive capability of the neural network model. The snapshot inspection data and graded pipe condition were used as the training data for the NNM's learning process. By assuming that the training data was randomly collected over different age groups and pipe factors, the NNM can learn sufficient deterioration patterns from the training data and thus is able to predict any query pipe. The NNM in Tran et al. (2009) had three output neurons which represented for three condition grades of stormwater pipes. Each output neuron produces a number in the range [0, 1] and the predicted structural condition then corresponds to the output neuron with highest value.

Training NNM is to estimate the model parameters, which are the number of hidden neurons and network weights. Mean square error (MSE) (Bishop 1995) between predicted output and observed values is used as the criterion in training process (Tran et al. 2009). Local optimum and weight uncertainty associated with training of NNM can adversely affect the performance of NNM (Leung et al. 2003; Kuncheva 2004; Curry and Morgan 2006, Tran et al. 2007). They were addressed in this study by using the confidence ranges of network weights. The confidence ranges can be obtained through the Bayesian approach and Markov Chain Monte Carlo (MCMC) simulation for training of the NNM. MacKay (1992) introduced the Bayesian approach for training neural networks in which the network weights are treated as random numbers whose posterior distribution depends on observed data and prior knowledge according to the Bayesian approach. The sampling data of network weights from their posterior distribution were used to compute the condition of pipes which resulted in 95% confidence

ranges (or interval prediction). Detailed implementation of the Bayesian MCMC simulation for training the NNM can be found in Kingston et al. (2006) and Tran et al. (2007).

Assessing Predictive Performance of Developed Models

This study adopted two scalar performance measures, namely, overall success rate and false negative rate derived from the confusion matrix (Tran et al. 2009) and the goodness-of-fit test (Micevski et al. 2002; Baik et al. 2006) for assessing the performance of the developed deterioration models on a test dataset. The confusion matrix provides a comparison between three possible conditions of pipes against four possible situations that occur when comparing the predicted structural condition to the observed condition. From the confusion matrix, two scalar performance indicators, namely overall success rate (OSR) and false negative rate (FNR) can be computed to evaluate the predictive performance of the developed models. The OSR represents the percentage of all test cases that were correctly predicted by the models. It indicates how well the deterioration models predict the condition of individual pipes for all cases. The FNR shows the percentage of incorrect predictions when pipes are actually in poor condition. The FNR can be considered as a surrogate measure of the risk associated with the use of the models in terms of cost of failures, if pipes in poor condition are predicted to be in good condition. The goodness-of-fit test using Pearson chi-squared test statistic (χ^2) is based on a null hypothesis that the number of predicted pipes was consistent with the number of observed pipes in each condition.

Case Study

The case study used the dataset of Tran et al. (2009) which was supplied by the City of Greater Dandenong (CGD) in Victoria, Australia. The dataset contained a sample of 417 stormwater drainage pipe segments. Nearly half of the dataset contained randomly selected pipes for CCTV inspection conducted in 2006-2007 and the remainder contained old pipes that were selected for CCTV inspection during 1999-2005. However, the inspection program was of a single snapshot type, in that none of the pipes has received a second inspection. Nine pipe factors provided by CGD are given in Table 1. The entire dataset was randomly split into the calibration (75%) and test (25%) datasets for calibrating and testing the Markov model and NNM.

Results and Discussion

This study used MATLAB[®] computing software for all computational tasks. For the Markov model, the MHA was run with 13,000 iterations for the calibration dataset and entire dataset (i.e. calibration and test datasets together) to achieve convergence of the chain to stationary conditions. The last 3,000 results were used to estimate the mean and confidence ranges of the transition probabilities. The mean values of the transition probabilities estimated by the MHA with the calibration dataset were given in Table 2. The mean values of the transition probabilities and their 95% confidence ranges (values within brackets) estimated by the MHA on the entire dataset are given in Table 3. The transition probabilities obtained from the entire dataset is considered closer to the true values than those obtained from the calibration dataset because more data points are used. Therefore, the transition probabilities obtained from the calibration dataset will be used to test the Markov model and the transition probabilities obtained from the entire dataset will be used for the application of Markov model as described later.

For the NNM, the calibration dataset was further randomly divided into the train and validation datasets. The validation dataset was also used in the training process (with train dataset) in order to avoid the over-fitting of NNM by employing the early stopping technique (Bishop 1995; Tran et al. 2009). The number of hidden neurons was determined by increasing the number from a starting value of 4 and observing the corresponding MSE values. MSE was computed for both calibration and validation datasets for each set of hidden neurons, and the training process was stopped if the MSE value in the validation dataset started to increase. Fig. 1 shows the changes of MSE values of the train and validation datasets against the increasing number of hidden neurons. A set of 18 hidden neurons was chosen as it appears to have the lowest MSE values on train and validation datasets as shown in Fig. 1. The Bayesian MCMC was then used to estimate the network weights of the NNM.

The results of testing the Markov model and NNM are as follows. In the Markov model, the computed Chi-square values are 0.22 and 0.34 for the calibration and test datasets respectively. These values are smaller than the critical value of 5.99 which implies a good fit for the Markov model. This finding is consistent with the previous study by Micevski et al. (2002) and thus the Markov model calibrated by the Bayesian MCMC simulation is considered as a reliable method for modelling the structural deterioration of stormwater pipes. One may argue that older pipes in reality tend to deteriorate faster

than newer pipes, i.e. non-stationary transition. Micevski et al. (2002) and Tran et al. (2008) showed that a stationary Markov model fitted well with the observed data of stormwater pipes. Micevski et al. (2002) explained that due to the uncertainty, models which try to mimic the reality could pay the price of poor model performance. However, the non-stationary Markov model was not tried in this study to confirm the view by Micevski et al. (2002). This is because statistical estimation can be appropriately made for the model parameters if the number of observed data is sufficiently larger than the number of model parameters. The number of observed data in this study is considered small compared to the number of model parameters (i.e. transition probabilities) required by the non-stationary Markov model as can be seen in the non-stationary Markov model developed for sewers by Wirahadikusumah et al. (2001).

To answer the question of annual budget, the structural condition changes of pipe population obtained from the Markov model with transition probabilities estimated from the entire dataset is plotted against pipe age as shown in Fig. 2. This figure was constructed assuming that all pipes come from a homogenous population (i.e. effects of contributing factors were ignored). The figure shows an initial steep upwards slope for distribution curves of structural conditions 2 and 3 with a peak at the age of about 45 for condition grade 2. The proportions of conditions 1 and 3 continuously decreased and increased respectively over the years. If maintenance and rehabilitation (M&R) actions are not carried out until the age of 120 year, about 80% of pipes would be predicted to be in the structural condition 3. Furthermore, the age of 40 years can be seen as the critical time of the stormwater pipe network in this study, when the probability of pipes in condition 3 starts to exceed 0.6, although some pipes in reality are observed as still in good condition at the age of 100 or more. The value of 0.6 is selected because this value corresponds with the timing that the probability of pipes in condition 1 is well below both probabilities in condition 2 and 3 as can be seen in Fig. 2. This means that if maintenance is deferred, pipes at the age of 40 and older should be inspected. To select the candidate pipes for CCTV-inspection, the NNM can be used to predict the condition of each pipe because older pipes do not necessarily have poor condition.

The NNM, on the other hand, achieved an OSR of 84% and 81% for the train and test datasets respectively. Furthermore, the FNRs of the NNM are 17% and 19% for the train and test datasets

respectively. These are considered substantial improvement over the NNM calibrated by genetic algorithm in Tran et al. (2009). This relatively good performance of NNM can be seen in Fig. 3, which shows the predicted condition with 95% confidence ranges versus the observed condition for the first 25 pipes in the test dataset. The figure shows the predictive range of NNM due to the uncertainty of network weights (or model parameters).

The interpretation of this interval prediction is that (1) the use of interval prediction provides a better fit to the observed data than the use of point prediction because it considers the uncertainty associated with model structure which is reflected in the network weights, (2) however, this also indicates that training NNM is not straight forward and contains local optima which are not easily to be detected and overcome, (3) consequently, it is practically difficult to identify the most likely condition of pipe in real life application if interval prediction is used and thus additional consideration such as failure consequence might be used for making decision on maintenance action. Furthermore, the meaning of showing a line on a scale that is discrete can be explained as follows. The deterioration of pipe is a progressive process and thus the deteriorated condition should be shown as a continuous value. However, for ease of use, the deteriorated condition of pipes is converted into discrete values in order (i.e. ordinal numbers). When presented in diagram, the condition shown in line could provide a better visualization and closer approximation to the true deteriorated condition. This practice was also used in other papers (Wirahadikusumah et al. 2001; Micevski et al. 2002, Baik et al. 2006). Some predictive ranges collapsed into a point value and some observed values were outside the ranges. The reason for the latter can be explained as follows. Since the factors such as traffic condition and joint material, which possibly relate to the structural deterioration, were still missing in the (supplied) dataset, the classifying capability of the NNM model is not fully utilized.

Conclusions

This paper described two models for predicting the structural deterioration of rigid stormwater pipes using Markov chain and neural networks. The Markov model provides information on the structural condition changes over time for the whole population of stormwater pipes which can be used for preparing annual budget. The neural network model (NNM) classifies the condition of any particular pipe given its pipe factors. Pipes which are predicted as in poor condition by the NNM can then be subjected to CCTV inspection and subsequent repair actions. Both models were calibrated using the

Bayesian Markov Chain Monte Carlo (MCMC) simulation and their performance was assessed using Goodness-of-fit test and analysis of confusion matrix. The case study with CCTV inspection data was used to test both models. The Markov model passed the Goodness-of-fit test and thus was found to be a reliable method for modelling the structural deterioration of stormwater pipes with snapshot data. The NNM has a relatively good performance on the classifying task which achieved an overall success rate (OSR) of 81% and false negative rate (FNR) of 19% on the test dataset. Increasing the number of pipe factors could possibly improve the predictive performance of the NNM because it can fully utilize the classifying capability of neural networks. The Bayesian MCMC simulation was found to be an adequate calibration method for both models as it can handle the uncertainty associated with model parameters which come from the model configuration.

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Table 1. Input Factors Used in the Case Study

Table 2. MHA Estimated Transition Probabilities with the Calibration Dataset

Table 3. MHA Estimated Transition Probabilities with the Entire Dataset

Table 1. Input Factors Used in the Case Study

Input factors	Description
Pipe size	Scale (225 to 1950 mm)
Pipe age	Scale (0 to 65 years)
Pipe depth	Scale (0 to 4.83 m)
Pipe slope	Scale (0 to 22.85%)
Tree-count	Scale (1 to 22) (number of trees around pipe)
Hydraulic condition	Ordinal (1-3); '1'=good, '2'= fair and '3'= poor
Pipe location	Nominal (1-4); '1'=under street, '2'= under easement, '3'= under reserve and '4'= under nature strip
Soil type	Nominal (0-1); '0'=clay soil, '1'= mix soil
TMI	Nominal (0-1); '0'=wet, '1'= dry

Table 2. MHA Estimated Transition Probabilities with the Calibration Dataset

		(Future Condition State)		
		1	2	3
(Current	1	0.9455	0.0202	0.0343
Condition	2	0	0.9996	0.0004
State)	3	0	0	1

Table 3. MHA Estimated Transition Probabilities
with the Entire Dataset

		(Future Condition State)		
		1	2	3
(Current Condition State)	1	0.9432 (0.9404-0.9461)	0.0209 (0.0199-0.0219)	0.0359 (0.0341-0.0377)
	2	0	0.9995 (0.9994-0.9996)	0.0005 (0.0004-0.0006)
	3	0	0	1