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APPLICATION OF NEURAL NETWORKS IN MODELLING SERVICEABILITY DETERIORATION OF CONCRETE STORMWATER PIPES

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Abstract: Stormwater pipe systems in Australia are designed to convey water from rainfall and surface runoff only and do not transport sewage. Any blockage can cause flooding events with the probability of subsequent property damage. Proactive maintenance plans that can enhance their serviceability need to be developed based on a sound deterioration model. This paper uses a neural network (NN) approach to model deterioration in serviceability of concrete stormwater pipes, which make up the bulk of the stormwater network in Australia. System condition data was collected using CCTV images. The outcomes of model are the identification of the significant factors influencing the serviceability deterioration and the forecasting of the change of serviceability condition over time for individual pipes based on the pipe attributes. The proposed method is validated and compared with multiple discriminant analysis, a traditionally statistical method. The results show that the NN model can be applied to forecasting serviceability deterioration. However, further improvements in data collection and condition grading schemes should be carried out to increase the prediction accuracy of the NN model.

Keywords: Deterioration model, neural networks, stormwater pipes, multiple discriminant analysis.

1. Introduction

Flooding damage has cost Australia approximately $314 million annually [1]. Designed to only convey stormwater and surface water, stormwater pipe systems in Australia need proactive maintenance plans to enhance their serviceability to reduce the frequency of flooding events caused by pipe blockage and thus the property damage. Furthermore, obstruction free stormwater pipes are needed so that CCTV inspection for their structural condition can be carried out properly.

This paper focuses on modelling the deterioration process of serviceability for concrete stormwater pipes. The outcomes of model are the identification of the significant factors influencing the serviceability deterioration and the forecasting of the change of serviceability condition over time for individual pipes based on the pipe attributes. This study is restricted to concrete pipes because more than half of small to medium size stormwater pipes and most of large and important pipes in the stormwater system are of concrete.

The serviceability deterioration is estimated from three apparent conditions [2]. Condition 1 indicates pipes in good condition, condition 2 indicates pipes in fair condition and condition 3 means the pipes need further investigation. Pipe attributes consist of pipe factors and site factors. Pipe factors comprise design and construction related factors such as pipe size, buried depth etc. Site factors are the characteristics of the environment in which the pipes operate such as soil type, traffic load and so on.

This paper applies a neural network approach to model the serviceability deterioration using the CCTV sampled images supplied by the City of Greater Dandenong, Australia. The proposed method is compared with multiple discriminant analysis, a classical statistical method.

2. Background

2.1 Factors Influencing Deterioration in Serviceability

In a systematic study of deterioration problem on sewers in UK, the Water Research Centre [3] listed visual defects of serviceability deterioration as tree root penetration, debris deposits, scale, encrustation and obstruction. Building up over time, such defects result in a substantial reduction of hydraulic capacity or a complete blockage [4]. Debris can accumulate in pipe segments having low flow-rates but might sometimes be washed away in a storm event. However, such peak flows may also bring in larger obstructions [5]. Pohls [6] conducted research on tree root penetration causing sewer blockage and concluded that other factors such as climatic condition, soil type, quantity, type and height of trees and pipe design information such as pipe size, buried depth and pipe joint material. are also influential factors that should be considered in study of deterioration of stormwater systems. On the other hand, an increase in runoff quantity due to infiltration and storm events can also contribute to the reduction of serviceability.

2.2 Existing Deterioration Models

At present, no deterioration models for the serviceability of separate stormwater pipe systems have been developed. Hence, the models developed for sewers and other infrastructure facilities will be examined for application. Based on historical records of blockage events that had occurred, Pohls [6] applied the Poisson model to predict the mean number of blockages per unit length of a sewer cohort and the Logistic model to estimate the probability of a blockage occurrence to a sewer segment given its attributes. However, such predicted outcomes do not provide enough information for a proactive maintenance plan since they fail to separate a pipe in good condition from a pipe in poor condition that is subject to the occurrence of a potential blockage. Furthermore, in a young system, the blockage events happen rarely and thus the data may not be enough for analysis [7].

Using CCTV inspection to record defects, the serviceability conditions of pipes are graded for assessment and sample data can be taken as many times as practicable. A few more deterioration models have been developed to predict structural condition using this kind of information and Markov chain theory [8]. Based on the predicted outcomes, they could be classified into “group” or “population” performance prediction [4,9-11] and “individual” prediction of performance [12]. The former does not indicate which pipes within the group should be cleaned/repaired in priority order. Prediction can be improved by increasing the numbers of groups to reduce the members of each group but this requires a lot more sample data [7].

The “individual” model needs regular inspection data to validate the model and requires the random error of the condition data for each pipe to follow the same probability density. However, the sample data of stormwater pipe system are limited in quantity. The pipe conditions are not regularly inspected but data is collected on a “snapshot” basis i.e. information on condition of the whole network of pipes is collected over a short period of time, rather than at regular intervals over a substantial period of time. Furthermore, such a requirement for random error may not hold for storm water pipes.

Free from such limitations, a neural network (NN) approach (a class of soft computing techniques), has been used recently in prediction models for infrastructure systems [13-15]. From the NN model, a list of influential factors can be obtained by ranking the weights assigned to input factors [16,17]. The basic application of NN is for pattern classification which is done by learning from sample data (training stage) and using the gained knowledge (generalizing stage) to predict the new patterns [18].

3. Case Study

The City of Greater Dandenong in Victoria, Australia operates 800 kms of stormwater pipes. In an attempt to understand the condition status of the stormwater pipe system, CCTV inspections have been carried out from 1999 to 2002 on snapshot base, that is, a pipe segment received only one inspection, rather than being inspected at regular intervals over a long period of time. There are approximately 650 data points accounting for 3.4% of the total system length collected from inspections. However, based on the thought that older pipes would be more likely to be in critical condition, the City’s inspection strategy was focused on the oldest pipes with ages from 40-65 years and on some locations that reported flooding or blockages. During the system operation since installation, reportedly, some minor maintenance and cleaning was conducted but no maintenance was recorded in the database.

The structural and serviceability condition was graded separately using three condition states as mentioned in the Section 1. The dataset provided only seven pipe factors for analysis, as listed in Table 1. The factor indicating the numbers of tree in vicinity of pipes was incomplete with half the amount of total rows in the dataset. Since the distribution of available tree data seems to follow the lognormal distribution, simulated data were used to compensate for the missing points. After cleaning the data, only 583 data points are acceptable for analysis.

Table 1. Input factors used in the study

Pipe Factors	Data type	Descriptions
Size	Value	Min 225 / Max 1950mm
Age	Value	0 / 65 years
Depth	Value	0 / 4.83metres
Slope	Value	-1.85 / 22.85%
Tree_New	Value	1 / 22 counts (Number of trees around pipe)
Location	Category	1-under reserve 2-under road 3-under nature strip 4-under easement
Structural condition	Ordinal	1-good 2-fair 3-poor (need further investigation)

4. Neural Network Model

The methodology of this study used a feed forward neural network (NN) [19,20] to classify different deterioration patterns in the serviceability deterioration of stormwater pipes. Seven characteristics of pipes in case study were used as inputs to the neural network model. Each serviceability condition is assigned to a set of deterioration patterns that are closely related. Therefore, the NN model can forecast the serviceability condition of a pipe given its characteristics. A NN can capture the unknown non-linear or linear relationships [14] which seem suitable to describe the complicated relations between serviceability condition and pipe attributes in stormwater pipes. It can also account for the maintenance and rehabilitation effect easily, if recorded, by treating that information as an input attribute.

4.1 Data Preparation

The dataset of case study was randomly split into three subsets, namely calibration (60%), validation (25%) and test (15%) to be used by the NN model. The calibration subset was used to estimate the parameters of the model (training process) while the validation subset was used to control estimation process. The test subset was used to evaluate the performance of the NN model in classification work. All data were normalized between [0 1].

4.2 NN Configuration and Training

The determination of the NN model configuration was iterated with training process. Figure 1 presented configuration of NN model where there are three neurons in the output and seven neurons in the input layer. Each neuron output represents one serviceability condition and each input neuron corresponds to one input pipe factors. The use of one hidden layer and 10 hidden neurons and back-propagation Levenberg-Marquardt (LM) training function were based on trial and error searches. The Neural Network Toolbox (NN tool) of MATLAB® software package was used to support the computation. The mean square error (MSE) used as key criteria and the Tansig and Logsig functions employed for hidden and output layers respectively were available in NN tool.

Table 2 showed comparison of MSE for different training functions that were tried. L-M training function was considered better than others. More details on training functions can be referred to NN tool manual [21]. Similarly, Figure 2 showed MSE performance in search for suitable number of hidden neurons where 10 hidden neurons appeared to be the best compromise between calibrating and testing errors. Furthermore, Table 3 showed layout of 2 hidden layers (10-5) outperformed other layouts with more hidden layers. However, it did not show much more improvement comparing to one hidden layer (10 neurons) which therefore was finally chosen for efficiency and simplicity.

Table 2. MSE Performances of training functions for one hidden layer and 15 hidden neurons

Training Function	MSE
Levenberg-Marquardt (LM)	0.11
Resilient Back-propagation	0.182
Scaled Conjugate Gradient	0.19
BFGS Quasi-Newton	0.2
Gradient Descent	0.265
Gradient Descent with Momentum	0.28

Table 3. MSE Performances of different hidden layer numbers using LM training function

Layout of Hidden layers	10-5	10-5-5	10-5-5-5
Calibrating MSE	0.17	0.173	0.18
Testing MSE	0.22	0.225	0.23

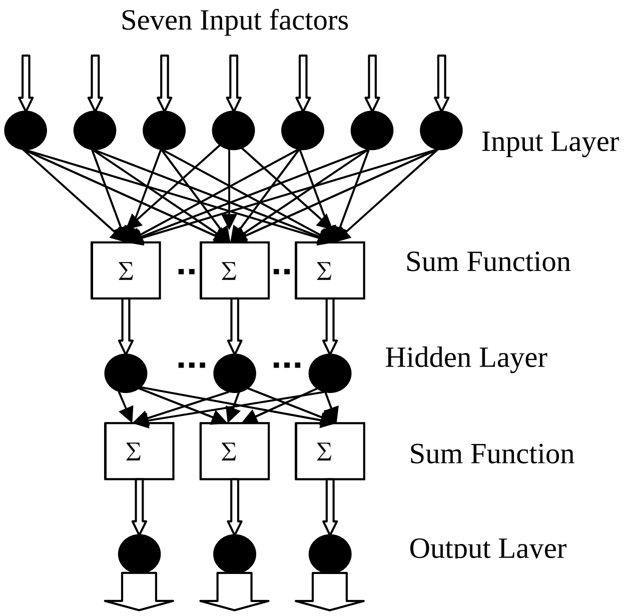

Fig.1 Configuration of NN model

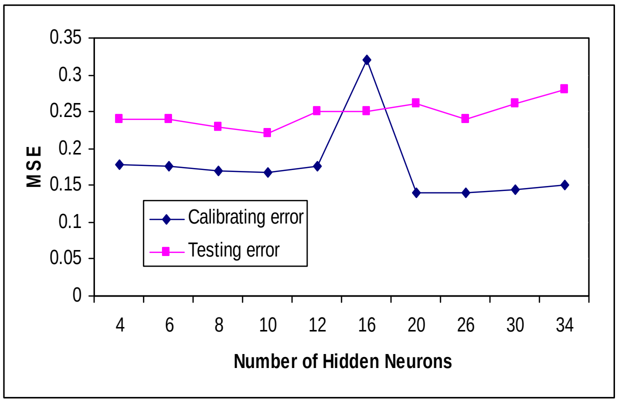

Fig.2 MSE with different number of hidden neurons

4.3 Influential Factors

The influential factors relating to serviceability deterioration are determined by ranking overall importance of the factors. The overall importance is computed using the connection weight analysis [17] with one proposed step to suit this study. Table 4 presents an example of steps to compute overall importance of the *j*th factor in the NN model, consisting of one hidden layer of three neurons and one output layer of two neurons. Under the joint probability principal, the overall importance of the *j*th factor is the product of the magnitudes of its important weights that are computed to each of the output neurons (pipe conditions). Then, the ranking from the most to least influential factors will be established by sorting the overall importance value of each factor in descending order.

Table 4. Example of computing steps for overall importance of an input factor.

Factor Xj	Hidden neuron		
	1	2	3
Weight assigned between Xj and hidden neuron	A1	A2	A3
Weight assigned between hidden neuron and *k*th output neuron	B1	B2	B3
Importance weight of Xj to *k*th pipe condition	$Z_k = \sum A_i \times B_i$ where i =1 to 3		
Overall importance of Xj to prediction model (Proposed step)	$OZ = \prod abs(Z_k)$ where k =1 to 2		

4.4 Model Performance Evaluation

The predicted outputs are compared with the observed ones to identify whether the prediction is correct or not. The performance rate of the model or the rate of correct prediction on calibration set and testing set was calculated using the Equation 1 [22]. The results were shown in Table 4.

$$PerformanceRate(\%) = 100 * \frac{Number\ of\ correct\ prediction}{Number\ of\ data\ points} \quad (1)$$

5. Multiple Discriminant Analysis (MDA)

In order to confirm the superiority of NN model over classical methods, MDA was also carried out in this study. The popular multiple regression model [12,23] can not be used because its outcomes must be in metric unit which is not suitable for this case. Instead, MDA can discriminate categorized objects from the assumed linear relationship of independent factors (factors) describing that object [24].

The classifying task in MDA is performed simply. A set of linear discriminant functions, as shown in Equation 2, is used to compute a set of corresponding discriminant Z scores for each test object. The number of discriminant functions is equal to the number of classes minus one i.e. *K-1*. The constant and coefficients of discriminant functions are determined by maximizing the between-class variance relative to the within-class variance from sample data. The set of computed Z scores for the test object locate the position of that object in the *K-1* dimensional real space as shown in Figure 3. The test object is assigned to the class whose centroid is closest to the test object. The centroid of the class is computed by averaging the Z scores of sample data on each discriminant function.

$$D_k = B_{k0} + B_{ki1} X_1 + B_{k2} X_2 + ... + B_{kj} X_j \quad (2)$$

where $k = 1$ *to* 2; D_k is the *k*th discriminant function; B_{k0} is the constant and B_k is the 7-dimensional vector of standardized coefficients for the *k*th discriminant function; X is the vector of *7* input factors.

The significant factors in the MDA model are determined using the stepwise method and statistical F-test [24]. The stepwise method puts the factors into the model one at a time. The factor just entered will be rejected if the F-test fails.

The SPSS® statistical software package version 13 [25] was used to estimate parameters using joint calibration and validation subset and classify the testing subset for MDA model.

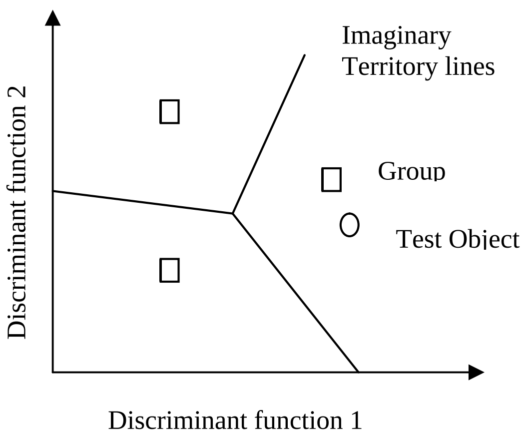

Fig.3 Three-group classification

6. Findings and Discussions

6.1. Goodness of Fit test

The Chi-Square test χ^2 for Goodness of Fit [26] was carried out on the testing dataset for NN model using null hypothesis (H_0) that the predicted targets and observed targets are not statistically different. The result ($\chi^2 = 8.8 < \chi^2(0.01,2) = 9.2$) accepted the null hypothesis, suggesting that the NN model is a worthwhile option for modelling serviceability deterioration of stormwater pipes.

6.2. Comparison of Model Performance

It can be seen from Table 5 that NN model is performing a little better than the MDA model in classification work at both calibration and testing dataset. However, the Performance Rate is not high for either model.

Table 5. Comparison of performance rate between NN and MDA model

	Performance Rate (%)	
	Calibration dataset	Testing dataset
NN model	55	53.5
MDA model	49.4	47.8

6.3. Significant Factors

A stepwise method using the statistical *F*- test [24] was applied to the MDA model to identify significant factors influencing serviceability deterioration. Among the seven input factors, only four input factors were significantly influential as shown in Table 6, which indicated the ranking from highest to lowest. Similarly the ranking of significant factors identified from the NN model were computed using the above mentioned modified connection weight analysis. The top four factors from NN model were identical with those from the MDA model except the order was reversed for the top three factors (Slope, Size and Structure) as can be seen from Table 6.

Table 6. Significant factors in descending order

NN model	MDA model
Slope	Structure
Size	Slope
Structure	Size
Depth	Depth
Location	
Age	
Tree_new	

In order to clarify how each factor affects the serviceability deterioration, a univariate one-way ANOVA test [27] was carried out. The results in Figure 4 indicated that the pipes with the steeper slopes and the larger size have a better serviceability condition. However, the influence of the depth factor is not clear. Incongruously, the serviceability condition seems to get poorer with better structural condition of the pipes.

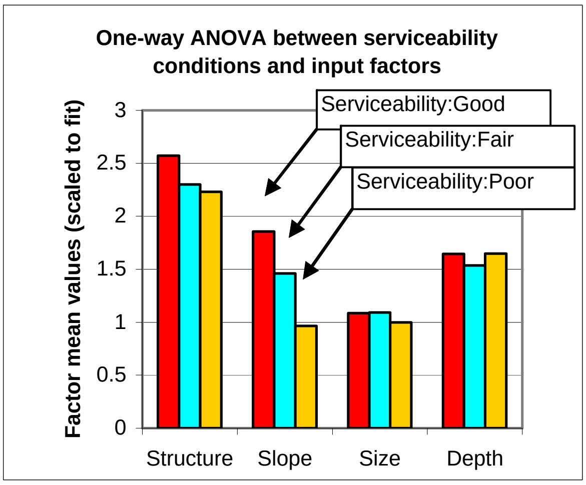

Fig.4 Comparisons of factor mean values.

6.4. Discussion

The low performance rate of both models might be due to the following factors. Firstly, using an overall condition-grading scheme and one model may not be adequate to capture many different mechanisms in play causing deterioration of serviceability such as root intrusion, debris deposition and pipe structural failure. Each mechanism should be modelled with its specific factors. The overall prediction will be based on the outcomes from different models. Secondly, many factors were missed in the supplied dataset such as traffic condition, tree type, pipe joint etc. Thirdly, subjective grading and measurement errors of existing inspection techniques may be the contributing factors. Lastly, MDA using straight line (linear relationship) to separate classes of object might not be suitable, the use of non-linear discriminant functions could be a considerable solution. From performance rate of NN models, there is a probability of *0.5* that a prediction of NN model may be wrong hence; an expert opinion should be sought to evaluate the predicted outcome when applied in reality.

It is not surprising that age was not a significant factor, since serviceability deterioration seems to depend on the users' treatment and associated factors. As expected, structural condition, pipe slope, pipe depth and pipe size were found to be significant factors.

Steeped pipes will not favour the accumulation of sediment. The larger pipes usually are the deeply buried main drainage pipes. Since stormwater pipes use gravity flow the sediment will be washed away in high flow rates. A correlation test was then conducted for pipe size and pipe depth to check whether an indirect inference for pipe depth could be made. The significance of fair correlation indicated that the deeper the pipes the better the serviceability. This is consistent with the assumption of gravity flow.

However, the association of the good serviceability condition with the poor structural condition of pipes as shown in Figure 4 was not expected. The reason could be that the inspections for structural condition were performed only in clean pipes and were reportedly focused on old pipes. Therefore, the number of recorded pipes in poor structural condition may have been unusually high. Randomly sampled data in the future may provide for a more accurate assessment of the relationship between the structural and serviceability conditions. Furthermore, the lack of significance in the test for the tree and location factors implied that more detailed information should be collected. For example, trees on top of pipes would have much more affection than distanced trees. Tree type and tree age would allow a better relationship to be established to the occurrence of root intrusion. The four groups in the location factor did not appear to cause much different effects on serviceability deterioration. Instead, information on the existence of below sewers or ground water would be more adequate.

7. Conclusions

This paper has presented a study using a Neural Network model for modelling serviceability deterioration of concrete stormwater pipes. The proposed model was compared against MDA model using a traditionally parametric method. The results show that prediction performance of NN was not much higher than of MDA. Despite the low performance encountered in this study, the application of NN in modelling deterioration of stormwater pipes seems promising. A better and more consistent data collection regime may help to improve the performance levels of the NN model. On the other hand, the use of non-linear discriminant functions could possibly increase the performance of MDA as well. Both models also identified the top four significant factors controlling the deterioration process. They are pipe size, depth, slope and structural condition. The less significant of remaining three factors namely, age, location and number of trees implied that collecting adequate factors with useful information is also essential to the model's performance.

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