Neural Network Based Prediction Models For Structural Deterioration of Urban Drainage Pipes

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EXTENDED ABSTRACT

Structural deterioration of drainage pipes has been a major concern for asset managers in maintaining the required performance of the urban drainage systems. Structural deterioration is the reduction of physical integrity, which can be characterized through structural defects such as cracks and fractures that are identified through condition assessment. Due to limited budget and the massive number of pipes, condition assessment often is carried out on a fraction of the pipe network using closed circuit television (CCTV) inspection and a condition grading scheme. The condition assessment identifies the serviceability of pipes in a scale from one to three with one being the perfect, two being the fair and three being the poor condition.

The challenge for researchers is to use the sample of CCTV inspected pipes for developing deterioration models that can predict the structural condition of remaining pipes as well as the future condition of pipes. In this study we consider an ideal deterioration model, which describes that each particular pipe has its own structural deterioration curve or pattern (i.e. structural condition versus age) owing to a number of contributing factors including its design standard, construction method and operating condition.

Two neural network based prediction models for classifying or predicting the structural deterioration patterns (i.e. structural conditions) of urban drainage pipes are developed. The inputs to these models are the contributing factors such as pipe size and pipe age, and the output is the pipe condition. One prediction model uses back-propagation neural networks (BPNN) with supervised learning, and the other uses probabilistic neural networks (PNN). In the training process (or determining network weights) of the BPNN, a genetic algorithm was used to generate the initial values of network weights, which were then used by the back-propagation algorithm in order to avoid the well-known problem of local optimum. The PNN, on the other hand, does not require such a complex training process but uses the Parzen-Cacoullos theory to find the best possible approximation of multivariate probability density function for each of structural conditions to be classified by Bayesian rules. A case study using BPNN and PNN is discussed in this paper together with the advantages and limitations pertaining to the application of the two models.

1. INTRODUCTION

Structural deterioration of urban drainage pipes has been identified as a major cause for a number of pipe collapses with consequences of interrupted services and traffic. Structural deterioration is the reduction of physical integrity, which can be characterized through structural defects such as cracks and fractures. On the other hand, hydraulic deterioration, another type of deterioration, is due to reduction of cross-sectional area of pipes and an increase in surface roughness, which reduce the hydraulic conveyance of the pipes. The hydraulic deterioration is characterized via hydraulic defects such as tree root intrusions and sediment deposition. The ultimate result of hydraulic deterioration is blockage with consequences of flooding.

Condition assessment of pipes for structural and hydraulic deterioration throughout their service lifetime is important for constructing a proactive maintenance and rehabilitation program. However, in the current management practice, due to limited budget and the massive size of the pipe network, only a fraction of drainage pipe networks is subjected to a condition assessment program, which comprises two steps. The first step involves the inspection of pipe segments (defined between two pits) using direct observations such as closed circuit television (CCTV) or man-walk through. Recently adapted non-destructive inspection techniques (e.g. radar, ultrasound) which have some outstanding capabilities can also be used (Wirahadikusumah *et al.*, 1998). However, CCTV inspection is still the most commonly used technique because of its good productivity, low cost and relative safety. The second step involves the interpretation of these CCTV observed defects by using a condition grading scheme to determine the condition state of the pipe segments at the time of inspection. The condition grading defines the changing structural and hydraulic conditions of a pipe throughout their service lifetime using a scale from one to three (WSAA, 2002) or one to five (WSAA, 2006) with one being perfect and three or five being failure.

The challenge for researchers is to use the sample of CCTV inspected pipes for developing deterioration models that can predict the condition of remaining pipes as well as the future condition of pipes. A number of studies on deterioration mechanisms and deterioration models for sewers and drainage pipes were previously conducted. For example, the deterioration process was considered probabilistic and affected by various contributing factors such as pipe size and soil type in Wirahadikusumah *et al.* (2001) and Baik *et al.* (2006). Statistical techniques such as Markov chain theory (Wirahadikusumah et al., 2001, Micevski *et al.*, 2002), ordered probit technique (Baik et al., 2006) and logistic regressions (Davies *et al.*, 2001b) were used in deterioration models for sewers and drainage pipes.

In this study, we propose to use neural networks as an alternative method to the statistical techniques. We compare two neural networks based prediction models for classifying or predicting structural conditions of drainage pipes on a case study. One prediction model used back propagation neural networks (BPNN) with supervised learning, whilst the other used probabilistic neural networks (PNN). In the training process (or determining network weights) of the BPNN, a genetic algorithm was used to generate the initial values of network weights which were then used by the adopted back-propagation algorithm (BPA) in order to avoid the well known problem of local optimum. The PNN, on the other hand, does not require such a complex training process but depends on the Parzen-Cacoullos theory (Cacoullos, 1966) to find the best possible approximation of multivariate probability density functions for each of structural condition states to be classified by Bayesian rules.

2. DETERIORATION PATTERN OF PIPES

The structural deterioration of drainage pipes and sewers was generally considered to experience three-phase development (WRC, 1983, Davies *et al.*, 2001a) as shown in Figure 1. This figure shows how pipes change their condition over time represented by age from start-up phase (first construction) to operation phase and until they reach rehabilitation phase when pipe collapse will likely to occur if no maintenance is carried out. It can be noted from this figure that a threshold line, which is at condition three, defines the rehabilitation phase.

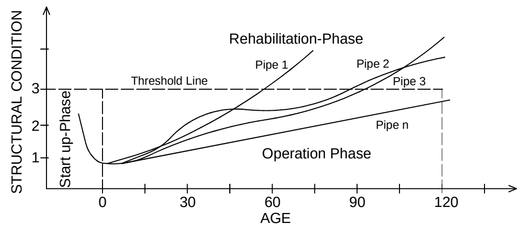

Figure 1. Ideal individual deterioration model for structural condition (modified from Davies et al., 2001a)

Based on the general three-phase development of pipe deterioration, we consider an 'ideal individual deterioration model' where the individual pipe has its own deterioration curve as marked Pipe *1*, Pipe *2*,…, Pipe *n* in Figure 1. This ideal model is aimed to reflect the fact that pipes have different deterioration rates due to many contributing factors that arise from design standard, construction methods and operating conditions. Each deterioration curve can be seen as a deterioration pattern whose shape can be broadly identified when a number of points (i.e. inspected pipe condition) along the age axis are captured. This view of 'deterioration pattern' is incorporated in developing the two prediction models in the subsequent sections.

3. PREDICTION MODELS

3.1. Back-propagation neural networks (BPNN)

A back-propagation neural network (BPNN) using feed forward and supervised learning is adopted as a prediction model for modelling the structural condition of drainage pipes. The basic idea is that the BPNN learns deterioration patterns from a sample of CCTV inspected pipes with associated contributing factors and generalizes the ‘knowledge’ to predict a new query pipe. The use of ‘feed-forward’ property is 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 classifying capability of the BPNN. The supervised learning is a commonly used learning strategy which is achieved through modifying the connection weights between neurons in order to minimize the differences (or errors) between observed and predicted outputs (Samarasinghe, 2006). Back-propagation (BP) is a commonly used training method for the supervised learning strategy.

The schematic of the BPNN is shown in Figure 2, which contains an input layer with input neurons (i.e. contributing factors), one hidden layer and an output layer with two output neurons.

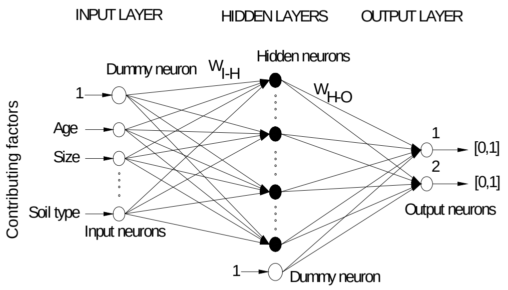

Figure 2. A schematic of the BPNN

Two output neurons with expected values in range [0, 1] are used because the structural condition takes only integer values of 1, 2 and 3 (WSAA, 2002) in the case study. In other words, two output neurons are used to code three integer values as shown in Table 1.

Table 1. Values of output neurons and corresponding condition states

Output neurons		Condition state
1	2	
>= 0.5	<0.5	1
< 0.5	>= 0.5	2
>= 0.5	>= 0.5	2
< 0.5	< 0.5	3

The Tansig and Logsig functions (Bishop, 1995) are used as activation functions for hidden neurons and output neurons, respectively. According to Bishop (1995), for a BPNN with one hidden layer, the selected activation functions can handle most non-linear patterns. Over-fitting which may occur in learning process of the BPNN is also addressed in this study by using the early stopping technique (Bishop, 1995).

The number of neurons in the hidden layer is the only parameter to be identified during training process of the BPNN. The Levenberg-Marquardt (L-M), a BP training algorithm of fast convergence, and batch learning are used in a trial and error search to find the best suitable number of hidden neurons on the criterion of minimizing mean square error (MSE) between the observed outputs O_n and predicted outputs Y_n over the N training data as described in (1).

$$MSE = \frac{1}{N}\sum_{n=1}^{N}(O_n - Y_n)^2 \qquad (1)$$

Although the L-M training algorithm would converge with a solution for almost any initial values of connection weights, the ‘good’ solution depends on the ‘proper’ initial values. Since the ‘proper’ initial values are unknown, it is common to randomly generate initial values within a guessed range. Furthermore, the error surface of neural network problems is reportedly non-convex and contains large number of local optima (Gori and Tesi, 1992). As a result, the best possible solution of the L-M algorithm is not always guaranteed.

A genetic algorithm (GA) is used to generate the initial values of weights for the L-M algorithm. GA is considered a directed ‘global’ search algorithm (Goldberg, 1989) that is especially useful for complex optimization processes with many local optimum or when the analytical solutions are difficult to obtain (Pham and Karaboga, 2000). The use of GA in neural networks problems has proved efficiency and continues to increase at a faster rate in diversified areas (VanRooij *et al.*, 1996, Kim *et al.*, 2005b). Although GA can replace the L-M algorithm as an independent training method, the convergence of GA may take long time in the large search space of NN parameters. This is because, unlike the L-M algorithm, GA does not make use of local knowledge of parameter space. Therefore, a hybrid GA and L-M algorithm was used in the BPNN in this study.

The fitness function of GA is the MSE as given in (1) which will be minimized in the GA training process. However, the reason that the performance of GA does not depend on the initial values (or seeds) is because GA randomly generates an array of initial values (called a population) which increases the chance of capturing the potentially good initial values. More importantly, in each step toward the 'global optimum', the new population is created by taking the best 'individuals' (called elite count) from the old population and by creating new individuals using 'genetics exchange' (called crossover and mutation). This type of GA operation is more advantage than the 'hill climbing' of BP algorithms and thus GA is more likely to avoid local optimum. However, GA operators need to be properly chosen for maximizing performance of the GA. In this study, the population size and crossover rate are two parameters to be tried and the other operators, elite count and mutation rate, are set to default values of 2 and 0.5 respectively.

3.2. Probabilistic neural networks (PNN)

The foundation of the PNN approach is well known for a long time but the first implementation of the PNN was attributed to Specht (1990) who demonstrated how to adapt the attributes of neural networks and use the increased computation power of computers for the PNN to solve engineering problems (Sinha and Pandey, 2002, Kim *et al.*, 2005a). Since the PNN is primarily based on the Bayesian classification rules and Parzen-Cacoullos theory, it is of interest to discuss them briefly.

Consider a population G of pipes which is made up of 3 classes or condition states: G_1, G_2 and G_3. A measurement $\boldsymbol{X}$ representing a pipe and consisting of p characteristics or pipe factors is observed for G. Our task is to develop an assignment rule for $\boldsymbol{X}$ that will allocate this observation to either G_1, G_2 or G_3. To assist in defining a rule, we have access to N observations of which N_1 are for G_1, N_2 are for G_2 and N_3 are for G_3 (i.e. $N=N_1+N_2+N_3$). Assuming that the prior probability that the measurement $\boldsymbol{X}$ belongs to the condition class i is h_i, the cost associated with misclassifying is c_i and that the true probability density function (PDF) of all three classes $f_1(X)$, $f_2(X)$ and $f_3(X)$ are known, the Bayesian rules classify the measurement $\boldsymbol{X}$ into the condition class i using (2),

$$h_i * c_i * f_i(X) > h_j * c_j * f_j(X) \qquad (2)$$

for all classes $i \neq j$. The misclassifying cost can include such costs as pipe repair costs and damage costs due to the consequences of pipe failures. However, the misclassifying cost and the prior probability are not considered in this study due to lack of data that are also observed in other studies (Hajmeer and Basheer, 2002).

It is obvious that finding the true PDF for each of the classes is critical to the Bayesian approach. Since the true underlying process of each class is unknown, more often normal (Gaussian) distribution is assumed; however, the assumption of normality cannot always be safely justified (Masters, 1995). The Parzen-Cacoullos theory (Cacoullos, 1966) offers a robust way to estimate the PDF from the N observations. The PDF for a condition class is called a multivariate PDF as given in (3) and is constructed by averaging kernel densities or univariate PDFs of all observations found within the class. Among kernel density functions (Masters, 1995), Gaussian kernel density is often chosen for an observed pipe $\boldsymbol{X}_n$ whose measurement becomes the mean value and its standard deviation σ (smoothing parameter) must be properly selected.

$$f(\mathbf{X}) = \frac{1}{(2\pi)^{p/2}\ N\ \sigma^p} \sum_{n=1}^{N} \exp\left(\frac{(\mathbf{X}-\mathbf{X}_n)^T(\mathbf{X}-\mathbf{X}_n)}{2\sigma^2} \right) \qquad (3)$$

A network topology with four fixed layers is commonly used for PNN as shown in Figure 3. The input layer has the number of neurons, which are equal to the dimension p of the measurement $\boldsymbol{X}$. In the pattern layer, observations of each class, which are called, training patterns, are clustered together. As can be noted from the figure, there are three boxes of different shapes, which represent three classes. The neurons in the pattern layer compute the exponential part of (3) and transfer the computed values to the summation layer. The summation layer then computes the multivariate probability of a query pipe belonging to each of three classes. In the output layer, the Bayesian classification rules are carried out to assign a class to the query pipe with the highest probability.

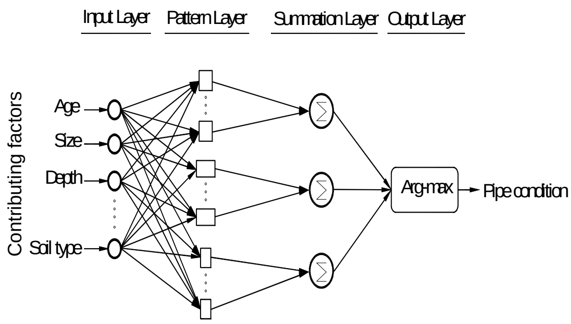

Figure 3. Topology of a PNN for three classes (modified from Hajmeer and Basheer, 2002)

3.3. Evaluating prediction models

The accuracy of a prediction model is tested by comparing its predicted outputs with corresponding observed targets. In general, those that were not used in the training process are preferred in order to provide an unbiased and reliable result. The predicted output as compared to the observed target will always take one of four possible situations: (1) true negative (TN) when the prediction model correctly predicts a negative case (i.e. pipe observed in poor condition), (2) true positive (TP) when the prediction model correctly predicts a positive case (i.e. pipe observed in good or fair condition), (3) false negative (FN) when the prediction model incorrectly predicts a truly negative case as a positive case, (4) false positive (FP) when the prediction model incorrectly predicts a truly positive case as a negative case.

It is obvious that the FN rate is the critical indicator and the larger the FN rate is the poorer the performance of the prediction model since the cost incurred when a FN pipe collapses is substantially higher than the inspection cost for a FP pipe. Besides the FN rate, the performance of the prediction model can also be measured using fraction correction (FC) (Kuncheva, 2004) and Goodness-of-fit test using Chi-Square statistics (Micevski et al., 2002). The FC is a ratio between the numbers of correctly classified cases to the total cases. The Goodness-of-fit test is based on the null hypothesis that the classified outputs are consistent with the observed targets. If the Chi-square value χ^2_M of a prediction model as given in (4) for prediction models is larger than the critical Chi-square value $\chi^2_{0.05,df}$, then the null hypothesis is rejected.

$$\chi^2_M = \sum_{i=1}^{3} \frac{(O_i - P_i)^2}{P_i} \quad (4)$$

where O_i and P_i are the number of pipes that are respectively observed and predicted in condition *i*.

4. CASE STUDY

This study used a dataset supplied by the City of Greater Dandenong in Victoria, Australia. A sample of 417 pipe segments (each defined between two pits) was CCTV-inspected during the period 1999-2007, which is equivalent to 3.4% of the total length. However, the inspection program was of a single snapshot type, in that none of the pipes has received a second inspection. Nine pipe factors were provided as given in Table 2. The ‘location’ factor refers to pipes buried under street, under easement, under reserve and under nature strip. The ‘soil’ type refers to clay and mix soil around pipes. The ‘moisture’ factor which refers to dry and wet condition (McManus *et al.*, 2004), were inferred from the depth factor. The structural condition of individual pipes was graded into three condition states with one being good, two being fair and three being poor as per Sewer Inspection Reporting Code (WSAA, 2002).

Table 2. Input factors used in the study

Input factors	Description
Size	Scale (225 to 1950 mm) (e.g. 600)
Age	Scale (0 to 65 years) (e.g. 45)
Depth	Scale (0 to 4.83 m) (e.g. 2)
Slope	Scale (0 to 22.85%) (e.g. 5)
Tree-count	Scale (1 to 22) (number of trees around pipe) (e.g. 2)
Hydraulic condition	Ordinal (1-3) (e.g. 2)
Location	Nominal (1-4) (e.g. 1)
Soil type	Nominal (0-1) (e.g. 0)
Moisture index	Nominal (0-1) (e.g. 1)

The supplied dataset was randomly split into train and validation dataset of 75% and 25% respectively for use with the PNN. For the BPNN prediction model, the supplied dataset was randomly divided into train dataset, validation dataset and test dataset of 60%, 15% and 25%, respectively. The validation dataset was used for early stopping technique in order to avoid the over-fitting (Bishop, 1995).

If a query pipe has the information as given within the brackets in Table 2, then what will be the structural condition of this particular pipe? This question can be answered by predicting the structural condition of this pipe using the two prediction models developed.

5. RESULTS AND DISCUSSION

The computational tasks for BPNN and PNN based prediction models were carried out using the MATLAB toolboxes.

5.1. Training prediction models

For the BPNN prediction model, the suitable number of hidden neurons for one-hidden layer BPNN was searched using the L-M algorithm and minimizing MSE of train dataset. The results are given in Figure 4 where 18 hidden neurons appear to be the best based on MSE values on train and validation datasets. As for the GA operators, the suitable population size and crossover rate were found to be 230 and 0.8, respectively, as can be seen in Figure 5.

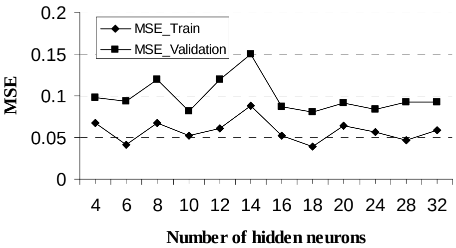

Figure 4. MSE values for different number of hidden neurons

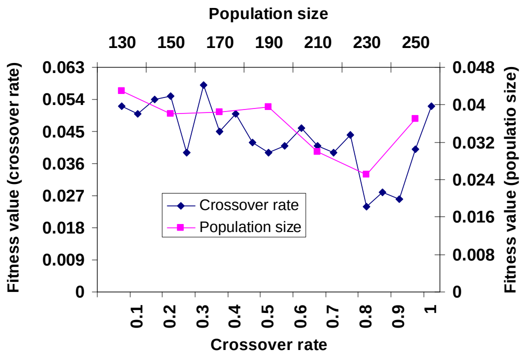

Figure 5. MSE changes on train dataset with two GA operators

For the PNN prediction model, a smoothing parameter (σ) of 0.5 was chosen since other values resulted in poorer predicting accuracy.

5.2. Discussion of model performance

The comparison of classification accuracy between two prediction models on train and test datasets is given in Table 3. As can be seen from the table, two prediction models appear to be suitable for structural deterioration of drainage pipes as substantiated by the acceptance of the Goodness-of-fit tests. For the case study, the critical value of Chi-square statistics is 5.99 for 2 degree of freedom and 95% confidence limit.

Although the PNN prediction model is ranked first in terms of FC and FN in the train dataset, its performance for the test dataset is ranked second. The BPNN with GA came second in the train dataset but becomes ranked first for the test dataset. The BPNN without GA shows the lowest performances in both train and test datasets.

Table 3. Comparison of predictive performance

Data-Set	Model	Training methods	FN rate (%)	FC rate (%)	Chi-square χ^2_M
Train	BPNN	without GA	23	70.2	2.95
		With GA	19	79.4	2.44
	PNN		10	91.6	1.97
Test	BPNN	without GA	32	65.1	4.16
		with GA	22	73.5	3.28
	PNN		26	67.3	4.21

The lower performance of the BPNN without GA compared to the BPNN with GA is understandable because of the problem of local optimum which is consistent with previous studies (Bennell *et al.*, 2006, Yu *et al.*, 2006). On the hand, although the performance of PNN is slightly poorer than the BPNN with GA in the test dataset, the fact that it outperformed the BPNN with and without GA in the train dataset may suggest a preferred choice of PNN over the BPNN in this study because of the simplicity in the construction of the PNN model. The lower performance of the PNN in the test dataset could be associated with the use of all training patterns in the train dataset. Some training patterns may be redundant and thus the PNN becomes oversensitive to the training patterns and exhibits poor generalization capacities to the unseen patterns (Mao *et al.*, 2000). Further study on methods to eliminate the redundant patterns is recommended. Finally, the predictive performances of BPNN and PNN were found better than those of statistical models using multiple discriminant analysis and ordered probit technique in another study by Tran (2007).

However, the high FN rate and the above average FC rate of the PNN and BPNN based prediction models imply the probability of incorrect classification and thus field expert opinions should be sought for double checking the predicted results before committing any repair actions.

6. CONCLUSION

In this paper, two neural network based prediction models (BPNN and PNN) for predicting structural deterioration of urban drainage pipes were developed on the basis that structural deterioration is affected by many contributing factors such as pipe size and pipe location. The developed prediction models were applied to a case study using a sample of CCTV inspected pipes and corresponding contributing factors. The two prediction models were compared in terms of predictive performance on a dataset that was not used for training. The comparison was based on three scalar performance measures; namely fraction correction (FC), false negative (FN) and Goodness-of-fit test. The results show that the two prediction models are suitable for modelling structural deterioration of drainage pipes. The PNN outperformed the BPNN in the train dataset but its performance was lower in the test dataset. However, the high FN rate and the above average FC rate of the PNN and BPNN based prediction models imply the probability of incorrect classification and thus the expert opinions should be sought to reconfirm before committing any repair actions. As expected, the use of GA improved the training efficiency and the generalization for the BPNN since it can avoid the local optimum.

As for development issues of the prediction models, the PNN based model appear simpler to build but the use of all training patterns may reduce its predictive performance and thus a further investigation of this issue is suggested. Although the BPNN model shows a better performance in the test dataset, it requires time and effort for selecting optimal parameters such as the number of hidden neurons, initial values of weights and dealing with the problem of local optimum.

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