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Application of probabilistic neural networks in modelling structural deterioration of stormwater pipes

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In Australia, when stormwater systems were first introduced over 100 years ago, they were constructed independently of the sewer systems, and they are normally the responsibility of the third level of government, i.e., local government or city councils. Because of the increasing age of these stormwater systems and their worsening performance, there are serious concerns in a significant number of city councils regarding their deterioration. A study has been conducted on the structural deterioration of concrete pipes that make up the bulk of the stormwater pipe systems in these councils. In an attempt to look for a reliable deterioration model, a probabilistic neural network (PNN) model was developed using the data set supplied from participating councils. The PNN model was validated with snapshot-based sample data, which makes up the data set. The predictive performance of the PNN model was compared with a traditional parametric model using discriminant analysis on the same data set. Structural deterioration was hypothesised to be influenced by a set of explanatory factors, including pipe design and construction factors—such as pipe size, buried depth—and site factors—such as soil type, moisture index, tree root intrusion, etc. The results show that the PNN model has a better predictive power and uses significantly more input variables (i.e., explanatory factors) than the discriminant model. More importantly, the key factors for prediction in the PNN model are difficult to interpret, suggesting that besides prediction accuracy, model interpretation is an important issue for further investigation.

Keywords: Deterioration model; Probabilistic neural networks; Stormwater pipes; Discriminant analysis

1. Introduction

In Australia, stormwater systems and sewer systems have been constructed independently for over 100 years. In comparison to sewers, stormwater pipes contain very little chemical waste (Micevski *et al*. 2002). The downstream end of stormwater systems is connected directly to rivers or waterways, while sewers end in wastewater treatment plants. Deterioration of stormwater pipes not only contributes to flooding, but also causes occasional traffic disruption due to structural failure. Because stormwater is the third tier in the pipe distribution network behind water and sewer distribution, and because it is controlled by local government, it has tended to be the last pipe network to receive attention with regards to maintenance and rehabilitation This is reflected in the *2001 Australian Infrastructure Report Card*, in which the Institution of Engineers Australia (2001) has warned that stormwater pipe systems in Australia have a poor condition rating nationally.

Because of the increasing importance being placed on asset management strategies at both a national and local level, the deterioration of stormwater systems is causing serious concerns to a number of city councils. In this study,

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data sets supplied by a number of participating councils were used to develop models to predict the deterioration of stormwater pipes over time, at both population level and at single-pipe level. The former could be used to estimate the annual budget required for rehabilitation and maintenance, and to compute the lifecycle cost of the system. The latter is needed to identify which pipes should be rehabilitated and in what priority order this should occur. Currently, a stormwater pipe is assessed through its defect scores, which are collected visually using either walk-through inspection or closed-circuit television (CCTV) inspection, or by non-destructive testing methods (Chang and Liu 2003). The defect scores are used to grade the condition of stormwater pipes which are then translated into predictive models. The condition of stormwater pipes is commonly divided into structural and hydraulic condition (Micevski *et al.* 2002) in order to recognize two different deterioration processes and consequences. The former deteriorates in most cases as a result of physical impacts such as overloads and soil pipe interaction and the ultimate result is pipe collapse accompanied with traffic disruption. The latter is caused by gradual reduction of the sectional diameter of pipes due to tree roots or debris which eventually results in blockage and flooding.

This paper proposes a probabilistic neural network (PNN) model that can classify the structural condition status of a concrete pipe with a number of given attributes (input factors). Concrete pipes were chosen because they form the major proportion of the pipe assets existing in stormwater pipe systems. The proposed model is also compared against a traditional parametric model developed using discriminant analysis on the same data set. Structural deterioration is hypothesised to be influenced by a set of installation and construction factors, including pipe design, pipe size, buried depth, and site factors such as soil type, moisture index and tree root intrusion.

2. Background

2.1 *Influential factors in structural deterioration*

In a comprehensive review of factors influencing the structural deterioration and failure of rigid sewers, Davies *et al.* (2001a) concluded that a bath tub curve can be applied to describe the failure probability of sewers over time. Curves such as these are simplistic and using one curve to describe the deterioration process for the whole population of stormwater pipes seems inadequate, as factors influencing individual pipes (such as installation practices) can have a significant effect. Thus, it seems that many different deterioration curves should be employed instead. For example, it is commonly assumed that the older the pipes, the poorer the pipe condition; however, this is often not the case and collapse events sometimes happen with young pipes, resulting in a reduced level of serviceability. The deterioration of each pipe needs to be considered independently and each curve can be considered as a deterioration pattern, and hence the introduction of different patterns can cover the uncertainty and complication in structural deterioration of stormwater pipes. Each pattern is determined from site factors, pipe design and construction factors.

Davies *et al.* (2001a) listed 25 factors that were thought to influence the structural condition of rigid sewers. However, in current stormwater databases, only a few of them are collected and an even smaller set is found to be statistically significant. These are pipe size, soil type, pipe material, location for stormwater pipes (Micevski *et al.* 2002), plus additional factors normally associated with sewers such as waste type, age, debris, soil corrosiveness, soil fracture potential and groundwater regime (Ariaratnam *et al.* 2001, Davies *et al.* 2001b).

2.2 *Existing deterioration models*

In order to model the deterioration of individual pipes and the effects of the factors that control deterioration, a number of methodologies can be applied. Multiple regression models (Madanat *et al.* 1995, Wirahadikusumah *et al.* 2001) were employed in first attempts at modelling deterioration of infrastructure facilities because of their simplicity in mathematical operations and capability to describe the direct relationship between the input factors and the outcome. However, they fail to reflect the probabilistic nature in the deterioration process, require assumptions to be made on data errors that are difficult to verify and, finally, try to fit data-sensitive sample means from a limited data set to a full population mean (Tran *et al.* 2005).

Micevski *et al.* (2002) discussed the relevance of a multistage Markov model for modelling the deterioration of stormwater pipes and concluded that they were suitable. However, the model was based on pipe cohorts and was not intended to predict the future condition for a single pipe. A few Markov models for sewers using different techniques to calibrate Markov transition probability have been developed. They are non-linear optimisation (Wirahadikusumah *et al.* 2001), expert opinion (Kathula 2001) and rule-based simulation (Ruwanpura *et al.* 2003), which can be used to predict pipe condition at cohort (group) level. Madanat *et al.* (1995) proposed a probit technique to link input factors with the targets in a Markov model for the deterioration of bridge decks. This proposed model could be used to predict the future condition at the level of a single pipe. However, its use would require regular inspection for each pipe segment in the sample so that the model could be validated. Unfortunately, there are not many stormwater pipe databases available with enough data to allow this validation process to take place.

On the other hand, as discussed by Flintsch and Chen (2004), soft computing techniques can be a promising and powerful tool for modelling various aspects of infrastructure systems, such as condition assessment, performance prediction and rehabilitation prioritisation, and the development of neural networks (NNs) shows promise in this area. In comparison with the soft computing techniques, case-based reasoning (CBR) may be better than NN in terms of predictive performance and flexibility in certain cases (Arditi and Tokdemir 1999). However, CBR models require a large and continuously updated database (case library) so that a new query case can be solved properly (Arditi and Tokdemir 1999). Whilst fuzzy logic techniques may be applicable, they appear to depend mainly on expert opinions to establish the relationships between input factors and output targets (Kleiner *et al.* 2004). In comparison, NNs use a mathematically flexible platform to construct the relationships for various applications (Lou *et al.* 2001, Attalla and Hegazy 2003, Osman *et al.* 2005). As an improvement to NN in modelling uncertainty within the requirements of probabilistic outcomes, the PNN, which was originally developed by Specht (1990), has been recently adopted for the prediction of concrete strength (Kim *et al.* 2005) and in the reliability assessment of oil and gas pipelines (Sinha and Pandey 2002).

3. Methodology

The methodology developed in this study used a PNN to classify the different deterioration patterns for stormwater pipes. In the PNN model, each deterioration pattern is developed from an input pattern, consisting of a combination of input factors including pipe design, construction and site factors. Hence, it can predict which structural condition that a pipe with a number of given attributes belongs to. Using the NN platform, the PNN model can be validated with a snapshot based upon sample data, and it can mimic the non-linear relationships and probabilistic nature of pipe deterioration which will be explained later. Additionally, it can be easily updated with new sample data (Wasserman 1993). Similarly to the NN model when applied to pavements (Lou *et al.* 2001), the PNN can also account for the Markov property of historically independent transition between structural condition grades. For example, if the structural condition of a pipe is being collected consecutively, then such information can be treated as a pipe attribute, which may contribute to the prediction of future condition. Furthermore, the maintenance and rehabilitation history, if recorded, can be easily accounted for in a PNN as a pipe attribute for the input pattern. To allow comparison of the outcomes of the PNN with an alternative methodology, discriminant analysis was also carried out. Discriminant analysis can be adopted to classify ordinal data and identify statistically significant input factors using a stepwise method (Dillion and Goldstein 1984). The following sections present the PNN architecture and discriminant analysis.

3.1 *PNN classification*

A PNN is actually a special form of NN used to implement Bayesian classification techniques incorporating Parzen univariate estimation.

Bayesian classifiers, as shown in equation (1), can be used to classify two categories (Wasserman 1993):

$$d(\mathbf{X}) = \begin{cases} C_1 & \text{if } l_1 h_1 f_1(\mathbf{X}) > l_2 h_2 f_2(\mathbf{X}) \\ C_2 & \text{if } l_1 h_1 f_1(\mathbf{X}) < l_2 h_2 f_2(\mathbf{X}) \end{cases} \tag{1}$$

where $\mathbf{X}$ is a p-dimensional random vector, $d(\mathbf{X})$ is an image of $\mathbf{X}$ in a set of categories, C_i is the i*th* category, l_i is the loss associated with misclassifying a vector of the i*th* category into other category, h_i is the prior probability of occurrence in the i*th* category, and $f_i(\mathbf{X})$ is the probability distribution function (pdf) for i*th* category.

The purpose of equation (1) is to minimise the expected risk (Kim *et al.* 2005) in classification, and the product of h_i and $f_i(\mathbf{X})$ is a posterior probability from Bayesian theorem that allows the updating of existing knowledge h_i with new information $f_i(\mathbf{X})$. The existing knowledge h_i could be obtained from a previous sample or expert opinion and $f_i(\mathbf{X})$ is determined by applying an established mathematical foundation (Parzen 1962) to estimate the univariate pdf of a population from its sample, by taking an average sum of suitably chosen kernel (pdf) values for each observation in the sample. Estimation of the multivariate density function, as discussed by Cacoullos (1966), can be achieved by firstly taking the multivariate pdf of an observation as a product of its univariate kernel, then applying Parzen's average sum to estimate the multivariate pdf.

An example of using the Gauss kernel for each observation of a random variable to estimate its density function is shown in equation (2). The meaning of the smoothing parameter σ in the case of the Gauss kernel, is that univariate Gauss is sharply peaked with σ smaller than one, and tends to flatten with increasing σ (Wasserman 1993).

$$f(\mathbf{X}) = \frac{1}{n}\frac{1}{(2\pi)^{p/2}\sigma^p}\sum_{i=1}^{n} e^{\frac{(\mathbf{X}-\mathbf{X}_i)^T(\mathbf{X}-\mathbf{X}_i)}{-2\sigma^2}} \tag{2}$$

where $\mathbf{X}$ is a p-dimensional random vector, $f(\mathbf{X})$ is the pdf of $\mathbf{X}$, and n is the number of observations in the sample (sample size).

The loss l_i can be calculated or subjectively estimated, but usually it is assigned the same value for all classes. For example, when considering repair cost, the loss for the large size pipe will be higher than the smaller size pipe; when considering pipe failure's consequence, the loss in a urban area might be higher than in a rural area. The criteria can be extended for more than two classes in which the chosen class would have the largest product value.

Figure 1 shows a configuration of the PNN with four layers that was used in the case study described in section 4. There were nine input factors, which created a nine-dimensional input vector $\mathbf{X} = (X_1, X_2, X_3, \ldots, X_9)$. Each pipe had a combination of specific values of the input vector—called an input pattern—that described the operating environment of the pipe. For example, an input pattern could be pipe size 1000 mm, age 30, depth 2 m, slope 0.5%, under road, five counts of trees, poor hydraulic condition, clay soil and the Thornthwaite moisture index (TMI) of dry condition. The PNN model classifies that pipe from its input pattern into one of three structural categories (output targets or classes) as follows:

- In the input layer, the number of neurons is equal to the number of input factors.
- In the pattern layer, the total number of neurons is the sum of the numbers of neurons used to represent the patterns for each category. Each category may contain many training patterns (training vectors) whose dimension is equal to the number of input factors, and taking a set of specific values of input factors. The training vectors are imported from sample data and hence they are not always necessarily representative of all existing patterns for that class. However, this is the advantage of PNN, in that it can generalise to allow recognition of a new pattern of a class (Wasserman 1993). The activation function in the pattern layer can be chosen from some kernel density functions (Scott 1992), but the Gauss kernel is more commonly used.
- In the summation layer, the number of neurons is equal to the number of categories. The activation is simply a weighted sum function. The outgoing signals can be adjusted according to loss and prior probability value.
- In the output layer, there is one neuron to represent the classification result. The activation function is an *arg max* function, which outputs the category associated with the largest value between incoming signals (Kim *et al*. 2005). It can be seen from here that the PNN configuration can allow us to express the non-linear

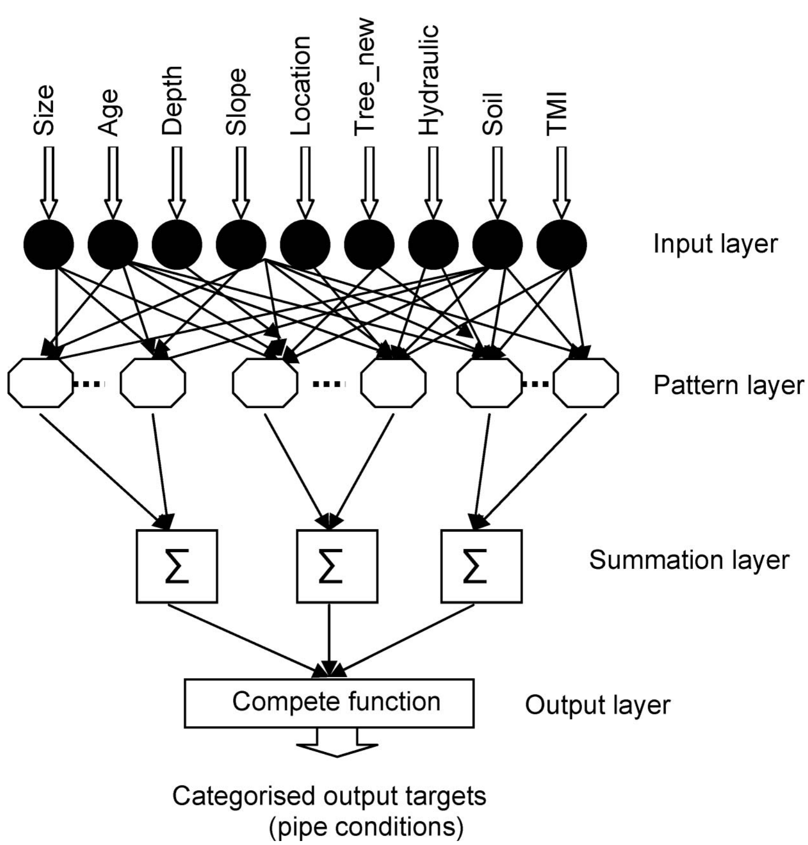

Figure 1. PNN configuration for one output target with three categories.

combination effects of all input factors as a single function detailing the pipes' deteriorated condition. This is done via choosing an appropriate shape for the kernel (e.g., Gaussian kernel) and the sum of kernels which creates a non-linear deterioration curve for each pipe condition. Therefore, each curve represents those pipes with different attributes (e.g., age, size) but having a common deterioration rate. The resulted set of deterioration curves will be used for classifying a query pipe.

Similar to a NN operation, a PNN also needs a training stage before being used for classification. However, the differences are that the training stage of a PNN is actually to keep the training vectors in the system by assigning their value into weights connecting the neurons in the input layer to corresponding neurons in the pattern layers. Also, a smoothing parameter can be determined by either using trial and error in testing vectors (Kim *et al.* 2005) or applying a genetic algorithm to minimise the classification errors in the training vectors (Mao *et al.* 2000).

In the classifying stage of a new test vector, the incoming signals to the pattern neurons are the distances between test vector and pattern vectors. The distance can be computed using one of the dissimilarity functions; however the Euclidean distance function, as shown in equation (3), is often used (Yue and Tao 2005):

$$D(\mathbf{X}, \mathbf{Y}) = \|\mathbf{X} - \mathbf{Y}\| = \left(\sum_{i=1}^{p} (x_i - y_i)^2 \right)^{1/2} \qquad (3)$$

where $D(\mathbf{X},\mathbf{Y})$ is the distance between the two vectors $\mathbf{X}$ and $\mathbf{Y}$, x_i and y_i are coordinates of $\mathbf{X}$ and $\mathbf{Y}$, respectively, and p is the dimension of the vector. In the pattern layer, the pattern probability that the test vector may come from one pattern vector in a category (pipe condition) is known by applying the computed distance to the kernel density. In the summation layer, the probability that the test vector belongs to that category is the sum of all pattern probabilities. Finally, in the output layer, the category with the highest computed probability will be assigned to the test vector.

3.2 *Discriminant analysis*

As discussed earlier, discriminant analysis can be used as an alternative to PNN analysis. Discriminant analysis is one of the multivariate parametric methods that can classify the groups or categories in a dependent variable, given the set of independent variables or explanatory factors. Dillion and Goldstein (1984) mentioned the analogy and differences between multiple discriminant analysis and multiple regression that are commonly used to compare with NN applications (Chao and Skibniewski 1995, Tarefder *et al.* 2005). The similarity is that both discriminant and regression methods assume a linear relationship between input factors and the dependent variables. However, the former requires categorised dependent variables and minimises the probability of misclassifying, while the latter is suitable for scaled dependent variables and for finding the population mean of dependent variables. Furthermore, in terms of analysis methods for categorised dependent variables, the straightforward outcome in connection with the observed values of dependent variables is the reason why discriminant analysis is selected in this paper; though it requires more assumptions than logistic regression methods (Dillion and Goldstein 1984).

In discriminant analysis, a set of uncorrelated linear functions of explanatory factors is estimated using a maximum likelihood technique from sample data, to separate the groups in the dependent variables. The maximum number of applicable linear functions is equal to or less than the number of groups minus 1, since some functions may fail a statistical significance test. A generic linear function d_i is shown in equation (4):

$$d_i = \beta_0 + \beta_{i1} X_1 + \beta_{i2} X_2 + \cdots + \beta_{ip} X_p \qquad (4)$$

where $i = 1$ to (k-1) with k being the number of groups, β is the vector of standardised coefficients and $\mathbf{X} \subset R^p$ is the vector of p explanatory factors. Each observation of pipe attributes contained in the sample data can be visualised as a point in p-dimension space, and d_i is a set of new estimated axis that can separate that point into corresponding groups when projected on the axis in succession. The projections of a point and group centroids on a new axis are defined as a discrimination score and mean scores, respectively. The group centroid is estimated from sample data by taking mean values of each factor. A point is considered to belong to a group if its distance to the group centroid (represented by an absolute score difference) is smaller than to other groups. In other words, the cut point value is the middle between group centroids. However, the position of cut points would be moved away from the middle position under the following circumstances: unequal sample size between groups; a prior probability for a point belonging to a group is known and cost of misclassification is included (Dillion and Goldstein 1984).

4. Case study

This study used a data set supplied by the City of Greater Dandenong in Victoria, Australia, for 800 km of stormwater pipes. From 1999 to 2002, CCTV inspections were carried out, resulting in nearly 650 data points being obtained from a total length of 27 km, which is equivalent to 3.4% of the system length. The inspection strategy focused on older pipes and on some locations reporting flooding or blockages. However, the inspection was of a single snapshot type, in that none of the piping has received a second inspection. Also, no records of maintenance or rehabilitation have been recorded. Hence, the deterioration model developed for the case study does not account for rehabilitation effects.

The supplied data set provides seven factors, as detailed in table 1, which are used as inputs for analysis. The structural and hydraulic conditions appeared to be graded into three separate levels—(1) good, (2) fair and (3) poor (need further investigation)—following the grading protocol recommended by the Water Services Association of Australia (WSAA 2002). Firstly, each pipe segment was further divided into individual lengths equal to 1 meter. Defect scoring was carried out for structural and hydraulic conditions, respectively. A total score was computed for the whole segment and individual length. The mean score is the average of total score over the segment length. Peak score is the highest total score found among individual lengths. Peak score reflects the fact that a pipe with low mean score still deserves attention if its peak score is high since several defects at one location may cause the pipe failure at that location. Finally, each pipe segment was graded into one of three levels when comparing its peak and mean score with threshold values. Based on a review of existing knowledge, the soil type and TMI—which is a climatic classification that can relate to soil movement (McManus *et al.* 2004)—were added into the input factors by inferring data from soil maps and pipe installation depths. Both soil type and TMI factors are of nominal data types and categorised into four and six groups, respectively. Unfortunately, the data relating to trees was only available in about 50% of the cases compared to the other factors. After checking the distribution of the available tree data, a lognormal distribution was used to create estimated data to complete the missing data in the set. Nine input factors were finally used in this study, as detailed in table 1. After data cleaning, only 583 data points were valid for analysis, and these were randomly divided into a calibration data set (75%) and a validation data set (25%). The calibration data set was used to train the PNN and calibrate the parameters of the discriminant analysis. Both methods were then tested using the validation data set. The numbers of pipes observed in conditions 1, 2 and 3 in the calibration data set were 114, 36 and 282, respectively. For the validation data set, the numbers were 47, 12 and 92, respectively. Even though unbalanced numbers of observations existed for each pipe condition, the prior probability of the PNN model and the cut point adjustment of the discrimination model were ignored. This was because the unbalance was not caused by the inspections and no prior knowledge was available. Furthermore, the loss of misclassification was not applied considering that all pipes are equally important.

Table 1. Input factors used in the study.

Input factors	Description
Size[a]	Scale (225 to 1950 mm)
Age[a]	Scale (0 to 65 years)
Depth[a]	Scale (0 to 4.83 m)
Slope[a]	Scale (−1.85 to 22.85%)
Location[a] (1–4)	Nominal (1—reserve, 2—under road, 3—under nature strip, 4—under easement)
Tree_new*	Scale (1 to 22 counts) (number of trees around pipe)
Hydraulic condition[a]	Ordinal (1—good, 2—fair, 3—poor (needs further investigation))
Soil type (1–4)	Nominal (1—dark grey sand (0–0.3 m), 2—light grey sand (0.3–0.5 m), 3—clay (0.5–1.5 m), 4—other (>1.5 m))
TMI (1–6)	Nominal (1—wettest (0–1.5 m), 2—wetter (1.5–1.8 m), 3—wet (1.8–2.3 m), 4—dry (2.3–3.0 m), 5—drier (3.0–4.0 m), 6—driest (>4.0 m))

[a]Data provided by the City of Greater Dandenong.

4.1 *PNN model*

The Probabilistic Neural Network Tool of the MATLAB® software package was used as a PNN classifier for the case study. The radial basis function (Demuth and Beale 2001), as shown in equation (5), was used as a kernel function to compute a probability value of the test vector **X** (a new input pattern):

$$f_k(\mathbf{X}) = \sum_{i=1}^{m_k} e^{-\frac{(\mathbf{X}-\mathbf{X}_{ki})^T(\mathbf{X}-\mathbf{X}_{ki})}{2\sigma^2}} \tag{5}$$

where **X** is a nine-dimensional test vector, $f_k(\mathbf{X})$ is the probability value of **X** in the k*th* category, $\mathbf{X}_{ki}\mathbf{X}_{ki}$ is the i*th* observation in the k*th* category from the calibration data set, $k = [1\ \ 3]$ since there are three categories of pipe condition, m_i is the number of observations associated with pipe conditions 1, 2 and 3, respectively, in the calibration data set, and $\sigma = 0.775$ (determined by trial and error).

Training the PNN was done in just a fraction of a second—it simply created the number of sets of weights, which are equal to the number of observations in each pipe condition. Then each set of weights was assigned the corresponding values of factors found in observations.

4.2 *Discriminant model*

A discriminant model using all of the input factors was also developed for the case study. All computations and statistical tests were performed by the SPSS® software package. The criterion for all statistically significant tests was a 95% confidence level. Tables 2 and 3 show two types of discriminant functions (DFs) with coefficients estimated from the sample data. The first one, called the standardised canonical DF, showed estimated parameters of equation (4) and allowed a comparison of input factors measured on different scales. Coefficients with large absolute values correspond to factors with greater discriminating ability. However, the second type of DF, called Fisher DFs, are more useful practically in reducing computing steps, since a group is assigned to a given pipe if its Fisher DF value is the largest among three computed function values.

5. Findings and discussion

The results obtained from applying the two models to the validation data set were compared with each other. The goodness-of-fit test, performance rate and significant factors were the three areas considered in the comparison of the methodologies.

Table 2. Standardised canonical discriminant function coefficients.

	Function	
Factors	1	2
Size	0.422	0.219
Age	0.100	0.619
Depth	0.122	0.018
Slope	−0.196	−0.291
Location	−0.358	0.616
Tree_new	0.124	−0.092
Hydraulic	0.736	0.198
Soil	0.156	−0.258
TMI	−0.150	−0.216

Table 3. Factor coefficients of three Fisher functions corresponding to three structural conditions.

	Structural condition		
Factors	Good	Fair	Poor
Size	−0.001	−0.001	−0.001
Age	0.799	0.841	0.797
Depth	8.819	8.792	8.725
Slope	0.629	0.577	0.666
Location	1.780	2.156	1.971
Tree_new	0.393	0.345	0.352
Hydraulic	5.207	5.138	4.782
Soil	20.489	20.166	20.320
TMI	−9.574	−9.647	−9.519
(Constant)	−58.522	−59.441	−56.865

5.1 *Goodness of fit*

The chi-square test χ^2 (Micevski *et al.* 2002) for goodness of fit was carried out on the validation data set for the PNN models using the null hypothesis (H_0) that the predicted targets and observed targets are not statistically different. The result ($\chi^2 = 1.20 < \chi^2(0.05,2) = 5.99$) accepted the null hypothesis, which suggests that the PNN model is a potential model for the prediction of structural condition. The chi-square test for the discriminant model showed a unacceptable result ($\chi^2 = 63$).

5.2 *Performance rate*

The performance rate is a useful tool to assess the prediction performance of the models (Kuncheva 2004). A correct prediction is counted when the predicted value is consistent with the observed. The performance rates for both the PNN model and discriminant model were computed on calibration and validation data sets using equation (6). The results are shown in table 4, where it can be seen that the PNN model is significantly better than the discriminant model:

$$\begin{aligned} &\textit{Performance rate } (\%) \\ &\quad = 100 * \frac{\textit{Number of correct prediction}}{\textit{Number of data points}} \end{aligned} \tag{6}$$

5.3 *Significant factors*

A stepwise method (Dillion and Goldstein 1984) was used for the discriminant model to identify the statistically significant factors that are the best predictors for pipeline condition. Among the nine input factors, hydraulic condition is the only significant predictor. This implies that the remaining eight factors could be withdrawn from the discriminant model without significantly reducing the prediction performance of the model. Table 4 shows that using only the hydraulic condition factor with the discriminant model increases the performance of that

Table 4. Comparison of performance rate between PNN and discriminant model.

	Performance rate (%)	
	Calibration data set	Validation data set
PNN model	71.5	66.9
Discriminant model (using all input factors)	42.8	36.4
Discriminant model (using only hydraulic factor)	55.6	51.0

model and moves it closer to the performance of the PNN model.

A univariate analysis using the chi-square test for factors with nominal and ordinal measurements, and a one-way ANOVA test (Tabachnick and Fidell 2001) for factors with scale measurement, were also conducted to test the marginal significances of the factors. The results of the one-way ANOVA test, as shown in table 5, indicate that pipe depth and slope factors could be considered to affect the structural deterioration individually. Figure 2 presents change patterns of mean values for each factor when structural conditions get worse (increasing from 1 to 3). Since these values are substantially different (e.g., mean pipe size is 716, mean depth is 1.73 on structural condition 1), they are all scaled to fit for presentation on the same figure 2 without detracting from its purpose. It can be seen from figure 2 for two significant factors that the greater the slope the poorer the condition, but the reverse might be true for the depth factor.

As detailed in table 6, the outcomes from the chi-square test show that only the hydraulic condition factor is found to significantly affect the structural deterioration in the data set. This is consistent with the result of the stepwise method discussed above that structural conditions depend on hydraulic conditions. Tests of soil and TMI factors were restricted between groups 3/4 and between groups 1/2/3/4, respectively, since the number of data points in the remaining groups failed to meet the requirements of the chi-square test. However, they are not found to be statistically significant factors.

Table 5. Comparisons of mean value between factors (one-way ANOVA).

Structural condition	Counts	Mean values				
		Size	Age	Depth	Slope	Tree_new
1	161	716.46	38.38	1.73	1.10	2.74
2	68	678.13	40.48	1.51	1.12	2.65
3	374	655.35	38.45	1.59	1.56	2.45
P-value		0.15	0.23	0.06[a]	0.05[a]	0.3

[a]Statistically significant factors.

5.4 *Discussion*

There are some possible reasons for the observed performance rate of both models, which are not as high as expected. Firstly, there are many other factors such as tree age, annual rainfall and historical pipe condition that can influence the structural deterioration of stormwater pipelines, but which were not included in the supplied data set. Secondly, the use of a three-state grading scheme (WSAA 2002) in conjunction with an old pipe-skewed CCTV inspection program, resulted in a biased distribution of pipe conditions that did not represent the actual distribution of pipe conditions across the network, i.e., the number of pipes in condition 3 was unnaturally high since more of the pipes in this condition were targeted for CCTV analysis. This caused a improper probability estimation. The use of popular 5-state grading schemes in UK and Canada (Vanier and Rahman 2004) should be considered since they can differentiate pipes in poor, worse and near collapse condition. This will reduce the number of pipes graded in condition 3. As a result, there will be more and adequate deterioration curves which can subsequently improve the performance rate of both models and factorial analysis.

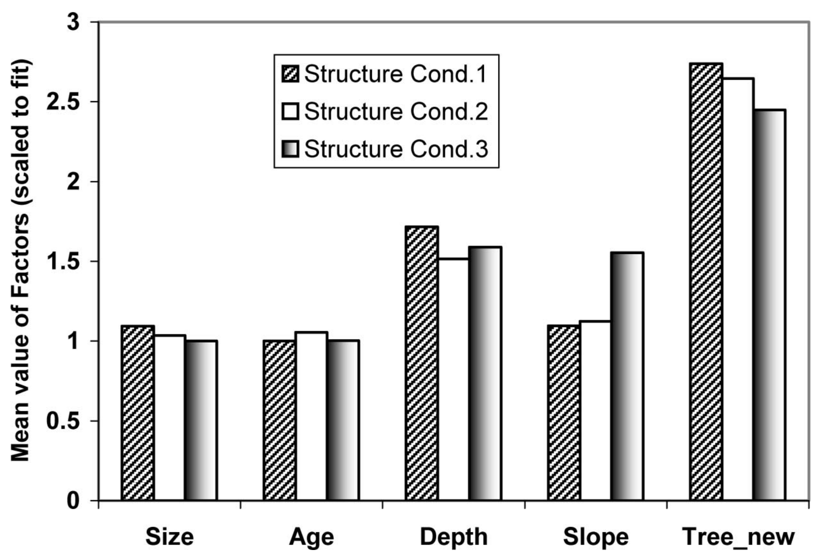

Figure 2. Comparison of factor mean values.

Table 6. Summary of χ^2 (univariate analysis).

	χ^2	Degree of freedom (df)	χ^2 (0.05, *df*)
Location	8.2	6	12.6
Hydraulic[a]	21.9	4	9.5
Soil (3/4)	5.2	2	6
TMI (1/2/3/4)	4.5	6	12.6

[a]Statistically significant factors.

Lastly, subjective condition grading based on existing (mainly visual) inspection techniques may produce too much error.

After analysing the results, it is not surprising that age was not a significant factor in controlling deterioration, since structural deterioration seems to be the result of the combined effect of various factors that were marginally tested in this study and those not yet recorded. Rather, the age factor should be used as a reference point in monitoring structural deteriorations. Pipes with steeper slopes would be subjected to more damage possibly due to voids in the soil, soil movement and pipe joint defects. Shallowly buried pipes would be subject to more damage due to surface load, illegal connections and tree root intrusion. The significance of hydraulic condition found in this study was contradicted by another study in New South Wales (Micevski *et al.* 2002), which found that hydraulic condition was not a prime indicator of pipe deterioration. The results obtained by Micevski *et al.* (2002) can be explained because structural damage such as joint defects, pipe fracture and wide cracks allow the intrusion of debris, soil, obstacles and tree roots into the pipe network. Hence, the hydraulic condition can be associated with these factors to act as an indicator or predictor to forecast the structural condition of pipes.

Surprisingly, the size factor was not found to be significant. However, larger pipes are usually buried deeply since stormwater pipes are gravity systems, and smaller pipes feed into larger pipes at greater depths. This implies that for larger pipes, the structural condition is better, which is consistent with the trend shown in figure 2.

The effect of the location factor on structural conditions did not indicate the effect of any critical environments such as coastlines or industrial zones in either this study or in the previous study by Micevski *et al.* (2002).

The insignificance of the 'number of trees' factor found in the study did not fully support a conclusion that trees do not affect structural condition. It is recommended that a further investigation on tree types, tree age and tree height be carried out to fully investigate the effects of these factors on pipeline deterioration.

6. Conclusions

In this paper, the effects of a number of different factors on the deterioration of concrete stormwater pipe networks are analysed. The probabilistic neural network (PNN) model used in this study was found to marginally outperform a discriminant analysis model in terms of prediction performance. The PNN was found to be a promising tool for predicting the deterioration of single stormwater pipes. However, since the predictive performance of the PNN model is still not high, a pipe with predicted condition 3 should be given more attention in any maintenance program and expert opinions should be sought for final decision. Furthermore, the key factors for prediction in the PNN model were found to be difficult to interpret, suggesting that besides prediction accuracy, the model interpretation is an important issue for further investigation. When using the discriminant analysis model, hydraulic condition was determined to be the only significant factor affecting structural deterioration. However, when local statistical tests were used instead, pipe depth, slope and hydraulic conditions were found to be marginally significant factors.

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