INVESTIGATION OF DETERIORATION MODELS FOR STORMWATER PIPE SYSTEMS

by

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ABSTRACT

Like other engineering structures, buried stormwater drainage pipes deteriorate and fail over time in terms of pipe collapses due to structural deterioration or pipe blockages due to hydraulic deterioration. The deterioration of service infrastructure was a concern in Australian in recent times, where stormwater drainage pipes in Australia were rated as 'poor condition'. The information on current and future condition of stormwater pipes is therefore important for making decisions on when and how to carry out maintenance and rehabilitation. As the major objective, this study attempted to develop separately structural and hydraulic deterioration models that can predict the condition changes of pipe population and condition changes of individual pipes as compared to the 'like-new' condition. The outcomes of the models can be used for planning annual budget and prioritizing repairs. Furthermore, this study aimed to identify the significant factors that affect the structural and hydraulic condition of stormwater pipes, which could support design and operation of stormwater pipes.

To achieve these objectives, this study first considered an ideal deterioration model which recognized that pipes deteriorate differently due to their contributing factors such as pipe size and soil type. Based on the ideal deterioration model, five practical deterioration models were developed using statistical techniques and neural networks (NNs), and were calibrated using different optimization techniques in searching for the best suitable model. These deterioration models were selected considering the availability of snap-shot (or once only) inspection data and the ordinal grading system of pipe condition. The model inputs were contributing factors and the model output was pipe condition in ordinal numbers. Methods for assessing the predictive performance of these models and determining the significant input factors were considered. A case study with data collected from a City Council in Melbourne (Australia) was used to demonstrate the applicability of the models developed in this study. The results showed that the NN model and the Markov (statistical) model were the best models for predicting condition changes of individual pipes and pipe population respectively. Several factors such as pipe size and pipe location were found significant factors in these models.

The significance of this study is the development of deterioration models that provide a basis for the construction of a comprehensive asset management system for stormwater pipes. The major innovation of this study is the exploitation of advanced modelling techniques for predicting the deterioration process of stormwater pipes.

DECLARATION

I, Huu Dung Tran, declare that the PhD thesis entitled 'Investigation of Deterioration Models for Stormwater Pipe Systems' is no more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes.

This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.

(Signed)[redacted] ……..

Huu Dung Tran

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CHAPTER 1 INTRODUCTION

1.1 Background

Separate systems are used in Australia for stormwater drainage and sewerage disposal, while many European countries such as England and France use combined systems. Both systems are important to all aspects of urban living and form one of the most capital-intensive infrastructure systems. The primary function of stormwater drainage systems is to remove stormwater runoff from urban areas (BTE 2001). The rationale for using separate stormwater drainage systems is to significantly reduce the hydraulic load and operation cost on wastewater treatment plants.

A stormwater drainage system consists of collector and conveyer components. The collector components include roof and street gutters (e.g. kerbs or channels). The conveyer components, which are generally referred as stormwater pipe systems, include property drains and public owned conduits or pipes. The majority of stormwater pipes are buried and connected via receiving pits and manholes. The common operation mode of stormwater pipes is by gravity feed, which means flow in pipes is not under pressure.

The design of a stormwater pipe system includes both structural and hydraulic considerations. The structural design deals with the capacity to resist external loads and the capacity to resist stresses generated from dimensional changes of the pipe. The structural capacity of the pipe relies on the properties of pipe material and dimensions such as the diameter and the wall thickness. There are basically three classes of stormwater pipes classified based on the material used namely, rigid (e.g. concrete and vitrified clay), semi-rigid (e.g. steel and brick) and flexible (e.g. plastic). The rigid pipes are commonly used for stormwater pipes in Australia.

The hydraulic design of a pipe concerns with the discharge capacity against the maximum likely inflow to the pipe. An additional requirement is the velocity of flow, which must be sufficiently high to keep the pipe clean and free of deposits that could settle in the invert of the pipe. The hydraulic or discharge capacity of pipes depends on the cross sectional area (or pipe diameter), the pipe roughness and the hydraulic gradient.

In general, the management including construction and maintenance of stormwater drainage systems is the responsibility of the following parties:

- The property owners - pipes outside the property boundaries that connects to Council pipes or to the kerb and channel,
- Councils - pipes and drains in the road reserve, nature strips and in easements serving several properties,
- Water authorities - large conduits (or pipes) and disposal points.

In the State of Victoria (Australia), 79 City or Shire Councils operate a total of 25,000 kms of stormwater pipes while Melbourne Water Corporation operates 2,500 kms of large conduits (Engineers Australia 2005).

Asset management is the process by which asset managers monitor and maintain built facilities, with the objective of maximizing facility performance within the limited resources (Kuhn and Madanat 2006). More specifically, the asset management concerns with the selection and scheduling of maintenance and rehabilitation actions to carry out on the facilities during a planning horizon. The infrastructure asset management systems (IAMS) are tools to support asset managers with the asset management processes. A number of IAMS have recently been developed in North America and Europe for sewers and they can also be applied to stormwater pipes. Examples are CARE-S project for sewers in European countries (Saegrov and Schilling 2002), COST-S project for combined sewers in UK (Cashman *et al.* 2006) and optimal model-based rehabilitation for sewers in US (Solomatine *et al.* 2006). One of the key elements in these projects is the deterioration models which were aimed to predict the asset condition or the remaining serviceability of assets, since assets deteriorate over time. Based on the predictive information from the deterioration models, a critical management decision can be made regarding when and how to inspect, maintain, repair and even renew the existing assets.

1.2 Motivation for this Study

Like other engineering structures, stormwater pipes deteriorate leading to pipe failures. The deterioration of stormwater pipes can be divided into structural deterioration and hydraulic deterioration. The structural deterioration is a continuing process that reduces the load bearing capacity and can be observed through the structural defects such as cracks and fractures. This structural deterioration leads to structural failure such as a pipe collapse as shown in Figure 1.1.

Figure 1-1: A pipe collapse event

The hydraulic deterioration is also a continuing process that reduces the discharge capacity of the pipe and can be observed through a reduction of cross-sectional area and an increase in pipe roughness due to hydraulic defects such as tree root intrusions and deposits. The hydraulic deterioration leads to hydraulic failure such as pipe blockage and overflow, with the consequences of flooding. An example of a flooding event, which occurred in Hawthorn, Melbourne (Australia) in December 2003 is shown in Figure 1-2. These failures of pipes can cause serious damage to business and environment, and in some worse cases, human loss. It has been estimated that urban flooding costs in Australia in terms of property damage were 314 million dollars over the last 3 years prior to 2001 (BTE 2001), in addition immeasurable emotional disturbance to flood-affected people. Furthermore, the Australian Infrastructure Report Card (2001) stated that in general stormwater pipe systems were in poor condition.

Recognizing the problem of pipe deterioration, the procedures such as Sewer Inspection Reporting Code (WSAA 2002, 2006) were developed in Australia to assess the condition of sewers and stormwater pipes. Consistent with these procedures, the closed circuit television (CCTV) inspection technique is widely used for detecting pipe defects including structural and hydraulic defects. Based on these pipe defects, the conditions of pipes are then graded into one of three or five condition states (from perfect to failure) considering structural deterioration and hydraulic deterioration. However, the stormwater pipe systems are still managed using a crisis-based or reactive approach in many cases. Snapshot inspections, instead of regular inspections (or longitudinal inspections over time), are commonly carried out in condition monitoring and assessment programs for stormwater pipe systems. This practice leads to the inefficient use of limited funds, causing more frequent failures of pipe, which results in difficult and costly rehabilitation.

Figure 1-2: A flooding event

As identified in Section 1.1, effective (or proactive) asset management can be supported by the use of deterioration models, which can predict current and future condition of pipes in terms of their structural and hydraulic conditions. This is because the predicted information can support decision-making on when, where and how individual pipes should be repaired or replaced to ensure uninterrupted services to the community.

Lack of such deterioration models for the management of stormwater pipe systems in Australia was the principle motivation for this study. This study was also motivated by the fact that although there was a recent study by Micevski *et al.* (2002) for modelling structural deterioration of stormwater pipes in the City of Newcastle in Australia, hydraulic deterioration was not considered in their study and their developed methodology cannot be applied to predict the structural and hydraulic condition of individual pipes unless regular data is available. Furthermore, although sewers and combined sewers have been subjected to much more studies and investigations than the stormwater pipes during the past two decades, it is not appropriate to simply use the findings from sewer deterioration models to stormwater pipes. This is because there are major differences between them in terms of the design standards and conveyed waste type. For example, the sewer is buried deeper than stormwater pipe; stormwater contain fewer corrosion chemicals (Micevski *et al.* 2002). On the other hand, the important commonalities are that they both use gravity flow, buried pipes and rigid material which make the modelling techniques for sewers can be adaptable for stormwater pipes.

1.3 Aims of this Study

The primary aim of this study was to develop structural and hydraulic deterioration models that can predict current and future condition of stormwater pipes. The outcome of the deterioration models is the condition changes of pipe population and individual pipes. The condition changes of pipe population show the predicted proportions of the pipe population in each condition state at each year; this predicted information can be used for planning annual budget required for maintenance and rehabilitation of pipes. The condition changes of individual pipes, on the other hand, show the predicted condition of any particular pipe, as compared to the 'like new' condition, given the contributing factors (e.g. pipe size and pipe age) of the individual pipes; this predicted information can be used to identify pipes that are in poor condition for repair works.

The secondary aim of this study was to identify significant input factors that affect the output of deterioration models and hence the deterioration process of stormwater pipes. By paying attention to these significant factors, the design and operation of stormwater pipes could be improved in order to reduce pipe failures and increase service life. For example the location of pipes may be a significant factor, meaning pipes should be designed differently if they are buried under street or nature strip. Another example is that the age of pipes may not be a significant factor, meaning the condition of pipes should not be judged by their age only.

1.4 Scope and Assumptions Used in this Study

1.4.1 Scope

The scope of this study is limited to the use of CCTV inspection pipe condition data for modeling the deterioration of stormwater pipes. It is noted, however, that the CCTV inspection data and their derived information were criticized as: (1) accountable for only surface defects, (2) dependent on CCTV operators' skills (i.e. subjective) and (3) non-consistent (Terry *et al.* 2006). Nevertheless, they were used in this study since they were the only technically and readily available pipe condition data at the time of this study. The more sophisticated and advanced inspection techniques such as ultrasound and radar, seem to be able to provide less subjective data and information (Ratliff 2003; Terry *et al.* 2006). However, they are not yet practically proved and commercially available for wider use for the condition monitoring and assessment of stormwater pipes. Once these advanced inspection techniques are applicable, their inspection data can be used with the deterioration models developed in this study.

It should also be noted that rigid pipes (i.e. concrete and vitrified clay pipes) were the focus of this study because the majority of stormwater pipes in Australia are made of rigid material and the case study dealt with sample data of concrete pipes. However, the methodologies developed in this study can be expanded to other material such as plastic and metal pipes.

1.4.2 Assumptions Used in this Study

The following assumptions were used mainly due to lack of data in developing deterioration models in this study:

- Pipe age, structural and hydraulic conditions were considered as time-dependent factors and other factors were considered as time-independent factors.
- No rehabilitation was considered in predicting the future condition of pipes.
- CCTV data were collected by trained operators for making CCTV condition data less subjective and consistent.
- Supplied datasets were considered to come from random sampling.

1.5 Methodology in Brief

The deterioration models developed in this study are called inferential models, which means the structural and hydraulic conditions of pipes (model outputs) were inferred or predicted by using the contributing factors of the pipes (model inputs). The contributing factors refer to a set of factors (e.g. pipe size and pipe location) that are considered possibly contributing to the structural and hydraulic deterioration of pipes. These contributing factors are also called influential factors or explanatory factors. The reason to use the inferential models in this study is that the structural and hydraulic deterioration of stormwater pipes are a complex process with multiple causes and many contributing factors (detailed in Section 2.2), and that it is virtually impossible to carry out experimental data collection for all possible combinations of contributing factors corresponding to different deterioration rates of pipes and to accurately measure the 'overall' deterioration rate.

The aims of this study were achieved by carrying out the following key tasks:

- Task 1 - Collect data
- Task 2 - Develop ideal deterioration models
- Task 3 - Develop practical deterioration models
- Task 4 - Identify methods for testing deterioration models
- Task 5 - Examine methods to identify significant factors that affect the outputs of the deterioration models
- Task 6 - Apply on a case study

Task 1 – Collect Data

A sample of 417 data points used in this study was supplied by the City of Greater Dandenong (CGD), Victoria, Australia. Each data point consisted of the structural and hydraulic conditions of pipes together with eight contributing factors (i.e. pipe size, pipe age, pipe depth, pipe slope, tree-count, pipe location, soil type and Thornwaite moisture index (TMI - as annual average value). The structural and hydraulic conditions were inspected using the CCTV inspection technique and were then graded into ordinal values of 1, 2 and 3 with one being the good, two being the fair and three being the poor conditions. This was done using the Sewer Inspection Reporting Code of WSAA (2002). It should be noted that the data obtained were of snapshot type, which meant that none of the pipes in the supplied sample dataset had received second or repeated inspections.

Task 2 – Develop an Ideal Deterioration Model

The ideal deterioration model was first developed in order to account for the fact that the deterioration of individual pipes (whether it is structural or hydraulic deterioration) is different from one pipe to another according to their contributing factors (e.g. pipe size, slope and soil type). From the ideal deterioration model, the condition changes of pipe population and individual pipes were established and were then used as the target for the development of practical deterioration models. A list of possible contributing factors was identified from literature and CCTV footages.

Task 3 - Develop Practical Deterioration Models

The practical deterioration models were developed to predict the condition changes of pipe population and individual pipes for both structural and hydraulic deterioration of stormwater pipes. These models must be able to (1) be calibrated and tested with the snapshot type data; and (2) handle the ordinal values of pipe condition. Several deterioration models were developed in this study with the aim of selecting the best models for the structural and hydraulic deterioration.

Among commonly used infrastructure modelling techniques, five deterioration models using three statistical techniques namely, Markov chain, multiple discriminant analysis and ordered probit, and two artificial intelligence techniques namely, neural networks and probabilistic neural networks were investigated. Furthermore, different calibration methods including non-linear optimization, genetic algorithm and Bayesian Markov chain Monte Carlo simulation were investigated.

Task 4 – Identify Methods for Testing Deterioration Models

The methods were identified to test the developed deterioration models considering the ordinal values of predicted condition. The goodness-of-fit test using Pearson Chi-square statistic has been commonly used in testing deterioration models for infrastructure facilities such as bridges, pavements and stormwater pipes. Similarly, the confusion matrix has also been used to provide details on how well the predicted values and observed values are matched. The goodness-of-fit test and confusion matrix were investigated to test the developed deterioration models.

Task 5 – Examine Methods for Identifying Significant Factors

Identification of significant factors that affect the underlying processes or that affect the output of models is already established and widely practised. The major work of this task was therefore to find the suitable and practical methods for use in the developed deterioration models except for the Markov model which used only one factor (i.e. pipe age). The forward stepwise method and the Wald-test were employed respectively for the multiple discriminant deterioration model and the ordered probit deterioration model. The connection weight analysis was used for the neural network deterioration model while the backward stepwise method was used for the probabilistic neural network deterioration model.

Task 6 – Perform the Case Study

This task included three major works. The first major work was to conduct a preliminary data analysis using standard and basic statistical techniques (for the collected data in Task 1). This would reveal the structure of data and the relationships between contributing factors, and between contributing factors and hydraulic and structural conditions. The second major work was to estimate or calibrate the model parameters and test the predictive performances of structural and hydraulic deterioration models. The third major work was to identify the significant factors that affect the prediction of the structural and hydraulic condition.

1.6 Outcomes, Significance and Innovation

1.6.1 Outcomes

The outcomes of this study are outlined below.

- The Markov model was found to be the most suitable model for predicting the condition changes of pipe population for both structural and hydraulic deterioration.

- Neural network model was found to be the most suitable model for predicting the condition changes of individual pipes for both structural and hydraulic deterioration.

- The Bayesian Markov chain Monte Carlo simulation was found the best calibration method for both the Markov model and neural network model.

- Pipe size, hydraulic condition and pipe location were found to be the significant factors to the prediction of the structural condition. Pipe size, structural condition, pipe location, pipe age and pipe slope were found to be the significant factors to the prediction of the hydraulic condition.

1.6.2 Significance

- The need for proactive management and prevention of catastrophic failures of stormwater pipe systems is more than ever intensifying. The prediction of the deterioration models developed in this study can make a significant contribution towards developing proactive management plans in preventing the catastrophic failures of stormwater pipes. For example, the annual budget for maintenance and repair of stormwater drainage pipes can be properly prepared based the predicted information on the condition changes of pipe population. Furthermore, the predicted condition changes of individual pipes can help asset managers in making 'optimal' decisions on when and how to carry out maintenance and rehabilitation actions.

- The output of the deterioration models, especially the hydraulic condition of stormwater pipes can be used as input to hydrologic and hydraulic models to investigate urban flooding in the area. This will provide a strong basis for development of a comprehensive asset management system for stormwater pipe systems for local government councils.

- This study has identified the significant factors that affect the prediction of structural condition and hydraulic condition of stormwater pipes. These significant factors can be given more consideration during design, construction and operation of stormwater pipe systems so that the service life and serviceability of pipes can be improved.

1.6.3 Innovation

Several innovative ideas developed in this study are outlined below.

- This study has considered an ideal deterioration model (IDM) to describe that pipes deteriorate differently from one to another due to their contributing factors. The implication of the IDM is that older pipes do not necessarily deteriorate faster than younger pipes.

- Neural networks (NNs) were used in this study for handling the poorly understood processes of structural and hydraulic deterioration as well as for handling the noisy data associated with the CCTV inspection technique in assessing the structural and hydraulic deterioration.

- Although structural deterioration models for sewers were already developed using statistical models such as Markov model, logistic model and ordered probit model and by the use of neural networks, this study has added the diversity of models for infrastructural buried pipes through multiple discriminant analysis and probabilistic NN.

- The hydraulic deterioration models have not been well treated in the literature. In this study, three distinctive statistical techniques (i.e. Markov chain, multiple discriminant analysis and ordered probit) and two advanced neural network techniques (a standard NN and a probabilistic NN) were developed to model hydraulic deterioration.

- Although the advanced calibration techniques such as genetic algorithm (GA) and Bayesian Markov chain Monte Carlo (MCMC) simulation were already established in other fields of engineering, they were adapted in this study to handle uncertainty and local optima associated with calibration of the standard NN model for stormwater pipes.

- The predictive performance of developed deterioration models were assessed by the adaptation of both statistical test (Goodness-fit-test) and analysis of confusion matrix in this study, which can be applied to other infrastructure facilities such as sewers and water pipes.

1.7 Outline of the Thesis

The thesis consists of five chapters. The current chapter describes the background to the research project, motivation, aims, scope and assumptions, a brief methodology, and outcomes of this study, significance and innovation. The second chapter presents a critical review of literature relevant to the research project. The development of five deterioration models, methods for testing predictive performance of deterioration models and identification of significant factors that affect the performance of the deterioration models are described in Chapter 3. Chapter 4 presents the case study and discusses the application of the developed models. Finally, Chapter 5 presents conclusions and recommendations for future research.

CHAPTER 2 STORMWATER PIPE DETERIORATION, PIPE CONDITION AND MODELLING TECHNIQUES

2.1 Overview

The urban stormwater drainage systems in Australia collect stormwater runoff from properties (i.e. roof, backyard and playground), road surfaces and adjoining lands (i.e. parks, reserves) by a network of gutters, pits and buried pipes, and convey it to receiving waters (Dayaratne 2000). Among the system components, buried pipes constitute the largest investment in the system. These pipes are made of different material classes like rigid (e.g. concrete and vitrified clay), semi-rigid (e.g. steel) and flexible (e.g. plastic) materials; however, rigid materials are commonly used for stormwater pipes in Australia.

Like other engineering structures, stormwater pipes wear out or deteriorate with time which cause reduction of both structural integrity and hydraulic or discharge capacity of pipes. The effects of pipe deterioration can sometimes be observed on the street such as a pipe collapse with consequences of traffic disruption or a pipe blockage with consequences of flooding and environmental pollution. Therefore, managing and maintaining the performance of buried pipes is a significant task to asset mangers. This task requires the information on the current and future condition of stormwater pipes.

This chapter reviews both theoretical studies and empirical research on deterioration of rigid stormwater pipes (which is the focus of this study) and methods to predict the pipe deterioration. However, the literature search revealed that the research on the deterioration of stormwater pipes is limited. Therefore, the review was expanded to include deterioration of sewers and other infrastructure facilities such as bridges, pavements and water pipes when applicable. This expansion would provide a rich background for this study. Furthermore, the term ‘rigid pipes’ would be used whenever it is required to differentiate with other material classes of pipes; otherwise, ‘pipes’ would be used.

The chapter starts with a review on existing knowledge of deterioration process and its contributing factors of rigid stormwater pipes, sewers and combined sewers (conveying both stormwater runoff and sewerage). It then describes how structural and hydraulic conditions of rigid pipes are monitored and assessed in the current management practice. Following this, the chapter reviews modelling techniques that used contributing factors to predict the structural and hydraulic conditions of pipes. Finally, the chapter concludes with the selection of modelling techniques for this study.

2.2 Deterioration of Rigid Stormwater Pipes and Rigid Sewers

Considerable effort has been invested in the past in understanding the deterioration process leading to failures of sewers and stormwater pipes. One of the most influential works came from the UK-based Water Research Center (WRC 1986) in which deterioration of rigid sewers (i.e. concrete pipes and vitrified clay pipes) in UK were systematically studied using both site and laboratory experiments. The deterioration process of rigid sewers was divided into structural deterioration and hydraulic deterioration which are respectively characterized by structural defects (e.g. cracks and fractures) and hydraulic defects (e.g. intrusion of tree roots and deposits). The WRC then concluded that:

- The deterioration of rigid sewers is a complex and probabilistic process since the deterioration is more influenced by random events such as a storm or an excavation during the lifetime of the sewers.
- It is almost impossible to measure the rate of deterioration

Building upon this knowledge, many researchers have greatly advanced the understanding of structural and hydraulic deterioration as well as their contributing factors for both sewers and stormwater pipes using experiments and modelling tools.

2.2.1 Structural Deterioration and Contributing Factors

The structural deterioration of rigid sewers and stormwater pipes is characterized by structural defects that directly reduce the structural integrity, i.e. shape and load bearing capacity of pipes. The commonly found structural defects in the WRC's study include crack, fracture, deformation (shape distortion) and hole. The WRC also explained the process leading to collapse of rigid sewers using a three-phase development of structural defects in conjunction with a concept of random damage events.

Phase one is initiated from minor defects such as cracks or leaking joints that are possibly caused by poor handling and improper construction methods.

Phase two extends the initial deterioration of phase 1 in different rates depending on a combination of attacks such as external loads (both static and dynamic), chemical corrosion, erosion and ground loss. Particularly, the ground loss happens when surrounding soil is drawn into pipes through defects by groundwater. This would lead to the poor structural support of pipes.

Phase three usually occurs through probabilistic damage events such as nearby excavation or excessive load. Therefore, it is not possible to forecast when a sewer will collapse, but it is possible to judge whether a sewer has deteriorated sufficiently for collapse to be likely.

This three-phase development was described by a 'bath-tub curve' in the context of asset management as suggested by Davies *et al.* (2001a) for sewers and Kleiner and Rajani (2001) for water pipes as shown in Figure 2-1. There are three areas, namely, Zone 1, Zone 2 and Zone 3 in this figure. Zone 1 shows the high failure probability during the construction of pipes. This high failure probability then drops to the lowest when the construction was completed and pipes begin their normal operation. The Zone 2 shows a steady increase of the failure probability due to pipe deterioration during the operation of pipes. Finally, Zone 3 shows the high failure probability when the pipe deterioration has reached a hazard level. When pipes are considered in Zone 3, rehabilitation or replacement should be carried out.

It can be assumed that the rigid stormwater pipes also experience similar properties of deterioration and collapse process. This was substantiated in a study using data of Newcastle City in Australia by Micevski *et al.* (2002) who found that the structural deterioration of stormwater pipes can be described using a stochastic process and multi-stage transition between four development stages from perfect to collapse. Furthermore, they found that the deterioration intensity at the present time affects the deterioration intensity at the next period of time. This stochastic property was also found in structural deterioration of sewers in a number of studies in US (Kathula 2001; Wirahadikusumah *et al.* 2001; Baik *et al.* 2006).

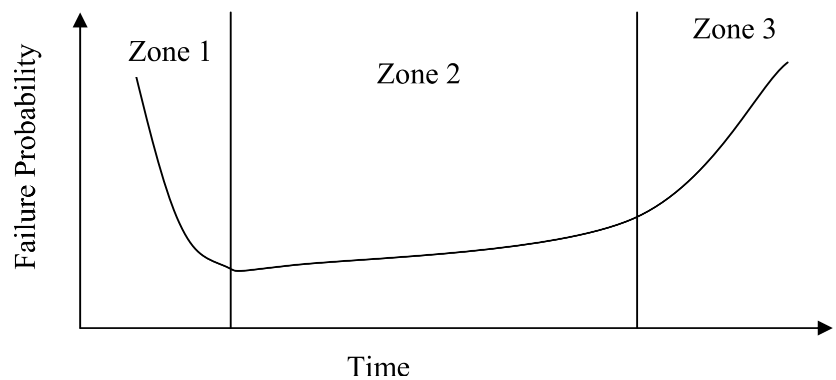

Figure 2-1: 'Bath tub' curve for structural deterioration of pipes

According to the synthesis of Makar and Kleiner (2000), the deterioration process or mechanism leading to pipe failure varies with pipe's material, but the rate of deterioration and failure depend on exposure to different environments and operational conditions. That is, individual pipes possess different rates of deterioration because of the so-called contributing or explanatory factors. Table 2-1 shows some of the contributing factors that were used in previous studies and investigations on structural deterioration of sewers and stormwater pipes. Note that the only study dealing with stormwater pipes is the study by Micevski *et al.* (2002) and this study is marked with '#' in Table 2-1. As can be seen from this table, 'pipe age', 'pipe material' and 'pipe size' are the most commonly used factors because they were often available in the pipe databases of host cities that supplied data for the research study. Although other factors such as pipe location and pipe depth are also considered in the literature (Davies *et al.* 2001b), their availability was found to vary with different cities. The effects of several contributing factors shown in Table 2-1 are described below.

<u>Pipe material</u> - According to an experimental investigation on shallowly buried pipes by Kawabata *et al.* (2003), a flexible pipe under wheel loads would be subjected to a maximum stress 5 times smaller than a rigid pipe (e.g. concrete and vitrified clay). Concrete pipes can sustain larger loads than the vitrified clay pipes; however, vitrified clay has a better chemical resistance (Moser 2001).

Table 2-1: Contributing factors used in previous studies

Contributing factors	Used in research study
Pipe material	(Ariaratnam et al. 2001) (Davies *et al.* 2001b) (Micevski et al. 2002)# (Mohammad and Guru 2005) (Baik et al. 2006)
Pipe size	(Ariaratnam et al. 2001) (Davies *et al.* 2001b) (Micevski et al. 2002)# (Mohammad and Guru 2005) (Baik et al. 2006)
Pipe depth	(Micevski et al. 2002)# (Mohammad and Guru 2005)
Slope	(Mohammad and Guru 2005) (Baik et al. 2006)
Location	(Davies *et al.* 2001b) (Micevski et al. 2002)#
Bus route	(Davies *et al.* 2001b)
Waste types	(Ariaratnam et al. 2001) (Davies *et al.* 2001b) (Mohammad and Guru 2005)
Ground water level	(Davies *et al.* 2001b)
Soil/backfill type	(Micevski et al. 2002)#
Age	(Ariaratnam et al. 2001) (Davies *et al.* 2001b) (Micevski et al. 2002)# (Mohammad and Guru 2005) (Baik et al. 2006)

#only study dealing with stormwater pipes

Pipe size - According to Young and O’Reilly (1983), small pipes have smaller moment of inertia, therefore, they are less resistant to bending moments. Failure of pipes due to bending stress is generally restricted to pipes of 300 mm or smaller size. Micevski *et al.* (2002) mentioned that pipe designers may underestimate the traffic loads or the cover requirements for small size pipes. These could be the reason that the deterioration of small pipes were found to be greater than that of large pipes in their study. Furthermore, It may be the case that larger sewers are laid with more care and precision by more experienced personnel (Davies *et al.* 2001b).

Pipe depth - In the review by Davies *et al*. (2001a), there is a decreasing influence of surface loads like traffic loads at lower depths on buried pipes. Kawabata *et al*. (2003), who investigated shallowly buried pipes subjected to traffic load, found that a rigid buried pipe with 2-meter depth of cover received earth pressure 4 times fewer than the one with 1-meter cover under similar traveling wheel loads.

Pipe location - In the review by Davies *et al*. (2001a), this factor refers to the location where pipes were buried such as beneath roads, footpaths, fields, gardens, buildings and even railway lines. In general, the location of a pipe affects the magnitude of surface loading to the pipes. Surface loads may come from deterministic loads (daily traffic, cyclic load) and probabilistic loads (excavation, repair events). Micevski *et al*. (2002) also mentioned that location such as close to coast line may expose pipes to corrosion.

Bus route - Although external loads are the direct cause of structural deterioration and failures of pipes, the 'bus route' factor was sometimes used to represent for wheel loads and cyclic loads because in some cases, the magnitude and frequency of these loads vary from time to time which makes it difficult for data collection. Cyclic loads are further classified into large, one time events and smaller cyclic events with a variety of frequencies (daily, seasonally) (Hahn *et al.* 2002). The large, one-time events include periods of surface construction, in-ground utility construction, or non-construction events (earthquakes, landslide). The damages of these events become significant on pipes when coupled with the deteriorated pipe strength or voids in the soil. The smaller, cyclic forces may come from ground activities such as the maintenance of other facilities, routine truck and frost heave.

Waste types - According to the synthesis of Hahn *et al.* (2002), biochemical, electrochemical and physical reactions can degrade pipe material (or lose ability to resist forces) and make it vulnerable to structural deterioration, even if the pipe is installed properly and the risk of dynamic forces is low. Three primary types of material degradation are internal corrosion, external corrosion and erosion of invert.

Internal corrosion depends mostly on the properties of flowing liquids. For example, corrosion by hydrogen sulphide is the most common in a concrete sewer. On the other hand, the external corrosion of pipes associates with the presence of acidic soils and groundwater. The erosion of invert of the pipe is dependent upon the material type, flow velocity and presence of suspended solids.

Groundwater level - In the review by Davies *et al.* (2001a), the presence of groundwater potentially causes ground loss and subsequent lack of support to pipes.

Soil/Backfill type - According to sewer rehabilitation manual (WRC 1983), silts and fine sands are high risk soils that can cause ground loss while clay is considered a low risk soil. As investigated by Li (2003), the pipe bedding composed of deformed peaty soil would settle differentially which then causes pipe failures under external load (peaty soil is soil whose deformation occurs when soaked in water). The reaction force by soil-pipe interaction was significantly reduced by 50-60% when using expanded Poly-styrene (EPS) backfill compared with sand backfill (Yoshizaki and Sakanoue 2003). Furthermore, the horizontal and vertical displacements of existing pipes due to the impacts of a near-by deep excavation were reduced by 56% and 57% respectively when adjacent soil areas were treated by cement mixing piles to enhance the elastic modulus of the soil to 10 times of the original value (Li *et al.* 2003).

Age – City expansions have resulted in stormwater pipes of different ages. The age of pipes is an important factor that can describe the hidden effects on pipes by design approaches, improved technologies and other unknowns. Although previous studies as synthesized by Davies *et al.* (2001a) pointed out that the 'improved technology' could be the major reason for the decreased defect rate of sewers in the 25 years after the Second World War. A given pipe will always deteriorate with age. However, deterioration rates can vary significantly between pipes, therefore an older pipe is not necessarily in worse condition than a newer pipe.

2.2.2 Hydraulic Deterioration and Contributing Factors

Unlike with structural deterioration, very few studies have been conducted on hydraulic deterioration of sewers and none for stormwater pipes. According to Hahn *et al.* (2002), the hydraulic deterioration refers to a reduction of cross sectional area and an increase in the roughness coefficient. In the work by WRC (1986), the cross sectional area was found to be reduced by tree root intrusions and accumulation of silts, debris and obstructions (e.g. illegal waste and metals), while the roughness coefficient was increased by deposits such as scale and encrustation.

The hydraulic deterioration is affected by a number of contributing factors such as tree types and tree ages, pipe depth, pipe location and soil type. The effects of these factors are described below.

<u>Tree type and tree age</u> - Root masses are common in areas with older trees and often enter a sewer system via structural defects such as cracks, open joints and fractures (WRC 1986). In some circumstances, the biological growth of tree roots can force themselves through the wall of concrete pipes (ASCE 1994). Furthermore, Pohls (2001) found that the majority of sewer blockages occurred in parts of Victoria (Australia) where Eucalyptus and Melaleuca type trees exist in the proximity, and when temperature and evaporation are at lowest levels.

<u>Pipe depth</u> - According to Pohls (2001), shallowly buried pipes are more vulnerable to the intrusions of tree roots. On the other hand, deeply buried pipes are subjected to groundwater which may enter the pipes through structural defects and then cause encrustation. In this case, encrustation is deposits left by the partial evaporation of water containing salt (groundwater and sea water) (WRC 1986)

<u>Pipe location</u> – This factor affect the type and the level of deposit build-up or debris accumulation in pipes. The natural sources of deposit and debris vary significantly within catchments and depend significantly on site characteristics such as the fraction of impervious surfaces and traffic conditions. These sources include water-transported material from surrounding soils, dry and wet atmospheric deposition and biological inputs from vegetation (Sutherland and Tolosa 2000) and from automobiles (Tai 1991). The contribution of soil to the accumulation of particulates in pipes can be significant. Hopke *et al.* (1980) found that 76% of the total street dust mass originated from soil materials. Similarly, Tai (1991) found that most of the street surface particles originated from the erosion of local soils.

Soil type - According to Pohls (2001), dark grey sand over clay and deep sands free of lime in Victoria (Australia) are favored conditions for the growth of tree roots. Pipes buried in such soil types may be more likely to have blockages due to tree root intrusions.

2.3 Monitoring and Assessing Pipe Condition

Pipe condition (or status) is often used to describe the overall serviceability, i.e. structural and hydraulic capacity of pipes at a point of time in their lifetime. Because of pipe deterioration, the task of monitoring and assessing the changes of pipe condition over time becomes extremely important as part of proactive management strategies. In the current management practice of sewers and stormwater pipes, this task consists of three steps: (1) selection of monitoring frequency, (2) selection of inspection techniques and (3) grading of pipe conditions.

2.3.1 Monitoring frequency: regular versus snapshot

Bridges and pavements in USA are subjected to a regular (or repeated) inspection program to identify structural defects during their lifetime. In particular, every bridge is legally required to be inspected once every two years (Madanat *et al.* 1995) which resulted in a database with regular or longitudinal data. These bridge inspection data provide asset managers with information on the current condition of the bridges so that preventative maintenance can be decided in a timely manner. Furthermore, these longitudinal data can be used in deterioration models for predicting future conditions of bridges (to be detailed in Section 2.4.2).

Unfortunately, sewers in USA and stormwater pipes in Australia were not subjected to such regular inspection programs. Instead, their inspection programs were of snapshot type, that is, a sample of pipes was inspected for only once (Kathula 2001; Kleiner 2001; Wirahadikusumah *et al.* 2001; Baik *et al.* 2006).

2.3.2 Inspection Techniques: CCTV versus others

According to Ratliff (2003), inspection techniques can be grouped into three levels of assessment according to the capability of the inspection techniques and the required information by asset managers. The three levels are (1) field reconnaissance (level 1), internal inspection (level 2) and external inspection (level 3).

Field reconnaissance (level 1) aims to collect data of manholes, pits and pipelines and assesses the structure of manholes for accessibility of inspection equipment and even inspectors. Some of available inspection techniques for this level are:

- Manhole survey
- Sonde locators
- Global positioning system (GPS)

This basic step often associates with reviewing as-built drawings and existing information in order to form the backbone of any management database. This task continues throughout service lifetime of the pipe systems whenever new information such as pipe replacement or repair occurs.

Internal inspection (level 2) focuses on assessing the internal condition of pipes so that appropriate action can be taken for pipes in poor condition before the pipe collapse or occurrence of complete blockage of pipe. Some of available inspection techniques for this level are:

- Man-walk through
- Close circuit television (CCTV)
- Sonar (or ultrasonic)
- Focused electrode leak location (FELL)
- Sewer scanner and evaluation technology (SSET)
- Laser-based scanning system
- Multi-sensor pipeline inspection system (KARO, PIRAT)

External inspection (level 3) concerns with the soil structure that supports pipes. Any voids or loss of soil support is potentially leading to pipe collapse (Ratliff 2003). Some of available inspection techniques for this level are:

- Infrared thermographs
- Ground penetrating radar
- Micro deflection
- Impact echo wave impedance probe (WIP)

Although as described above, there are several inspection techniques available for each level of assessment, there are no guidelines for selecting these techniques for a particular application. In order to reduce time and effort in selecting the appropriate inspection technique, a number of researchers have provided comprehensive reviews of inspection techniques that were applied in many infrastructure facilities. Examples can be found in Wirahadikusumah *et al.*(1998), Morrison and Thomson (2003) and Koo and Ariaratnam (2006). Details of these individual techniques are described in Appendix A.

In current management practice of sewers and stormwater pipes, the GPS locator and the CCTV inspection were still the most used techniques for locating pipelines (i.e. level 1) and assessing internal condition of pipes (i.e. level 2) (Wirahadikusumah *et al.* 2001; Morrison and Thomson 2003; Baik *et al.* 2006). With hundreds of kilometers of pipelines, inspection costs become a critical factor for asset managers' decisions, not to mention productivity.

2.3.3 Grading of pipe condition

The Water Research Center (WRC) in UK devised the world first condition grading scheme that provided protocols and guidelines for assessing current condition of individual pipes using the CCTV inspection technique (WRC 1986). Based on the original scheme of WRC (1986), several condition grading schemes were later developed in Canada (McDonald and Zhao 2001), Europe (Cemagref 2003) and Australia (WSAA 2002). Although the structural and hydraulic deterioration of pipes are a continuous process (as explained in Section 2.2), ordinal grading systems were used in these schemes for mapping the pipe deterioration into pipe conditions at the time of inspection. For example, a grading system of 1 to 3 was specified in WRC (1986) with that condition 1 as 'perfect' condition, condition 2 as 'fair' condition and condition 3 as 'poor' condition. Similar grading systems can be found in the assessment of deterioration of bridges and pavements where grading scales of 0 to 9 and 1 to 8 were used respectively (Madanat *et al.* 1995). These assigned numbers do not indicate the distances between grades but a relative ordering. The use of ordinal grading systems is primarily for reducing the computational complexity of the M&R decision-making process (Madanat *et al.* 1997). Another justification is that detail is not necessary at this level of management.

The Australia Conduit Condition Evaluation Manual (ACCEM) produced by Sydney Water in 1991, was considered the first attempt in Australia to support water industry in dealing with increasing awareness of asset deterioration. This was then superseded by the Sewer Inspection Reporting Code (SIRC) by the Water Service Association of Australia (WSAA 2002) using a grading system of 1 to 3 as shown in Table 2-2. The SIRC was developed for assessing conditions of rigid sewers (concrete and vitrified clay pipes) using CCTV inspection data. The SIRC was then updated by the Conduit Inspection Reporting Code (CIRC) (WSAA 2006) with a grading system of 1 to 5 as shown in Table 2-2. Furthermore, the CIRC covered the plastic pipes which were not available in the SIRC.

Figure 2-2 shows the grading process based on the SIRC for a pipe segment from CCTV data. A pipe segment is defined between two manholes or pits. As shown in this figure, the CCTV robot was sent to the pipe of interest. During its movement along the pipe, the CCTV-recoded images were sent to a monitor where the operator can recognize any structural or hydraulic defects. He or she then coded the defects with the aid of computer. As shown in the lower line of the Figure, each coded defect was automatically or manually assigned a score according to the guidelines. For example a structural defect like crack has a score of 5. All defect scores were aggregated for two condition measures, namely, peak score and mean score. The peak and mean score were then compared against pre-defined thresholds for grading the pipe into either condition one, two or three.

Some notes and explanations are worth mentioning here in relation to the SIRC which are also applicable to the CIRC. Defects are separated for structural and hydraulic defects. The structural defects are distinguished for rigid pipes (concrete, vitrified clay material), brick pipes and flexible pipes (plastic material), while the hydraulic defects are the same for all types of material. Defect scores were a relative measure of contribution of defects to the likelihood of structural failures or hydraulic failures. Single defect score starts from zero and the largest scores are 165 (collapse state) and 80 (hazard obstruction) for structural and hydraulic condition respectively. In general, structural defects that receive high scores are surface damage, breaking and deformation, while debris, roots and obstruction get high scores for hydraulic defects. The peak score indicates the largest score from one defect or multiple defects in one location (often within a meter length) in the pipe segment. The mean score is the sum of all defect scores divided by the segment length.

Table 2-2: Description of condition states used in WSAA (2002, 2006)

Condition grading (or state)	WSAA 2002		WSAA 2006	
	Structural condition	Hydraulic condition	Structural condition	Hydraulic condition
1	No apparent need to investigate further	No apparent need for action	Insignificant deterioration of the sewer has occurred. Appears to be in good condition	No or insignificant loss of hydraulic performance has occurred. Appears to be in good condition
2	Consider overall circumstances on a program basis	Consider response on a program basis	Minor deterioration of the sewer has occurred.	Minor defects are present causing minor loss of hydraulic performance
3	Urgent need to investigate overall circumstances	Appropriate action to be investigated urgently	Moderate deterioration has occurred but defects do not affect short term structural integrity	Developed defects are present causing moderate loss of hydraulic performance
4			Serious deterioration of the sewer has occurred and affected structural integrity	Significant defects are present causing serious loss of hydraulic performance
5			Failure of the sewer has occurred or is imminent	Failure of the sewer has occurred or is imminent

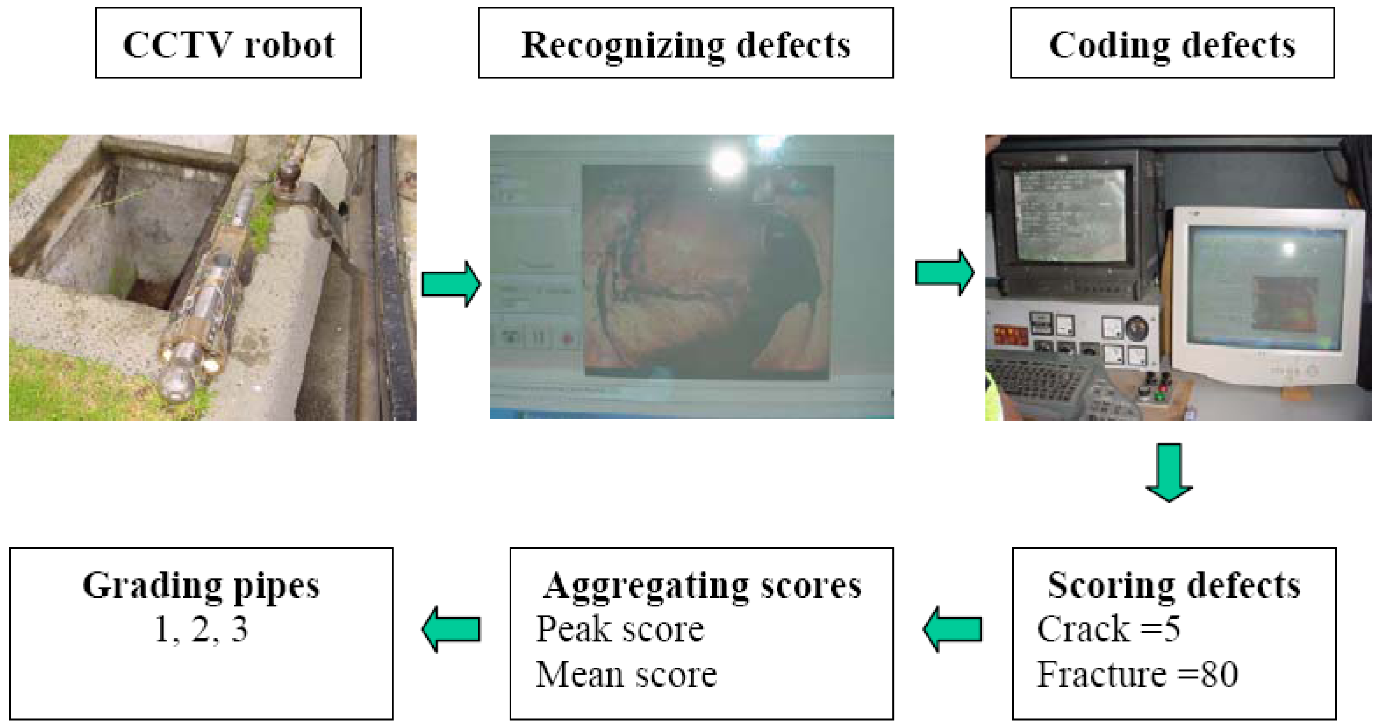

Figure 2-2: Grading process for a pipe from CCTV data

2.4 Modelling Techniques

Current and future condition data of stormwater pipes are crucial to all aspects of a stormwater pipe management system. Current condition data of pipes are often 'measured' through inspection techniques like CCTV and condition grading schemes. Consequently, their accuracy depends on the 'measurement' technology. Furthermore, in most cases, these data are available only for a fraction of the pipes in a stormwater drainage system. Therefore, the current condition data of 'unmeasured' pipes and the future condition data of all pipes need to be predicted.

Researchers frequently use models in problem formation and solution. Sometimes these models are based on physical, chemical or engineering science knowledge of the phenomenon. In such cases, the models can be theoretically established and tested with the experiments, and are called mechanistic models. Examples of mechanistic models are Ohm's law and Newton's gravity force. However, there are many situations in which two or more factors are combined in a complex or probabilistic way that is often poorly understood or unknown to affect a response of interest. In these cases, it is necessary to build a model relating the contributing factors with the response based on observed data. This type of model is called an empirical model, which were the type of almost all deterioration models found in the literature for infrastructure modelling. These deterioration models, which utilize samples of CCTV graded pipe conditions, are often used to predict the current and future condition of pipes. Therefore, accurate predictions become crucial for effective decision-making.

It is obvious that selecting the appropriate modelling techniques for structural and hydraulic deterioration of pipes will increase the accuracy of predictions. However, limited information is available in the literature on deterioration models for stormwater pipes. Hence, the deterioration models of sewers, bridges and pavements, which use similar graded condition data (Madanat *et al.* 1995), will be examined with the aim of using these modelling techniques in stormwater pipes.

Morcous *et al.* (2002b) classified existing deterioration models used for infrastructure facilities into three categories. They are (1) deterministic models, (2) statistical models and (3) soft computing or artificial intelligence based models, as shown in Table 2-3. Dasu and Johnson (2003) considered the deterministic models and statistical models as a model-driven type because the structures of these models are often decided by the experts. The artificial intelligence based models were considered as a data-driven type because the structures of the models are decided by the sample data. In each model type, there are several modelling techniques and those modelling techniques which were applied on infrastructure facilities are given in Table 2-3.

Table 2-3: Classification of deterioration models

Model-driven type		Data-driven type
Deterministic models	Statistical models	Artificial intelligence models
Linear, Exponential.	Markov chain, Ordinal regression, Linear discriminant analysis.	Case-based reasoning, Fuzzy set theory, Neural networks.

2.4.1 Deterministic Models

Deterministic models are often used for phenomenon where relationships between components are certain. Examples are time linear and power law models for water mains (Kleiner and Rajani 2001) and pavements (Lou *et al.* 2001). Deterministic models in the form of linear and exponential models were no doubt the first attempt at modelling deterioration of infrastructure facilities because of their simplicity in mathematical operations and capability to describe a direct relationship between the input factors and the output.

2.4.1.1 Linear Models

Madanat *et al*. (1995) described steps in building a common linear model for infrastructure facilities as follows:

Step 1 The facilities are grouped into cohorts, i.e. having similar attributes such as size, material and service type. These cohorts can then provide a direct relationship between asset condition and age as shown in next step.

Step 2 For each cohort, a linear model with condition state *Y*, as dependent variable and age *t*, as the independent variable is developed as in Equation (2-1).

$$Y_i = \beta_1 + \beta_2 t + \varepsilon_i \qquad (2\text{-}1)$$

where: i = index for facility,

Y_i = condition state for facility *i*,

β_1 and β_2 = parameters to be estimated,

ε_i = random error term.

The linear model is often calibrated using the common least square technique (see Aldrich and Nelson 1990 for more detail of this technique). Typical result is a straight line, as shown in Figure 2-3, which shows that the rate of deterioration is independent of time. However, the linear models are too simplistic to reflect the probabilistic nature of pipe failures, which are caused by a combination of time dependent deterioration process and random damage events (Morcous *et al.* 2002a). Furthermore, it is not appropriate to model discrete condition states using linear regression (Madanat and Ibrahim 1995; Madanat *et al.* 1997).

2.4.1.2 Exponential Models

Wirahadikusumah *et al*. (2001) pointed out that the deterioration rate of older sewers in City of Indianapolis (USA) should be faster than the young ones and used an exponential model with the mathematical expression of :

$$Y_i = e^{\beta_1 + \beta_2 t + \varepsilon_i} \qquad (2\text{-}2)$$

The model was also calibrated using the least square technique and the result, an exponential curve as shown in Figure 2-3, indicating an increasing deterioration rate over time. The exponential models also suffer similar shortfalls encountered with the linear models (in Section 2.4.1.1).

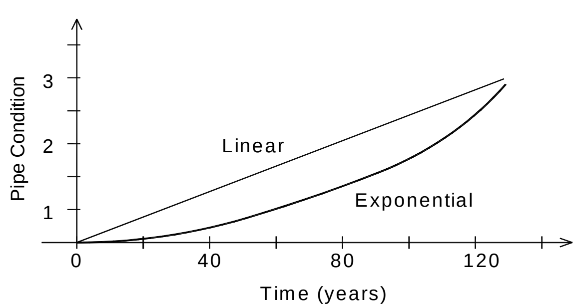

Figure 2-3: An illustration of linear and exponential models

2.4.1.3 Advantages and Disadvantages of Deterministic Models

A/ Advantages

- Mathematical expressions are in analytical form.
- The relationship between input factors and output is straight forward

B/ Disadvantages

- Age can represent majority of potentially contributing factors in the models, since pipes seem to deteriorate with age. However the age cannot describe the variation in rate of deterioration across pipes which are varied due to different other factors affecting deterioration.
- Partitioning pipes into groups or cohorts to fix the above 'age only' problem creates another problem of cohort. That is, each cohort must be small enough to be considered homogeneous but it also must be large enough to cover as many as input factors (Kleiner *et al.* 2007). Furthermore, the complicated interactions between factors, which have not been fully understood, but influence deterioration levels of pipes, could not be accounted when grouping pipes (Mishalani and Madanat 2002).
- The methods are too simplistic to reflect the probabilistic nature of pipe failures, which are caused by a combination of time dependent deterioration process and random damage events (Morcous *et al.* 2002a).
- It is not appropriate to model discrete condition states using linear or exponential models (Madanat and Ibrahim 1995; Madanat *et al.* 1997).

2.4.2 Statistical Models

Statistical models are based on statistical theory for modelling phenomenon where random noise in components exists. Statistical models have been used in many engineering problems (Henley and Kumamoto 1992; Johnson and Albert 1999; Kuzin and Adams 2005). Dasu and Johnson (2003) noted that the statistical models are of the model-driven type, which assumes parametric density functions for measurement errors and certain probabilistic relationships between input data and output data. The statistical models provide a more realistic approach to predict the current and future condition of pipes because their outcomes (i.e. predicted pipe conditions) are explicitly formulated in probability values rather than in quantitative values as in the deterministic models. The outcome could be a binary choice (i.e. 'yes' or 'no'), multiple category responses or even a matrix of transition probabilities. Markov models and ordinal regression-based models are two typical statistical deterioration models which have been used extensively in modelling the deterioration of infrastructure facilities.

2.4.2.1 Markov models

According to Morcous *et al.* (2002a), the Markov chain theory is still the most frequently used method in many statistical models. The basic idea of the Markov chain theory is that the prediction of the future condition over a unit time depends only on the current condition, regardless of its history. For example, a pipe which is in condition state 1 at the current time has a series of probability, namely P_{11}, P_{12}, P_{13}, P_{14} and P_{15} to stay still or proceed transition to one of poorer condition states 2, 3, 4 and 5 respectively at the next period. Thus, a transition matrix **P** can be established for 5 possible conditions as shown below:

$$\mathbf{P} = \begin{bmatrix} P_{11} & P_{12} & P_{13} & P_{14} & P_{15} \\ 0 & P_{22} & P_{23} & P_{24} & P_{25} \\ 0 & 0 & P_{33} & P_{34} & P_{35} \\ 0 & 0 & 0 & P_{44} & P_{45} \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{2-3}$$

where sum of row elements is always 1 and the size of matrix is equal to the grading range of facility. The structure of the transition matrix **P** implies that no rehabilitation effect is accounted for and the pipe cannot move from a higher condition grade to a lower grade. Mishalani and Madanat (2002) further classified Markov models into state-based and time-based models. The former is to estimate the probability of condition changes of an infrastructure facility over a unit time. In contrary, the latter predicts the probability distribution of time spent to have a unit change of the asset condition. The main task in calibrating Markov models is to estimate the transition probability matrix from sample data. The calibration techniques are classified according to the type of data whether they are regular or snapshot data. In the case of regular data, the techniques are then further divided into the state-based models and time-based models.

A/ Calibration techniques for state-based Markov models with regular data

As mentioned in Section 2.3.1, regular inspection of bridges in USA is required and graded into ordinal condition states every 2 years by law, and hence, a regular dataset is available (Madanat *et al.* 1995). This is a unique case for which a number of calibrating techniques were developed. For example, Madanat and Ibrahim (1995) who used the frequency analysis technique to test the Markov property of history independence on USA bridge dataset, concluded that Markov property is appropriate for infrastructure facilities. Frequency analysis technique was also suggested in the framework by Wirahadikusumah *et al.* (2001) as the simplest yet most accurate method to estimate transition probabilities of Markov deterioration model for sewers.

Alternatively Madanat *et al.* (1995) used a combination of two techniques, namely, incremental model and ordered probit model (see Greene 1990 for detail of this technique) to estimate the parameters of a Markov model for each bridge deck. The incremental technique mapped the continuous deterioration process into ordinal condition states by using thresholds which accounted for the ordinal nature of condition states. The ordered probit technique then linked the mappings with potentially contributing factors. It means that if the continuous deterioration value (determined by the linear combination of contributing factors) is larger than the thresholds, the bridge will be assigned to the corresponding condition state. Based on the two combined techniques, Baik *et al.* (2006) estimated the transition probabilities for inspected sewers of City of San Diego. However, as stated in their study, the supplied data set was of snapshot type, and hence their methodology may not be appropriate for their study.

Madanat *et al.* (1997) mentioned two issues namely, non-homogenous Markov property and heterogeneity found in bridge panel data - a combination of sample data collected over different areas and time. The non-homogenous (or non-stationary) Markov property suggests that the transition probability from condition state i to state j changes over time. For example, the transition probability from condition 1 to condition 2 for a pipe at the age of 20 should be different with that of the same pipe at the age of 40. This is to capture the possible reality that the deterioration rate of older pipes should be different with that of younger pipes. Heterogeneity indicates unequal variance in the dependent variables of panel data in which error learning, discretionary choice with aging, improvement of inspection techniques, outliers and inappropriate data transformations are listed as reasons for heterogeneity by Gujarati (2003). Madanat *et al.* (1997) used random effect method (REM) to improve the two combined techniques (i.e. incremental model and ordered probit model) and tested the above two issues on Indiana bridge dataset. REM considers all cross-sectional data to be from the same population. The mean value of this population was estimated by adding one more error term to the mean values of sectional data for capturing heterogeneity. The occurrence of heterogeneity and the suitability of non-stationary Markov property were found in their study together with improved success rate of prediction.

Madanat and Ibrahim (1995) used a different approach to model continuous deterioration process of bridge decks and assumed that the number of condition changes over a unit time for each condition state may follow Poisson distribution. The Poisson rate became the deterioration rate which is an exponential function of contributing factors. The negative binomial distribution was then used as an extension of the Poisson model that relaxed the assumption of equality between the mean and variance of the bridge deck condition. Their study demonstrated that the negative binomial distribution provided accurate estimates of transition probabilities.

B/ Calibration techniques for time-based Markov models with regular data

One critical problem with the above mentioned calibrating techniques for state-based Markov models is that they require truly uncensored regular data, i.e. continuous inspection (Mauch and Madanat 2001). An example is shown here to explain the censored and uncensored data (see Nelson 1982 for more details). If a new facility is observed during an experiment of 2 years and the facility still functions at the end of the experiment, a censored data point is obtained. If the facility failed during the experiment, an uncensored data point is obtained. The truly uncensored data requires that the timing when a facility changes its condition throughout their service life should be recorded. However, this requirement is impractical when considering cost even for important facilities like bridges. For example, a pipe was inspected and graded in condition 3 at the age of 30 years. Suppose that unit time for inspection is 2-year interval, the pipe was inspected again at the age of 32 years and graded 5. This means that the pipe either changed from condition 3 to 5 via 4 or jumped from 3 to 5 and the timing for those changes was not known. It is obvious that continuous inspection must be applied in order to find out when condition 3 has changed to condition 5. In order to address this problem, the time-based Markov model was proposed. Examples can be found in the works by DeStefano and Grivas (1998), Mauch and Madanat (2001), Kleiner (2001) and Mishalani and Madanat (2002). The common points of methods used in these works are:

- Assume that a facility change its condition in unit step (i.e. no multi-state jump) and the timing of change is in the middle of the change interval;
- Link contributing factors with facility deterioration via hazard rate function (see Nelson 1982 for a definition of hazard rate function);
- Transition time distribution is equivalent to survival function (see Nelson 1982 for a definition of survival function);
- Assign a uniform or Weibull density function for survival function;
- Transition time distribution is estimated using analysis such as Kaplan-Meyer method (see Nelson 1982 for more details); and
- Can be used for both censored and uncensored data.

Although the time-based Markov models were found to be adequate for modeling deterioration of bridge decks, the assumption of unit change of facility condition is not appropriate for stormwater pipes as found by Micevski *et al.* (2002) who concluded that the deterioration of stormwater pipes might undergo a multi-state transition (e.g. jumping from condition 1 to condition 3 within a time step).

C/ Calibration techniques for state-based Markov models with snapshot data

As stated in Section 2.3.1, snapshot-type inspection data are more common in current management programs of sewers and stormwater pipes. Therefore, the proper calibration of the state-based Markov models is not an easy task. This is because the Markov models require that at least three sets of data regarding the condition of facilities should be available for three consecutive periods so that proper calibration and testing of the Markov models can be carried out (Madanat and Ibrahim 1995; Wirahadikusumah *et al.* 2001). Different calibration approaches were used to handle the problem of scarce data (i.e. only snapshot data are available). According to a review by Madanat *et al.* (1995), optimization technique was one approach in calibrating Markov deterioration models for bridge and pavements. It was used to minimize the distance between predicted conditions of a deterministic linear (or exponential) model and a statistical Markov model (Madanat *et al.* 1995).

When applying this technique to calibrate the Markov deterioration model with snapshot data for combined sewers of City of Indianapolis (USA), Wirahadikusumah *et al.* (2001) assumed a non-stationary transition matrix and grouped sewers into 16 cohorts according to four contributing factors (pipe material, soil type, buried depth and groundwater table). They chose the cohort which had the highest correlation between pipe age and the pipe condition for constructing a deterministic exponential model. The Markov model was then calibrated using the predicted outputs from the exponential model. Wirahadikusumah *et al.* (2001) admitted that calibrating the Markov model using regression analysis was not appropriate. Furthermore, the Markov model could not be tested due to the lack of regular data.

Micevski *et al.* (2002) used Bayesian Markov Chain Monte Carlo (MCMC) simulation technique to calibrate the Markov model with the assumption of stationary transition matrix for structural deterioration of stormwater pipes in City of Newcastle, Australia. The Markov model calibrated by the Bayesian MCMC technique can be used to predict the future conditions for the whole population or sub-population (or cohorts) of pipes since the contributing factors of individual pipes were not used with their condition state in the calibration process for the models. They found a reasonable match between predicted and observed proportions of pipes for each condition state in each year of a test dataset. They further argued that using stationary Markov property can reduce the complexity and error in the calibrating process, yet provide an acceptable result. The applications of Bayesian MCMC technique were also found in deterioration models for bridge decks (Enright and Frangopol 1999) and pavements (Hong and Prozzi 2006).

One approach to cope with scarce data (i.e. only snapshot data are available) is to use expert opinions. For example, Kathula (2001) sent questionnaires to several Cities in USA to get expert opinion on future deterioration expressed in percentages of pipes.

This information was used to compute the stationary transition matrix. She validated the developed model against observed condition of combined sewers and found a reasonable match. Kleiner *et al.* (2004; 2006) proposed a fuzzy methodology to mathematically convert expert opinions into numbers for calibrating the transition matrix.

Although the calibrating techniques and Markov deterioration models developed for handling snapshot data seem to be successful in predicting future deterioration of the whole population of pipes, they still lack a mechanism to predict the future deterioration of a particular pipe (or single pipe prediction). Grouping pipes into cohorts according to 'pipe size or pipe location' as in the work of Micevski *et al.* (2002) or 'pipe material, soil type, groundwater table and buried depth' as in the work of Wirahadikusumah *et al.* (2001) work still encounter problems of cohort, as outlined in Section 2.4.1.

2.4.2.2 Ordinal Regression Models

Ordinal regression methods have become popular when dealing with a relationship between a integer valued output and one or more explanatory variables (Johnson and Albert 1999). The integer values are sometimes meaningfully ranked in increasing or decreasing order. The condition grading system of pipes is a typical example. In case of pipe deterioration models, these methods re-conceptualize the deterministic linear regression to predict the probability that a particular pipe is in a particular condition based on the value of its attributes (or contributing factors). Some common functions used in the ordinal regression models were logistic and probit functions (Tabachnick and Fidell 2001). The maximum likelihood method is the commonly used calibration technique for the ordinal regression models (Johnson and Albert 1999).

The ordinal regression models using the logistic function were developed in several studies to identify whether a particular sewer is in good or bad condition. Examples are Davies *et al*. (2001b), Ariaratnam *et al*. (2001) and Koo and Ariaratnam (2006) for studies of structural deterioration of combined sewers in UK, Canada and USA respectively, and Pohls (2001) for investigation of sewer blockages in Australia. However, these studies were focused with the investigation of factors that affect the structural deterioration and lacked goodness-of-fit tests comparing the results of the deterioration models with the observed data.

2.4.2.3 Linear Discriminant Models

Fisher's linear discriminant analysis - LDA (Huberty 1994) is a statistical method for classifying or predicting individuals or objects into mutually exclusive and exhaustive classes based on a set of independent variables (or predictors). Since a class contains similar objects which are often measured or observed with measurement errors, the objective of the LDA is to find a linear transformation of independent variables that maximizes the ratio of between-class scatter and the within-class scatter (Laitinen 2007). Maximizing this ratio is also called Fisher's criterion. In other words, the LDA takes the classes into consideration and searches for a subspace where the samples from the same class are as compact as possible, and meanwhile the samples from the different classes are as far as possible.

The LDA is similar to the popular multiple regression method in a way that both methods use a linear function of independent variables. The key difference between the LDA and multiple regression is that the dependent variable or output of the LDA must be of categorized values while that of multiple regression must be a real number. Furthermore, the LDA requires independent variables to be of multivariate normal distribution (Tabachnick and Fidell 2001).

The LDA can be applied for problems of two-class (binary) or multiple classes. When the LDA considers multiple classes, it is called multiple discriminant analysis - MDA (Huberty 1994). The LDA was used for engineering problems (Tan et al.; Galletti et al. 2003; Tsai 2006) and business research (Yang *et al.* 1999; Shan *et al.* 2002; Liu *et al.* 2007). However, no applications were found in infrastructure modelling. Maximizing Fisher's criterion is also the calibration technique of the LDA (Johnson and Wichern 2002).

2.4.2.4 Advantages and Disadvantages of Statistical Models

A/ Advantages

- The statistical models seem robust to handle outputs of ordinal data type.
- These models take into account the probabilistic nature of the underlying deterioration process.

B/ Disadvantages

- Grading condition state and collected data are subjective in nature whilst the mathematical and statistical methodologies used in the aforementioned models require objective and uniform data.
- The models are sensitive to noisy data (Leung and Tran 2000; Dasu and Johnson 2003). Furthermore, it is not easy to remove the noisy data since the precise cause and effect of the underlying process is not known (Terano *et al.* 1991).
- The models used assumptions such as standard normal distribution for measurement error, which are difficult to validate.

2.4.3 Artificial Intelligence Based Models

In comparison with the deterministic and statistical models, some of the artificial intelligence based models are of the data-driven type in which model structure is determined by data, i.e. no assumptions are made regarding the model structure. This is because that they were designed to mimic the operations of human brain and natural life which are learning and generalizing all the time (Taylor 1993, 1996; Soulie and Gallinari 1998). This learning and generalizing feature was often used for many engineering models (Moselhi and Shehab-Eldeen 2000; Seo *et al.* 2004; Singh and Tiong 2005; Wilmot and Mei 2005), where model outputs were classified from a set of input patterns by learning from the past data and generalizing the lessons to predict future targets. The artificial intelligence based models fall into category of 'black box' models, since they seem concerned only with input and output data without specifying the underlying mechanism. Among the artificial intelligence techniques, case-based reasoning (CBR), fuzzy set theory and neural networks (NNs) were used for modelling the deterioration of infrastructure facilities, (Flintsch and Chen 2004; Kleiner *et al.* 2004).

2.4.3.1 Deterioration Models using CBR

Morcous *et al.* (2002b) developed a case-based reasoning (CBR) methodology for modelling infrastructure deterioration. CBR is a problem-solving regime that relies on the specific knowledge of previously experienced cases (Aamondt and Plaza 1994) and the essence of how human makes judgment (Riesbeck and Schank 1989). In principle, CBR requires a longitudinal and diversified database (or experienced case library) be maintained and updated so that a query case (e.g. future condition of a facility) can be solved by retrieving and adjusting information from the case library. Morcous *et al.* (2002a) implemented the above methodology to predict the next 5-year condition of a highway bridge deck given the known current condition using a dataset provided by the Ministry of Transportation of Quebec (MTQ) in Canada. Their study demonstrated that the CBR provided correct predictions for 70% of the cases in the testing group. A framework of expert system, a close class of CBR, was also developed using expert opinion for prioritizing inspections of sewers (Hahn *et al.* 1999). The shortfalls with the CBR and expert system are the requirement of sufficiently large case library and the subjectivity of the inference rules.

2.4.3.2 Deterioration Models using Fuzzy Set Theory

Fuzzy set theory has been employed to mathematically convert linguistic inference rules into fuzzy numbers and fuzzy rules (Zhao and Chen 2002). Although fuzzy set theory was originally applied to reduce the complexity and response time in electronic control systems where a direct causal-effect model is too difficult to be constructed and mathematically solved (Terano *et al.* 1991; Klir and Yuan 1995), it has increased applications in infrastructure modeling. Examples are fuzzy expert systems for buried pipes (Makropoulos *et al.* 2003; Yan and Vairavamoorthy 2003; Najjaran *et al.* 2004; and Vamvakeridou-Lyroudia *et al.* 2005) and fuzzy decision support systems for construction and building (Chao and Skibniewski 1998; Liang *et al.* 2001; Seo *et al.* 2004; Singh and Tiong 2005). However, one shortfall with fuzzy models is the subjectivity of the inference rules which are constructed based on expert opinion. Recently, Kleiner et al. (2006) developed a fuzzy Markov model for deterioration of buried pipes. In their approach, fuzzy rules can be trained to given data, thus reducing subjectivity.

2.4.3.3 Deterioration Models using NNs

Researchers have been attracted to the vast, sophisticated and extraordinary functionality of human brain for centuries. In 1943, Warren Mc-Culloc and Walter Pitts proposed the first artificial model for a biological neuron of human brain. Since then, numerous methods for building neuro-inspired computational models, ranging from simple to very sophisticated mathematical models, have been proposed and investigated. This field of study is generally known as artificial neural networks or in a short abbreviation, neural networks (NNs). NNs are defined as a type of information processing system in a way that resembles human brain (Hassoun 1995). NNs 'learn' the patterns of the underlying process from past data and generalize the gained 'knowledge' (or mathematical relationships between input and output data) to predict or classify an output given a new set of input variables from the problem domain.

The application of CBR and fuzzy expert systems for sewers and stormwater pipes suffers two critical setbacks. The first is the lack of a case library for the application of CBR and the second is the subjectivity of expert opinions in Fuzzy expert systems, which tend to be more conservative. NNs, on the other hand, are able to tackle the problems found with CBR and Fuzzy expert systems. Furthermore, NN can sometimes be a practical alternative to well founded theoretical models such as the deterministic models and statistical models when causal relationships are ill understood. The strength and capability of NN models are the ability to identify the complex non-linear relationships between input and output data (Moselhi and Shehab-Eldeen 2000; Nilsson *et al.* 2006), the adaptability to solve problems that are poorly defined or not clearly understood (Chua and Goh 2003), and the flexibility to handle both integer and real values (Hyun-Suk et al. 1999; Ha and Stenstrom 2003). Furthermore, NNs accept limited data (Smith 1996), require no assumptions (Soulie and Gallinari 1998; Dasu and Johnson 2003), and are insensitive to noisy data (Bishop 1995; Lou et al. 2001). These capabilities were demonstrated in several studies recently such as the review by (Sexton and Dorsey 2000), and comparative studies by Lou *et al.* (2001), Christodoulou *et al.* (2003), Abdel-Aty and Abdelwahab (2004) and Bennell (2006).

A/ NN Models

NNs have been used in different research areas such as pattern recognition, linear and non-linear optimization, and parallel computing and prediction (Mukherjee and Deshpande 1995; Soulie and Gallinari 1998; Olden and Jackson 2002; Ferentinos 2005; Samarasinghe 2006). In infrastructure management modelling, an increasing number of researchers have recently used NNs. Examples are modeling of pavement crack conditions (Lou et al. 2001), defect classifications in sewers (Moselhi and Shehab-Eldeen 2000), deterioration and management of water mains (Luis and Naim 2001; Al-

Barqawi and Zayed 2006), modeling construction cost (Kim *et al.* 2005b; Wilmot and Mei 2005), and analysis of bridge condition data (Cattan and Mohammadi 1997).

Najafi and Kulandaivel (2005) adopted a feed-forward back-propagation NN model to predict the future structural condition of a particular sewer based on its contributing factors. A case study using 7 factors (size, sewer type, length, age, depth, material and slope) for predicting discrete conditions ranging from one (the best) to five (the worst) was demonstrated in their study. Although the NN model could learn with only 70% of the presented cases, their study indicated the feasibility of using NN to predict pipe conditions. One of the key elements affecting the performance of NN models that was not mentioned in their study is the occurrence of local optimum associated with the commonly used back-propagation calibrating technique (Gori and Tesi 1992). In several studies, other calibration techniques like genetics algorithms (McInerney and Dhawan 1993; Rooij *et al.* 1996) and Bayesian Markov chain Monte Carlo simulation (Mackay 1992; Kingston *et al.* 2006) were used to handle the problem of local optimum.

B/ Probabilistic Neural Network Models

Probabilistic neural network (PNN) was originally developed by Specht (1990) and is considered a hybrid technique that use a Bayesian classifier (Gelman *et al.* 1995) and a Parzen-Cacoullos theory (Cacoullos 1966) on an NN platform to produce the probability distribution of each pattern or class. Both Bayesian classifier and Parzen-Cacoullos theory are statistical techniques. PNN were successfully applied for reliability assessment of oil and gas pipelines (Sinha and Pandey 2002) and for prediction of concrete strength (Kim *et al.* 2005a). The PNN models in these studies had a fast calibration without any optimizing process which is the advantage of the PNN models over the NN models. However, the PNN models are still based on the statistical techniques with assumptions of probability distributions on their model structure. This may affect the predictive performance of the PNN models.

2.4.3.4 Advantages and Disadvantages of Artificial Intelligence Based Models

A/ Advantages

- These models are insensitive to noisy data (Hassoun 1995; Smith 1996).

- This can automatically detect non-linear underlying processes (Dasu and Johnson 2003).
- These models can handle both scale and ordinal data types.

B/ Disadvantages

- Determination of NN structure which greatly affect the predictive performance, is time consuming (Leung et al. 2003; Kuncheva 2004; Curry and Morgan 2006)
- Calibration or training of these models involves high-dimensional optimization (except to the PNN models) which contains many local optima (Gori and Tesi 1992).
- High demand for data
- Black box with no underlying model – danger of overfitting

2.4.4 Methods for Testing of Model Performance

Testing (or evaluating) model performance is to quantify the model error which is the difference between predicted values and corresponding true values (Wright *et al.* 2006). The model performance is high when the model error is low.

For continuous value outputs, the correlation coefficient (R) and the root mean square error (RMSE) are commonly used. Examples are modelling construction cost (Wilmot and Mei 2005), modeling bridge risks (Wang and Elhag 2007), and daily flow forecasting (Singh and Deo 2007).

For categorical and ordinal outputs, the confusion matrix is often used to assess the performance of classifiers which classify an object into one of the categorical targets. Examples are shrimp disease occurrence/no-occurrence (Leung and Tran 2000), bacterial growth/no-growth (Hajmeer and Basheer 2003), the credit ratings good/bad (Bennell *et al.* 2006). Another form of testing models is the goodness-of-fit test, which assessed whether the proposed model is consistent with a set of observations. This method of testing was often used in infrastructure modelling (Madanat *et al.* 1995; Micevski *et al.* 2002).

Basically, the testing process has two steps in which the first step is to present a dataset to the model and the second step is to compute the model error. It is obvious that the model performance must ideally be tested using unseen data (i.e. not used in the construction stage of the model or the calibration of the model) (Wilmot and Cheng 2003). To achieve this, one common method is to randomly divide the existing dataset into two portions in which one portion is used in the construction stage of the model and the other is used for testing the model. This method had been used extensively in testing deterioration models for infrastructure facilities such as bridge decks (Madanat and Ibrahim 1995; Madanat *et al.* 1995), pavements (Alsugair and Al-Qudrah 1998; Lou *et al.* 2001) and drainage pipes (Micevski *et al.* 2002; Baik *et al.* 2006).

2.4.5 Methods for Identifying Significant Factors

Identification of significant factors that define the underlying process is also one of the important tasks in construction of engineering models. The aim of this task is to determine a set of significant inputs from a superset of potentially useful inputs (Saxen and Pettersson 2006). This task obviously can result in a reduced number of inputs used in the models which have the following benefits:

- As the input dimensionality decrease, the computational complexity and memory requirements of the model decrease (Muttil and Chau 2007).
- As the number of inputs decrease, the number of training data (sample size) also decrease (Saxen and Pettersson 2006).
- Poor convergence and poor model accuracy can be reduced from the exclusion of irrelevant inputs (Olden *et al.* 2004).
- By paying more attention on the set of significant factors, the design and operation of the system being analyzed could be improved (Baik *et al.* 2006).

This task has long been addressed, as can be seen in the reviews by Gevrey *et al.* (2003). As a result, a number of quantification methods that attempt to identify the most significant factors have been developed. They can be broadly classified into screening methods, local sensitivity analysis methods and global sensitivity analysis methods (Saltelli *et al.* 2000).

Screening methods are often used for models that are computationally expensive to evaluate and have a large number of input variables. The most commonly used screening methods are principal component analysis and cluster analysis (Tabachnick and Fidell 2001). The objective of these two methods are to condense the information contained in a number of original variables into a smaller set of variables with a minimum loss of information (i.e. most accountable for variations between them).

Global sensitivity analysis methods are considered the most effective way to evaluate the impact on output of changes in input variables (Saltelli *et al.* 2000). They have two important properties. The first is the inclusion of the shape and scale of probability distribution functions of input variables. The second is the estimation of the sensitivity estimates of individual variables while varying other variables. However, these properties are less practical when the distribution of variables is unknown or costly to obtain and when there are a large number of variables which will require an enormous amount of computing time.

In the local sensitivity analysis, the impact of the individual variables to the model output can be evaluated by several simpler methods. Examples are statistical tests such as Wald or Student *t*-tests (Baik *et al.* 2006), stepwise methods (Coppola *et al.* 2003; Gevrey *et al.* 2003; Ha and Stenstrom 2003), partial derivatives (Olden and Jackson, 2002), connection weight analysis (Olden *et al.* 2004) and Garson's algorithm (Olden and Jackson, 2002). In particular, the connection weight analysis and Garson's algorithm were two specific methods for handling the specific structure of NN models. Furthermore, the connection weight analysis was shown, in the study by Olden *et al.* (2004) with simulated data, to be better than the other methods such as Garson's algorithm, forward stepwise method and partial derivatives in identifying the significant input variables to the output of NN models.

2.5 Review Conclusions

Rigid pipes (e.g. concrete and vitrified clay) are still dominantly used in sewer and stormwater pipe systems. The deterioration of rigid pipes is affected by various factors and probabilistic damage events. Currently, the signs of deterioration are often observed using the popular close circuit television (CCTV) inspection technique. The deterioration of rigid sewers and stormwater pipes can be divided into structural and hydraulic deterioration. The structural deterioration, which is characterized by structural defects, reduces the physical integrity of pipes and can eventually lead to pipe collapse. On the other hand, the hydraulic deterioration, which is characterized by hydraulic defects, reduces the internal cross-sectional area of pipes and increases the roughness coefficient, and eventually leads to pipe blockage.

In current management practice of stormwater pipes in Australia, only a fraction of pipe networks are subjected to one-time assessment using CCTV inspection and a condition grading scheme. A pipe can be assessed by its structural and hydraulic condition at the time of inspection which allows making decisions on whether maintenance and rehabilitation are needed to be carried out. Although the processing of CCTV-recorded defects is considered inherently subjective, these data are still the only available information for both asset managers and researchers in Australia.

Development of deterioration modes that can predict current and future condition of infrastructure assets has received increased attention. This has resulted in a number of deterioration models which can be broadly classified as deterministic models, statistical models and artificial intelligence models. These deterioration models in the past were often developed using samples of inspected assets (e.g. CCTV-inspected pipes) and contributing factors. A number of advanced calibration techniques such as genetic algorithm (GA) and Bayesian Markov Chain Monte Carlo (MCMC) simulation have also been mathematically developed to improve the predictive performance of the deterioration models considering the subjectivity and scarcity of sample data and the probabilistic nature of the deterioration process.

Although there are some disadvantages associated with the statistical models, these models are still better than the deterministic models in handling integer valued outputs (i.e. pipe conditions) and the probabilistic nature of the pipe deterioration. Therefore, the statistical models using Markov chain, ordered probit (OP) and multiple discriminant analysis (MDA) were chosen for this study. Furthermore, there are several advantages in artificial intelligence models in which neural network (NN) and probabilistic NN models emerge as powerful and flexible tools for modeling infrastructure facilities, where data scarcity, probabilistic deterioration process and noisy data are the major issues. Nevertheless, the NN and PNN models have not been used for stormwater pipes. Hence, NN and PNN models with advanced calibration techniques such as GA and Bayesian MCMC were also chosen as competing models against the statistical deterioration models in searching for the best suitable models for this study.

In order to compare the performance of these deterioration models, the goodness-of-fit test and the confusion matrix analysis were chosen in this study. These methods are popular and also can be used with outputs with ordinal values such as the pipe condition in this study. Finally the local sensitivity analysis was chosen to identify the significant factors that affect the output of the deterioration models except for the model using Markov chain (this is because the Markov model uses only age factor). The forward stepwise method was chosen for the deterioration model using MDA, the Wald-test was chosen for the model using OP. The connection weight analysis was chose for the model using NN and the backward stepwise method was chosen for the model using PNN.

CHAPTER 3 DEVELOPMENT OF DETERIORATION MODELS

3.1 Overview

The structural and hydraulic deterioration of stormwater pipes have been one of the major causes for the interrupted service of stromwater drainage systems. However, maintaining the intended performance of stormwater pipes is not an easy task because of the limited budget for maintenance and rehabilitation (M&R) and massive lengths of pipes. The need for deterioration models, which can predict current and future condition of pipes is increasing because the predicted information can be used for budget planning and effective M&R on the 'right' pipes (i.e. the pipes are in poor condition). Development of structural and hydraulic deterioration models for stormwater pipes is the primary aim of this study. The secondary aim of this study is to identify significant factors that affect the performance of these models.

The basic steps used in this study are summarized in Figure 3-1 which also shows the chapter layout. The details of these steps are given in various sections of this chapter. It should be noted that these models were developed to predict pipes in one of three conditions to suit the case study in Chapter 4 which uses data obtained based on the Sewer Inspection Reporting Code of Australia (WSAA 2002). The extension to a larger range like '1 to 5' (WSAA, 2006) can be done in a similar manner.

In Section 3.2, an ideal deterioration model is considered for both structural and hydraulic deterioration. From this ideal model, two targets were derived for the construction of practical deterioration models. The first target is the estimation of condition changes over time for the pipe population. The second target is the estimation of condition changes overtime for individual pipes. A list of potential contributing factors, which can be used as model inputs for practical deterioration models, is also presented in this section.

In Section 3.3, five practical deterioration models using five different modelling techniques are presented together with their calibration techniques. These five models can be applied to model both structural and hydraulic deterioration. These five models were compared on a case study (detailed in Chapter 4) so that the best possible deterioration model can be identified to satisfy the aim of this study.

In Section 3.4, the methods for assessing the predictive performances of these models are presented. In Section 3.5, the methods for identifying significant factors from these practical deterioration models are presented. Section 3.6 presents the chapter summary.

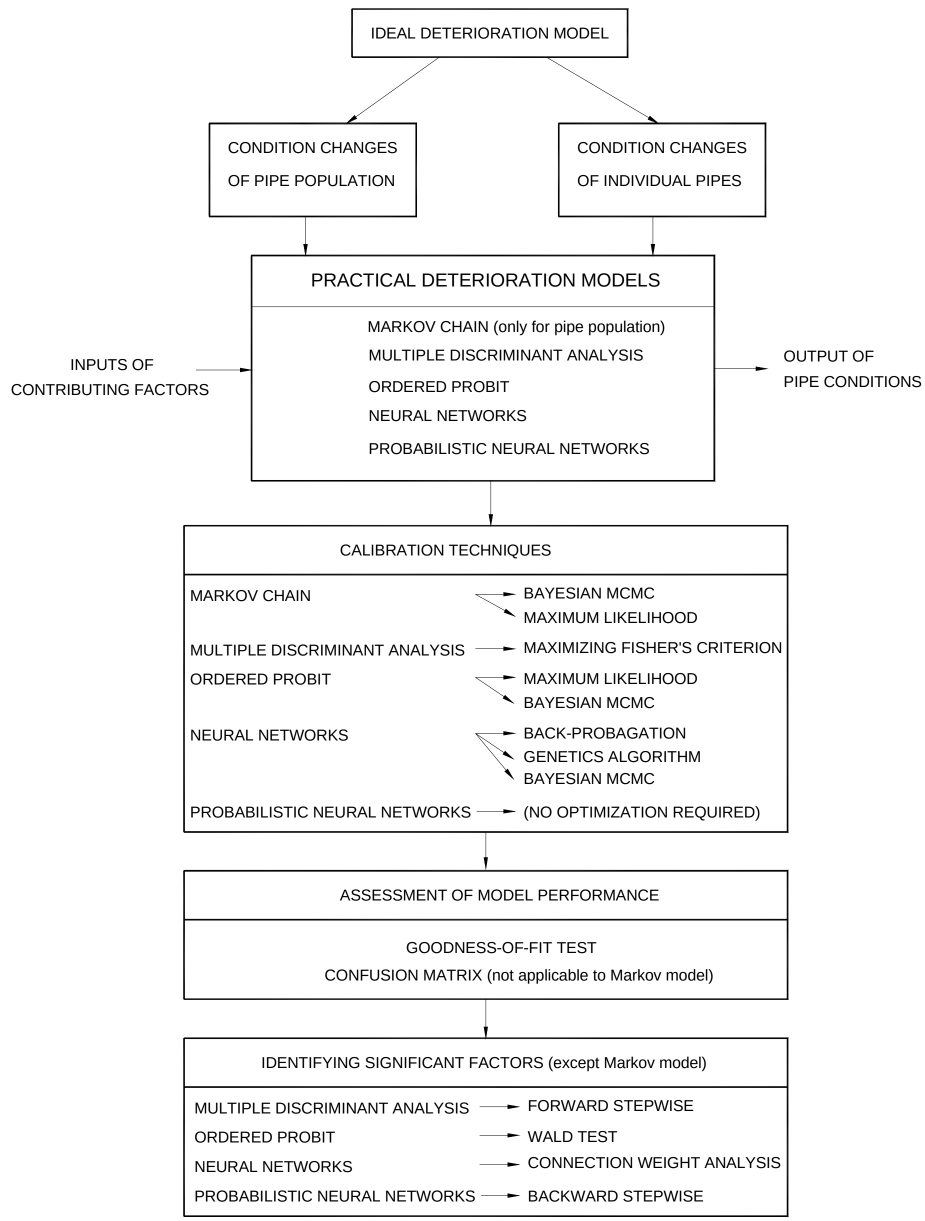

Figure 3-1: Summary of major steps in the development of deterioration models

3.2 Ideal Deterioration Model (IDM)

Section 2.2 clearly identified several major mechanisms leading to the deterioration of rigid sewers and stormwater pipes. These mechanisms are primarily attributed to many contributing factors (e.g. traffic load, static load, debris, tree roots, soil type, pipe size and buried depth). More importantly, a three-phase development of deterioration of combined sewers was considered in WRC (1983) and these three phases were translated into a 'bath-tub curve' for management planning by Davies *et al*. (2001a) for sewers and by Kleiner and Rajani (2001) for water pipes.

Based on the above ideas, the present study considered an ideal deterioration model (IDM) using assumed deterioration curves for both structural and hydraulic deterioration of stormwater pipes. The IDM defined each pipe by a different deterioration curve because pipes in reality deteriorate differently from one to another due to many contributing factors. For example, some young pipes may experience structural or hydraulic failures in one area whilst older pipes still work well in other areas or even in the same area.

Before going into the details of the IDM, it is worth mentioning that the IDM for the structural deterioration should be constructed separately to the IDM for the hydraulic deterioration in the case that regular or longitudinal data are available. This is because the structural deterioration process is different with the hydraulic deterioration process and the effects of contributing factors on the structural deterioration process are different with those of contributing factors on the hydraulic deterioration process.

The IDM is shown in Figure 3-2 where individual pipes presumably have their own deterioration curve pattern as marked Pipe *1*, Pipe *2*,..,Pipe *n*. This figure also shows how pipes change their condition over time represented by age from start-up phase to operation phase and until they reach the rehabilitation phase when structural or hydraulic failures are likely to occur if no maintenance is carried out. The 'age' is a unique factor that was used to express the change of pipe condition because 'age' complies with most M&R scheduling of asset management. It can be noted from this figure that a threshold line, which is at condition 3, defined the rehabilitation phase where pipes need rehabilitation or replacement, since they approach the condition that is considered not safe and economical to operate according to some criteria.

Phase 1 is called the start up-phase where any major defects identified during construction and system testing are fixed to bring pipes back to its original perfect condition (i.e. condition 1). Although some minor defects may not be detected when pipes step into the operation phase (phase 2), the condition of pipes at the beginning of phase 2 is assumed to be in condition 1. During the operation phase, pipes will deteriorate due to many causes such as chemical corrosion and mechanical loads in a way that deterioration rates of pipes may not be the same due to many contributing factors such as pipe size, pipe location and random damage events.

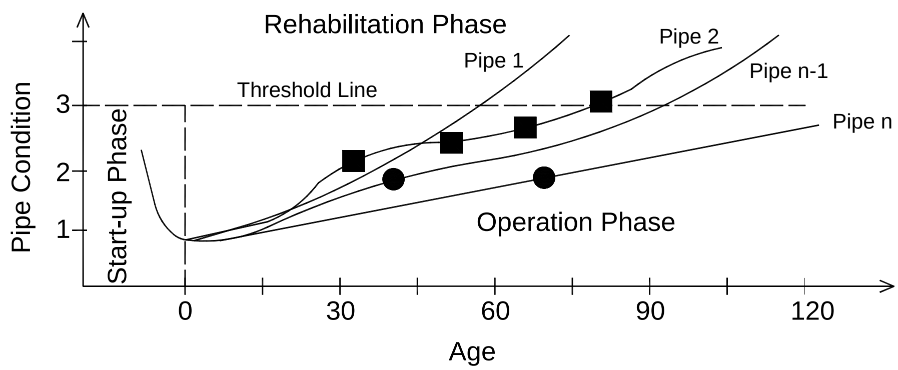

Figure 3-2: Illustration of ideal deterioration curves

When M&R occurs in a drainage system, two age definitions can be used. The first is the absolute age, which shows the absolute change of age from its construction. The second is the reference age, which shows the adjusted age of the pipe that receives M&R and return to a perfect condition in order to make a consistent dataset for the management of pipes. For example, after receiving an M&R action, a pipe of age 30 in condition 3 will return to condition 1 with reference age of zero and absolute age of 30. By doing this, the pipe is treated as a new pipe given that all defects are fixed.

3.2.1 Condition Changes of Individual Pipes and Pipe Population

The IDM allows monitoring the condition changes of individual pipes over time. The condition changes of individual pipes show the condition of any particular pipe, as compared to the 'like new' condition, given the contributing factors (e.g. pipe size and pipe age) of the pipe. This monitoring allows correctly directing M&R actions on pipes that are considered as at risk. Furthermore, this IDM also allows monitoring the condition changes of pipe population over time as shown in Figure 3-3. The curves in this figure show the proportions of pipes in each condition at any time during the expected life and thus are useful for budget planning and estimating of expected life of pipes.

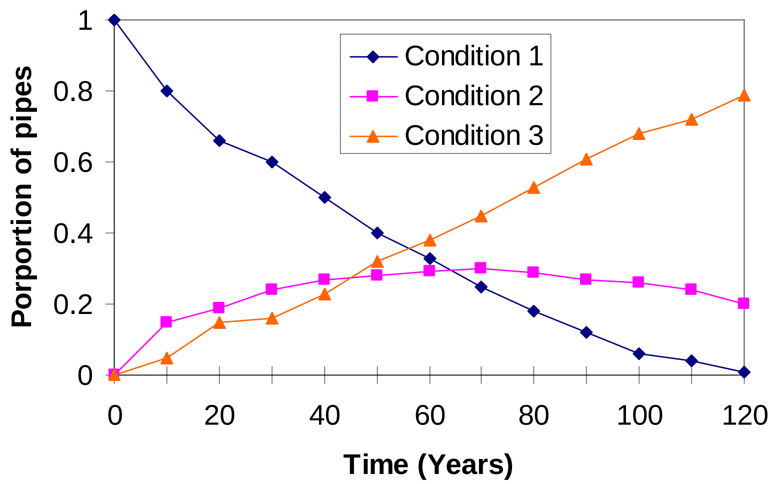

Figure 3-3: Condition changes of pipe population (hypothetical data)

3.2.2 Construction of IDM with Real Data

The shape of each deterioration curve pattern in the IDM can be broadly identified when several points (i.e. inspected pipe condition) as ‘squares’ marked in the Figure 3-2 along the age axis are available. This is the case of having longitudinal data which could be collected using CCTV inspection or recently advanced inspection techniques like sonar and radar. However, collecting such real data for the construction of the IDM is an impossible task when technological restraints, the massive number of pipes and limited budget are considered. Instead of longitudinal data, the current practice is to obtain snapshot data (one inspection only during the pipe lifetime) of a sample set of pipes. These snapshot data are marked as ‘circles’ in Figure 3-2. Therefore, only a point of the deterioration curve can be seen.

The IDM is still the basis for the development of practical deterioration models in Section 3.3 for capturing condition changes of individual pipes and pipe population with snapshot data. The pipe condition and proportions of pipe in each condition are the two outputs from the deterioration models to be developed.

3.2.3 Input Factors to Practical Deterioration Models

A number of factors were identified in Section 2.2, which directly or indirectly affect the structural and hydraulic deterioration of sewers and stormwater pipes. However, it is expected that many more factors will emerge as the knowledge of the complex deterioration process is increased. A list of potentially contributing factors that affect the deterioration process of stormwater pipes are compiled and synthesized from literature review and expert opinion. These factors, which are classified to account for structural and hydraulic deterioration, are given in Table 3-1. These factors are categorized into two groups, namely, construction and operation factors and M&R factors.

Factors can also be viewed as static and non-static (time-dependent). However, the distinction between static and non-static factors is not always clear-cut. For example, the pipe slope can be viewed as a static factor but in reality there is a slight change of slope over time due to the settlement of bedding. The rationale for introduction of time-dependent property is to increase the accuracy in finding the underlying deterioration process (Kleiner and Rajani 2000). However, it is obvious that the use of time-dependent factors in any model requires longitudinal data (continuous data over a certain period) that are normally not available and costly to obtain in the future. Therefore all factors were considered static (time independent) as outlined in Section 1.4 (Scope and Assumptions) of this thesis. This excludes pipe age, structural condition and hydraulic condition. Furthermore, M&R factors were not used in the implementation of deterioration models due to lack of data.

3.3 Development of Practical Deterioration Models

As outlined in Section 1.5 (Methodology), the practical deterioration models for predicting structural and hydraulic deterioration of stormwater pipes in this study were developed as empirical or inferential models. This is because the deterioration of stormwater pipes is a complex process due to multiple causes, probabilistic damage events and effects of many factors, which can not be determined experimentally. Therefore, it is attempted with the inferential models for achieving the objective in this study.

Table 3-1: List of potentially contributing factors

Factor Groups	Contributing Factors	
	Structural deterioration	Hydraulic deterioration
Construction and operation factors	Pipe size	Pipe size
	Pipe wall thickness	Pipe wall thickness
	Pipe depth	Pipe depth
	Pipe slope	Pipe slope
	Laid year	Laid year
	Pipe material	Pipe material
	Pipe joint material	Pipe joint material
	Pipe length	Pipe length
	Pipe location	Pipe location
	Soil type	Soil type
	Backfill material	Backfill material
	Ground water	Ground water
	Traffic counts	
	Bus route	
	Tree counts	Tree counts
	Tree types	Tree types
	pH of soil	pH of soil
	pH of water inside pipe	pH of water inside pipe
	Existing sewer below	Existing sewer below
	Hydraulic condition	Structural condition
M&R factors	Pipe collapse records (counts)	Blockage records (counts)
	Repaired year	Cleaned year
	Repaired length	Cleaned length
	Condition before repair	Condition before cleaning
	Condition after repair	Condition after cleaning
	Repair method	Cleaning method
	Repair unit cost	Cleaning unit cost
	Repair time	

As described in Section 3.2.2, the practical deterioration models can be constructed based on the IDM for the case of pipes with snapshot data. The snapshot sample of pipes with known pipe conditions was used to predict the conditions of the remaining pipes that were not inspected. This can be done by 'learning' the partially known deterioration patterns of different pipes in the sample in order to infer the pipe condition of the remaining pipes. Furthermore, the future condition of individual pipes can also be predicted by the same concept. This view of 'learning from deterioration patterns' was incorporated in the development of practical deterioration models (the term 'practical' has been omitted in subsequent sections).

The availability of snapshot data (against regular or longitudinal data), the use of ordinal grading of pipe condition and the probabilistic nature of the deterioration processes were the important factors in selecting the modelling technique to develop deterioration models. Based on the conclusions in Chapter 2, three statistical modelling techniques namely, Markov chain, multiple discriminant analysis and ordered probit (a member of ordinal regression), and two artificial intelligence techniques, namely, neural networks and probabilistic neural networks were selected in this study. They were used to develop five deterioration models, namely:

- Markov model
- Multiple discriminant deterioration model (MDDM)
- Ordered probit deterioration model (OPDM)
- Neural network deterioration model (NNDM)
- Probabilistic neural network deterioration model (PNNDM)

These deterioration models were constructed using the currently available snapshot data of CCTV graded pipe conditions and contributing factors. Furthermore, they are considered generic models because they can be applied to both structural and hydraulic deterioration of stormwater pipes in this study and can also be used for sewers.

The Markov model was developed to predict the condition changes of pipe population; this model was not able to be used for predicting condition changes of individual pipes due to the lack of regular pipe condition data. The four remaining deterioration models were developed to predict the condition changes of individual pipes. They can also be used for predicting the condition changes of pipe population by summing up the predicted conditions of individual pipes and computing the proportions.

With regards to the calibration of the deterioration models, optimization techniques were used for maximizing or minimizing an objective function. For the objective function with high dimensionality and complex solution space, the local optima may occur in such optimization processes, which adversely affect the results of model calibration and hence the performance of the deterioration models. As a result, different optimization techniques were used for the calibration of deterioration models in this study. Markov model was calibrated using two different techniques, namely, the Bayesian MCMC simulation using Metropolis-Hastings algorithm and the maximum likelihood method. The MDDM was calibrated by maximizing the Fisher's criterion. The OPDM was calibrated by two different competing techniques, namely, the maximum likelihood and the Bayesian MCMC using Gibb sampler as local optimum may occur. The NNDM was calibrated by three different techniques, namely, the back-propagation, the GA and the Bayesian MCMC simulation because of the problem of local optimum (as stated above) and weight uncertainty. The calibration of the PNNDM was based on a trial and error approach (since it required only one model parameter). These calibration methods are discussed in details later in the chapter.

3.3.1 Markov model

The Markov model was developed in this study for predicting the condition changes of pipe population using snapshot data. This Markov model was not able to predict the condition changes of individual pipes due to the lack of longitudinal data. This Markov model was based on the Markov model and calibration technique using the Bayesian MCMC simulation used by Micevski *et al.* (2002). The Markov model of this study can be applied to both structural and hydraulic deterioration. This is because the structural and hydraulic deterioration processes have similar Markov properties such as similar state space (condition states) and stochastic process as identified in Section 2.2. Furthermore, there are two types of Markov models, namely, state-based model and time-based model (Mauch and Madanat 2001; Mishalani and Madanat 2002). Their properties were discussed in Section 2.4.2.1 in which time-based model requires longitudinal data. Therefore, the state-based Markov model was adopted in this study, (the term 'state-based' has been omitted from now on).

3.3.1.1 Assumptions of Markov Model

The assumptions of the Markov model are:

- Stormwater pipe deterioration is considered to be continuous in time; however, they can be captured using discrete unit time of normally one year.
- Pipes exhibit the condition change over time following their stochastic process
- The future condition of pipes can be assumed to depend only on present condition
- Stationary transition matrix is used.
- Multi-state transition is possible; meaning the structural or hydraulic condition of pipes can jump from condition 1 to condition 3 over a unit time.
- No M&R action is accounted for due to lack of data.
- When applied to predict the condition changes of pipe population, all pipes are assumed to come from a homogeneous population and hence the 'average' deterioration characteristic of the population can be captured. This is acceptable when considering a population of stormwater pipes in a local catchment or within the local government council boundaries.

3.3.1.2 Structure of Markov Model

The structure of the Markov model is based on Markov chain theory (Ross 1972). 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 as one-year and was indexed using non-negative integers. The important property is that the probability P_{ij} depends only on the present state (state *i*), which means the process is independent of historical states (Ross 1972). The Markov model uses a square transition matrix **P** as shown in Equation (3-1).

It can be seen from Equation (3-1) that P_{ij}=0 if $i > j$, since no M&R action is accounted for and hence P_{33} is always equal to 1.

$$\mathbf{P} = \begin{bmatrix} P_{11} & P_{12} & P_{13} \\ 0 & P_{22} & P_{23} \\ 0 & 0 & 1 \end{bmatrix} \tag{3-1}$$

where: $\sum_{j=1}^{3} P_{ij} \quad = 1$

$i \quad = 1 \text{ to } 3$

$P_{ij} \quad = [0,1]$

If the initial condition state at year 0 expressed by $\mathbf{C}^0 = (C_1^0, C_2^0, C_3^0)$ is known deterministically or probabilistically, the probability distribution $\mathbf{C}^t = (C_1^t, C_2^t, C_3^t)$ of being in one of three condition states at year t can be computed using Equation (3-2) derived from Chapman-Kolmogorov formula (Ross 1972) as below:

$$(C_1^t, C_2^t, C_3^t) = (C_1^0, C_2^0, C_3^0) \bullet \begin{bmatrix} P_{11} & P_{12} & P_{13} \\ 0 & P_{22} & P_{23} \\ 0 & 0 & 1 \end{bmatrix}^t \tag{3-2}$$

where: C_i^t is the probability being in the condition state i at year t

C_i^0 is the probability being in the condition state i at year 0

$\sum_{i=1}^{3} C_i^t \quad = 1$

$t \quad = 0, 1, 2, 3\ldots$

It is clear that if the transition matrix and the condition at year '0' are known, then the future condition of a pipe at any time t can be calculated using Equation (3-2). However, as mentioned earlier, due to the lack of longitudinal data, it is impossible to estimate the transition matrix for each pipe. On the other hand, if the sample is assumed to represent a 'homogenous' population, the transition matrix for pipe population can be estimated from the sample of pipes. In this case, the effects of contributing factors are ignored. This means that all pipes now have the same transition matrix and this transition matrix represents the behavior of pipe population with regard to the condition changes over time.

The condition changes of pipe population can be established as follows. The initial condition of a pipe becomes the initial proportion of pipes in each condition. Since it is often assumed that the pipe was initially in condition 1 with certainty, this means that 100% of pipe population was also initially in condition 1. The proportion of pipes in each of three possible conditions at any time *t* can be computed using Equation (3-2) where C_i^t means the proportion of pipes in condition *i* at year *t*. Since the condition of pipes at year '0' is often assumed to be in good condition, the remaining task is to estimate the transition matrix, which is also called calibrating the Markov model.

3.3.1.3 Calibration of Markov Model

The calibration of Markov model is the task of applying the selected calibrating technique on a calibration dataset to estimate the model parameters or the transition probability. The calibration dataset is often randomly selected from a sample dataset and accounts for 70-80% the sample size. The remaining dataset is called the test dataset and can be used to test the Markov model. In the case of stormwater pipes, the dataset is a sample of pipes that were CCTV-inspected and graded using a condition grading scheme.

As discussed in Section 2.5, the calibration technique using the Bayesian Markov chain Monte Carlo (MCMC) simulation was used in this study since it was the proven technique that can be used with snapshot data currently available for stormwater pipes. Furthermore, a non-linear optimization technique implemented by the Excel Solver® was used as an alternative technique for calibrating the Markov model.

<u>Bayesian Markov Chain Monte Carlo Simulation</u>

The Bayesian theorem has been widely used to estimate random variables via their conditional distribution in many engineering problems (Brooks 1998). It is formulated in Equation (3-3):

$$P(\theta \mid D) = \frac{P(D \mid \theta) \times P(\theta)}{\int P(D \mid \theta) P(\theta) d\theta} \tag{3-3}$$

where: θ is a random variable whose value to be estimated

D is a random variable whose value or probability distribution is known

$P(\theta \mid D)$	is posterior distribution of θ given D which relates to θ via a model
$P(D \mid \theta)$	is the likelihood to observe D given unknown θ (in this study) or the sampling distribution of D given known θ
$P(\theta)$	is prior probability of θ
$\int P(D \mid \theta)P(\theta)d\theta$	is a normalizing factor and always resulted in a value

This Bayesian approach allows estimating true values of θ from both prior knowledge about θ and current knowledge obtained from data, depending on which ones are closer to the true values.

In calibrating Markov models (i.e. estimating the transition probabilities), the Bayesian approach was used to estimate P_{ij} based on the observed pipe condition and prior knowledge of P_{ij}. This was done via sampling a large number of P_{ij} from its posterior distribution as shown in Equation (3-4).

$$\pi(\mathbf{P} \mid \mathbf{Y}, M) \approx \mathrm{L}(\mathbf{Y} \mid \mathbf{P}, M) \times \pi_0(\mathbf{P}) \qquad (3\text{-}4)$$

where:

$\pi(\mathbf{P} \mid \mathbf{Y})$	is the posterior distribution of P_{ij}
$L(\mathbf{Y} \mid \mathbf{P}, M)$	is the likelihood to observe a set $\mathbf{Y}$ of pipe conditions, $\mathbf{Y} = \{y_1, y_2, ..., y_n\}$, where n is the number of pipes in the sample
$\pi_0(\mathbf{P})$	is the prior distribution of P_{ij}
M	is Markov model

In this study, the prior distribution $\pi_0(\mathbf{P})$ was arbitrarily chosen as a uniform distribution in interval [0, 1], since there was no available knowledge about the proper distribution of P_{ij}. As a result, the posterior distribution $\pi(\mathbf{P} \mid \mathbf{Y})$ is proportional to the likelihood function $L(\mathbf{Y} \mid \mathbf{P}, M)$ which was determined as follows. From the joint probability theory, the likelihood to observe $\mathbf{Y}$ can be expressed in Equation (3-5), which was then transformed into logarithm format as in Equation (3-6) for faster computing.

$$L(\mathbf{Y} \mid \mathbf{P}, M) = \prod_{t=1}^{T} \prod_{i=1}^{3} (C_i^t)^{N_i^t} \qquad (3\text{-}5)$$

$$\log[L(\mathbf{Y} \mid \mathbf{P}, M)] = \sum_{t=1}^{T} \sum_{i=1}^{3} N_i^t \log(C_i^t) \qquad (3\text{-}6)$$

where: t is the pipe age in years

T is the largest age found in the dataset

N_i^t is the number of pipes in condition i at year t

C_i^t is the probability in condition i at year t and can be computed by Equation (3-2)

The Metropolis-Hastings algorithm (MHA), a member of the MCMC simulation (Gelman *et al.* 1995), was chosen to perform sampling from the posterior distribution. MCMC simulation allows sampling from most types of posterior distributions with reliable results and easy coding for computer simulations. The basic idea behind MCMC simulation is the use of a Markov chain whose stationary probabilities are identical to the target posterior distribution (Ross 1997). This Markov chain is then run a large number of times until it converges to the stationary probability. After discarding the warm up runs, the remaining values can be used as the sampling data for the posterior distribution.

The MHA is based on the candidate-generating density $q(x, y)$ where $\int q(x, y)dy = 1$ for sampling from the target density $\pi(\cdot)$. In this study, $\pi(\cdot)$ is considered as the posterior distribution of the transition probability. The x and y are the values of transition probability. The candidate-generating density depends on the current state of the Markov chain, which means that when a process is at the point x this density generates a point y from $q(x, y)$. The new point y is always accepted if $\alpha(x, y) = \frac{\pi(y)q(y, x)}{\pi(x)q(x, y)} \geq 1$; otherwise, y can be accepted with a probability $\alpha(x, y)$. In other words, if the jump goes 'uphill', it is always accepted; if 'downhill', it is accepted with a non-zero probability. The density $q(x, y)$ is often chosen as a symmetric and multivariate density such as a multivariate normal distribution (i.e. $q(x, y) = q(y, x)$) for ease of implementation. The MHA using multivariate normal (MVN) density is shown below:

Step 1. Let n=0 and randomly generate initial values of P_{ij}, and choose variance-covariance matrix for MVN.

Step 2. Generate new value of P_{ij} using MVN with mean values equal to current P_{ij} and generate a random uniform number U.

Step 3. Evaluate posterior density with current values and new values of P_{ij}.

If the ratio of new evaluation and current evaluation is larger than U,

Accept new values

Current values = new values

Else

Reject new value

Step 4. $n = n+1$

Step 5. Go to step 2

The initial values of the MHA can be arbitrarily chosen, since in theory, they do not affect the convergence to the target distribution of the chain (Brooks 1998). The variance-covariance matrix for the MVN can be arbitrarily chosen as well. However, some notes are worth mentioning here. If too large a value is chosen for the variance-covariance matrix of MVN the MHA may reject most of proposed jumps and thus the chain gets stuck in one of several regions of search space. Choosing too small values makes the chain crawl to the target distribution. One popular way to find a suitable variance-covariance matrix is to run the MHA with a randomly generated variance-covariance matrix. A sample of the target density can be obtained which is called a pilot sample. This pilot sample is then used to compute the variance-covariance values. A criterion to check the suitability of the chosen variance-covariance matrix is that the acceptance rate in step 3 of the algorithm should be close to 0.234 (Roberts and Rosenthal 2001).

Once the sample data of transition probability P_{ij} are obtained using MHA, the point estimators and confidence interval (CI) for these transition probabilities can be determined as follows. Although the posterior distribution of the transition probability may not be of normal type, its sample data is considered to be a normal distribution from the Central Limit Theory. Furthermore, the sample mean can be used as an unbiased point estimator for the mean values of transition probability from basic probability theory. However, this point estimator could not tell how close it is to the 'true' mean value of the posterior distribution since this 'true' mean is not known. Therefore the confidence interval (CI) or interval estimate is required and the commonly used 95% CI can be computed for each transition probability P_{ij} as in Equation (3-7)

$$\begin{cases} \text{Upper-limit} = \bar{X} + t_{0.05,df}\dfrac{\sigma_X}{\sqrt{n}} \\ \text{Lower-limit} = \bar{X} - t_{0.05,df}\dfrac{\sigma_X}{\sqrt{n}} \end{cases} \tag{3-7}$$

where:

$\bar{X}$	is the statistical mean of the sample data of transition probability P_{ij}
σ_X	is the standard deviation of the sample data of transition probability P_{ij}
n	is the sample size
$t_{0.05,df}$	is the 95% confidence interval of the *t*-distribution
df	is the degree of freedom

<u>Non-linear optimization</u>

Apparently, the MHA looks similar to optimization techniques that maximize the posterior distribution. However, the fundamental difference is that during the run of the MHA, whenever the new evaluation is smaller than the current evaluation, the new value of P_{ij} can be accepted at an adequate rate. This situation is not acceptable in other optimization techniques. By doing this, the MHA sometimes steps back a while to avoid being stuck at a local optimum. Furthermore, the outcome of the MHA is the set of sampling data, which increases the chance of capturing the true global optimum. A non-linear optimization technique implemented in the Excel Solver® as shown in appendix C.4 was used as an alternative technique for calibrating the Markov model in order to confirm the superiority of the MHA. The implemented optimization technique is based on the Generalized Reduced Gradient nonlinear optimization code developed by Leon Lasdon, University of Texas at Austin, and Allan Waren, Cleveland State University.

3.3.2 Multiple Discriminant Deterioration Model (MDDM)

As mentioned in Section 2.4.2.2, multiple discriminant analysis (MDA) is a member of a statistical method, called, Fisher's linear discriminant analysis that can be used for classifying or predicting individuals or objects into mutually exclusive and exhaustive multiple-classes based on a set of features (also called as independent variables or predictors) (Hair et al. 1998).

In this study, the multiple dicriminant deterioration model (MDDM) was developed using the MDA for classifying individual pipes into one of three classes (i.e. pipe conditions). Pipes are described by the contributing factors (i.e. the features of the objects). The rationale for using the MDA is that a pipe must be in one of three condition states at any time during their service life. It is therefore possible to use the MDDM for classifying the pipe among its feature space if the MDDM was calibrated with a sample of training patterns (i.e. pipes with known condition and known values of the contributing factors). The following sections present the assumptions, the structure and the calibration of the MDDM.

3.3.2.1 Assumptions of the MDDM

The MDDM was developed based on the following assumptions:

- Dependent variable is the pipe condition.
- Contributing factors are assumed to follow a multivariate normal distribution, which is required to use MDA.

3.3.2.2 Structure of the MDDM

Suppose a pipe population G of a stormwater pipe system is at any time made up of 3 sub-groups or classes: G_1, G_2 and G_3 representing three pipe conditions with 1 being perfect, 2 being fair and 3 being poor respectively. Each pipe in G is defined by K features or contributing factors and belongs to any of these three classes.

Suppose there are N training patterns of $(\mathbf{X}_i, Y_i)$ with $\mathbf{X}_i \in R^K$ (feature space) and $Y_i \in G$ (pipe condition), of which N_1 are from G_1, N_2 are from G_2 and N_3 are from

G_3. The MDDM was developed to assign a query pipe into to either G_1, G_2 or G_3 by a classification rule.

The classification rule can be constructed by first finding linear composites of contributing factors that transform the feature space R^K of contributing factors into a reduced space so that the class centroids are best separated. The class centroid can be computed as the mean vector of contributing factors in that class as shown in Equation (3-8). The linear composites, which are called discriminant functions, act as axes in the reduced space. It has been shown that the dimensionality of the reduced space is **min(**K, number of classes – 1) (Hair et al. 1998). Suppose that $K \geq 2$, there are two discriminant functions as shown in Equation (3-9). The classification rule can then be established by comparing the Euclidian distances in the reduced space from the query pipe to class centroids. In other words, the query pipe is assigned to the class which has the shortest distance. According to the Fisher's criterion, the class centroids can be separated by maximizing the ratio of between-class scatter and the within-class scatter (Hair et al. 1998) as shown in Expression (3-10).

$$\overline{\mathbf{X}_c} = \frac{1}{N_c}\sum_{i=1}^{N_i}\mathbf{X}_i \tag{3-8}$$

$$\begin{cases} D_1 = \beta_{11}X_1 + \beta_{12}X_2 + \ldots + \beta_{1K}X_K \\ D_2 = \beta_{21}X_1 + \beta_{22}X_2 + \ldots + \beta_{2K}X_K \end{cases} \tag{3-9}$$

$$\text{maximize } \left\{\frac{\boldsymbol{\beta}^T\mathbf{B}\boldsymbol{\beta}}{\boldsymbol{\beta}^T\mathbf{W}\boldsymbol{\beta}}\right\} \text{ with respect to } \boldsymbol{\beta} \text{ (vector of factor coefficients)} \tag{3-10}$$

$$\mathbf{B} = \sum_{c=1}^{3} N_c(\overline{\mathbf{X}_c} - \overline{\mathbf{X}})(\overline{\mathbf{X}_c} - \overline{\mathbf{X}})^T \tag{3-11}$$

$$\mathbf{W} = \sum_{c=1}^{3}\sum_{i \in N_c}(\mathbf{X}_i - \overline{\mathbf{X}_c})(\mathbf{X}_i - \overline{\mathbf{X}_c})^T \tag{3-12}$$

where:

$\overline{\mathbf{X}_c}$ is the mean vector (or centroid) of the class c

N_c is the number of observations in the class c

$\boldsymbol{\beta}_1 = (\beta_{11}, \beta_{12}, \ldots, \beta_{1K})$ is the factor coefficients in discriminant function 1

$\boldsymbol{\beta}_2 = (\beta_{21}, \beta_{22}, ..., \beta_{2K})$ the factor coefficients in discriminant function 2

Figure 3-4 shows an example of classifying a query pipe into one of three conditions. The two discriminant functions appear to well separate the three class centroids. It can be seen that the query pipe has the shortest distance to the class centroid 2 which means that it should be in condition 2.

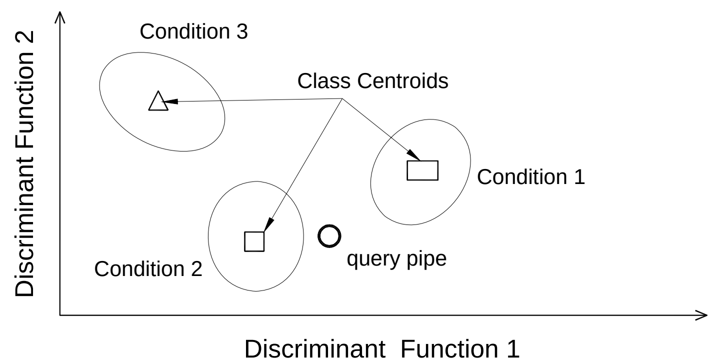

Figure 3-4. An illustration of three-group classifications

3.3.2.3 Calibration of MDDM

To effectively calibrate the MDDM, the sample size of each class must be larger than the number of factors used (Tabachnick and Fidell 2001). The calibrating process is to find $\boldsymbol{\beta}$ (or factor coefficients in discriminant functions) that maximize the Fisher's criterion. The problem of maximizing can be solved by taking partial derivative of Expression (3-10) with respect to $\boldsymbol{\beta}$ and set it equal to zero. After simplification, Equation (3-10) becomes the Equation (3-13) which can be solved using eigenvectors (Johnson and Wichern 2002).

$$(\mathbf{W}^{-1}\mathbf{B} - \boldsymbol{\lambda}\mathbf{I})\ \boldsymbol{\beta} = 0 \tag{3-13}$$

where: $\mathbf{W}$ and $\mathbf{B}$ are from Equations (3-11) and (3-12)

$\boldsymbol{\lambda}$ is the eigenvectors

$\mathbf{I}$ is the identity matrix

If the eigenvalues of $\mathbf{W}^{-1}\boldsymbol{\beta}$ are distinct, then there will be $r = \min\{K, \text{number of classes - 1}\}$ linear composites, i.e. $r = 2$ discriminant functions. Although the computing steps for calibrating MDDM appear to be time consuming, their solutions are incorporated in most statistical software packages such as SPSS®.

3.3.3 Ordered Probit Deterioration Model (OPDM)

The OPDM developed in this study was based on the ordered probit model of Madanat *et al.* (1995) for modelling bridge deterioration. The ordered probit technique has also been used in a number of other classification problems (Abdel-Aty and Abdelwahab 2004; Bennell et al. 2006) and modelling sewer deterioration (Baik *et al.* 2006). In general, the ordered probit technique was claimed to be the most appropriate technique in handling non-continuous valued (or discrete valued) dependent variables.

3.3.3.1 Assumptions of OPDM

The OPDM was developed based on the following assumptions:

- Dependent variable is the pipe condition which takes on ordinal values.
- Measurement error or random part of the linear function is assumed to a follow normal distribution, as required by the OPDM.

3.3.3.2 Structure of OPDM

The structural or hydraulic deterioration of a pipe *i* is considered a continuous process which can be described by a deterioration curve Z_i as shown in Figure 3-5.

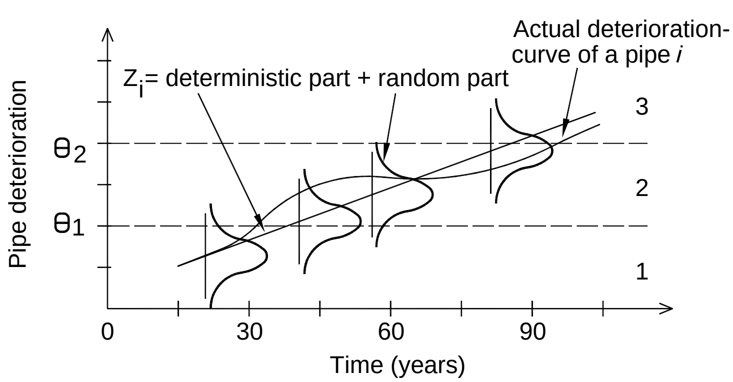

Figure 3-5. Illustration of the ordered probit model

This figure also illustrates the OPDM. The deterioration curve Z_i represents the continuous deterioration of pipes and therefore the values of Z_i are defined in $\left[0, +\infty\right]$.

The deterioration curve Z_i, which consists of a deterministic part and a random part, is modelled in Equation (3-14). The deterministic part m_i and the random part ε_i are given in Equations (3-14) and (3-15). The use of $\log(Z_i)$ ensures that the continuous deterioration Z_i is positive. The deterministic part m_i is often chosen as a linear composite of contributing factors such as pipe size and pipe depth, and thus allows prediction for individual pipes. The random part ε_i is often known as measurement error due to the subjectivity of the CCTV inspection method, random damage event and equipment noise. This random part is often assumed to follow a normal distribution with zero mean and unit variance. This implies that $\log(Z_i)$ can be treated as a random variable, which follows a normal distribution with mean value of m_i and unit variance.

$$\log(Z_i) = m_i + \varepsilon_i \qquad (3\text{-}14)$$

$$m_i = \sum_{k=1}^{K} \beta_k X_k \qquad (3\text{-}15)$$

where:

Z_i	is the deterioration for the pipe *i* and $Z_i \geq 0$
m_i	is a linear composite of contributing factors
ε_i	is measurement error
$\mathbf{X}_i = (X_{i,1}, X_{i,2}, ..., X_{i,K})$	is the vector of *K* explanatory factors for the pipe *i*.
$\boldsymbol{\beta} = (\beta_1, \beta_2, ..., \beta_K)$	is the vector of *K* coefficients.

The deterioration curve is segmented into three sections corresponding to three condition states by two threshold values (i.e. θ_1 and θ_2 in Figure 3-5). A pipe is considered in the condition one, two or three depending on its $\log(Z_i)$ value against two threshold values θ_1 and θ_2. Since $\log(Z_i)$ is modelled as a random variable, a pipe belongs to condition one, two or three can only be determined with probabilities $P_{i,1}$, $P_{i,2}$ and $P_{i,3}$ respectively. By using Equations (3-14) and (3-15) and the two threshold values, these probabilities can be formulated as in Equations (3-16) to (3-18) and the pipe *i* will be assigned or predicted to the condition that has the highest probability.

$$P_{i,1} = probability\left(\log(Z_i) < \theta_1\right) = F(\theta_1 - m_i) \tag{3-16}$$

$$\begin{aligned} P_{i,2} &= probability\left(\theta_1 < \log(Z_i) < \theta_2\right) \\ &= F(\theta_2 - m_i) - F(\theta_1 - m_i) \end{aligned} \tag{3-17}$$

$$P_{i,3} = 1 - P_{i,1} - P_{i,2} \tag{3-18}$$

where: $P_{i,c}$ is the probability that the pipe *i* belongs to condition c

F is the cumulative normal distribution function of ε_i

θ_1 and θ_2 are the threshold values.

3.3.3.3 Calibrating OPDM

The model calibration was used to estimate the model parameters from the sample data. Among others (Tabachnick and Fidell 2001), the Maximum Likelihood (ML) technique and the Bayesian MCMC simulation using the Gibb sampler were used separately to calibrate the OPDM. Although the ML technique is more frequently used, its solution was counterchecked by the Bayesian MCMC in this study as the local optimum may occur.

A/ Maximum Likelihood (ML)

Suppose that there is a sample of *N* observations of pipes $\{\mathbf{X}_i, Y_i\}$ in which $\mathbf{X}_i$ and Y_i are respectively the vector of contributing factors and the known (structural or hydraulic) condition of a pipe *i*. The problem of interest is to use this sample of observations to estimate the unknown model parameters which are the vector $\boldsymbol{\beta}$ of factor coefficients and θ_1 and θ_2. Let $f\left(\{\mathbf{X}_i, Y_i\} \mid \boldsymbol{\beta}, \theta_1, \theta_2\right)$ denotes the joint probability distribution function of *N* observations of pipes $\{\mathbf{X}_i, Y_i\}$ conditional on the model parameters. Since the model parameters are assumed unknown, the function f represents the likelihood that the *N* observations of pipes $\{\mathbf{X}_i, Y_i\}$ will be observed when the model parameters take their true values. It would therefore seem that the estimates of the model parameters would be those values that yield the largest likelihood to observe the N observations of pipes $\{\mathbf{X}_i, Y_i\}$. Thus it becomes a problem of maximizing the likelihood function as given in Equation (3-19).

$$f\left(\{\mathbf{X}_i, Y_i\} \mid \boldsymbol{\beta}, \theta_1, \theta_2\right) = \prod_{i=1}^{N} P_{i,1}^{a_i} P_{i,2}^{b_i} P_{i,3}^{c_i} \tag{3-19}$$

where:

	$P_{i,c}$	is the probability that the pipe i belongs to the condition c, as estimated from Equations (3-16) to (3-18).
	a_i	= 1 if pipe i was observed in condition 1 and zero, otherwise.
	b_i	= 1 if pipe i was observed in condition 2 and zero, otherwise.
	c_i	= 1 if pipe i was observed in condition 3 and zero, otherwise.
	N	Os the sample size

By substituting $P_{i,1}, P_{i,2}, P_{i,3}$ from Equation (3-16), (3-17), and (3-18) respectively into Equation (3-19), the likelihood function or the logarithm of likelihood function can be maximized. The SPSS® package can be used to run this maximizing process. Local optimum may occur and hence, an alternative Bayesian MCMC technique can be used to counter check.

B/ Bayesian MCMC using Gibbs Sampler

The Gibbs sampler is a member of the Bayesian MCMC simulation. In fact, the Gibbs sampler is considered as a special case of the MHA (Section 3.3.1.4) (Casella and George 1992). However, unlike with the MHA, the Gibb sampler allows sampling the random variables from a probability density without having to evaluate the density. Furthermore, in the Gibbs sampler only one variable can be updated at a time based on a conditional posterior distribution of the variable given other variables kept constant (Gelman et al. 1995; Altaleb and Chauveau 2002; Reis and Stedinger 2005). The conditional posterior distribution is required to be of analytical forms such as Gaussian or Weibull distributions. This process is different to the MHA where all variables are updated at a time and the posterior distribution can take any form. Through the use of the Gibbs sampler, it is able to avoid difficult calculations of the likelihood function as in the case of the MHA, replacing them with a sequence of easier calculations.

Similar to the MHA (Section 3.3.1.4), the Bayesian theorem in Equation (3-3) was used with the assumption of a uniform distribution for the prior probability of the model parameters (i.e. $\boldsymbol{\beta}, \theta_1$ and θ_2). As a result, the posterior distribution π of ($\boldsymbol{\beta}, \theta_1$ and θ_2) is proportional to the likelihood function as given in Equation (3-20).

$$\pi(\boldsymbol{\beta}, \theta_1, \theta_2 \mid \{\mathbf{X}_i, Y_i\}) = \prod_{i=1}^{N} P_{i,1}^{a_i} P_{i,2}^{b_i} P_{i,3}^{c_i} \tag{3-20}$$

The components $P_{i,1}^{a_i}, P_{i,2}^{b_i}$ and $P_{i,3}^{c_i}$ of Equation (3-20) are based on the cumulative Gaussian distribution as estimated from Equations (3-16) to (3-18). Therefore, the Gibb sampler can be used to estimate the model parameters by sampling from Equation (3-19). Suppose that there is a vector $\boldsymbol{\mu}$ of K model parameters including the factor coefficients $\boldsymbol{\beta}$ and two threshold θ_1 and θ_2, The Gibbs sampler works as follows:

Step 1: Randomly generate the initial values for K element (i.e. model parameters) of the vector $\boldsymbol{\mu}$ and set $n = 0$

Step 2: Simulate from Equation (3-19)

-A new value for the element 1 (denoted as μ_1^{n+1}) of vector $\boldsymbol{\mu}$ conditional on other elements (denoted as μ_{-1}^{n+1})

-A new value for the element 2 (denoted as μ_2^{n+1}) of vector $\boldsymbol{\mu}$ conditional on other elements (denoted as μ_{-2}^{n+1})

…

-A new value for the element k (denoted as μ_k^{n+1}) of vector $\boldsymbol{\mu}$ conditional on other elements (denoted as μ_{-k}^{n+1})

Step 3: Set n = n+*1* and go to Step 2

Similar to the MHA in Section 3.3.1.4, this iterative scheme of the Gibbs sampler generates a Markov chain whose stationary probabilities are identical to the posterior distribution of the model parameters. After the chain has converged at a selected number of iterations (Gelman et al. 1995), the simulated values can be used to compute the mean and variances of the model parameters. A free software, WINBUGS tool (Lunn et al. 2000), was used to run the Gibbs sampler in this study.

3.3.4 Development of Neural Network Deterioration Model (NNDM)

A neural network deterioration model (NNDM) was developed in this study to model both the structural and hydraulic deterioration of stormwater pipes. Each deterioration curve of pipes (as was shown in Figure 3-2) is considered a time varying pattern characterized by its contributing factors. NN was adapted to detect or classify these patterns in a similar way to human brains that 'learn' from past data and generalize the 'gained knowledge' to predict a new pattern. Generalization can be defined as the capability of an NN to identify deterioration patterns that are common to a presented sample of pipes and store them in the network. Then the NN effectively uses these characteristics to make prediction for query pipes.

The snapshot-type inspection data and graded pipe conditions were used as the training data for the learning process of the NNDM. By assuming that the training data were randomly collected over different age groups and contributing factors, the NNDM can learn sufficient deterioration patterns from the training data and thus was able to predict the pipe condition of any query pipes, whose contributing factors are given (or known). This section presents the structure of the NNDM and the methods of training or calibrating the NNDM used in this study.

3.3.4.1 Structure of NNDM

The NNDM was based on the theory of neural networks (NNs) which consist of many information processing elements, called artificial neurons or neurons (in short). NNs mimic the human brain in processing information through a network of neurons which are connected together. An NN receives the input signals, processes them and produces output signals in the required format according to the design of the NN.

The structure of the NNDM is shown in Figure 3-6. There are two types of neurons which are filled circles and empty circles as shown in this figure. According to the function of neurons, these neurons are grouped into three layers in NNDM, namely, input layer, hidden layer and output layer. Therefore, the neurons in these layers are called input neurons, hidden neurons and output neurons respectively. The connections between neurons are attached by connection weights (CWs), which are grouped into CWs from input to hidden layer (CW_{I-H}) and from hidden layer to output layer (CW_{H-O}).

The input signals to the NNDM are the contributing factors which are received by input neurons (i.e. the empty circles). These input neurons simply pass the signals to the hidden neurons.

The output signals are the three possible pipe conditions represented by three output neurons with output values in range [0, 1]. Since the pipe condition takes on ordinal values, the use of scale valued output neuron is not appropriate. With this design, the NNDM is required to produce the value of '1' for one output neuron and the values of '0' for the remaining output neurons so that the classification of a query pipe can be clearly identified. Furthermore, the use of range [0, 1] for output neurons can be interpreted as the probabilities that the query pipe can be in one of the three possible conditions. The query pipe is therefore assigned to the condition that it has the highest probability.

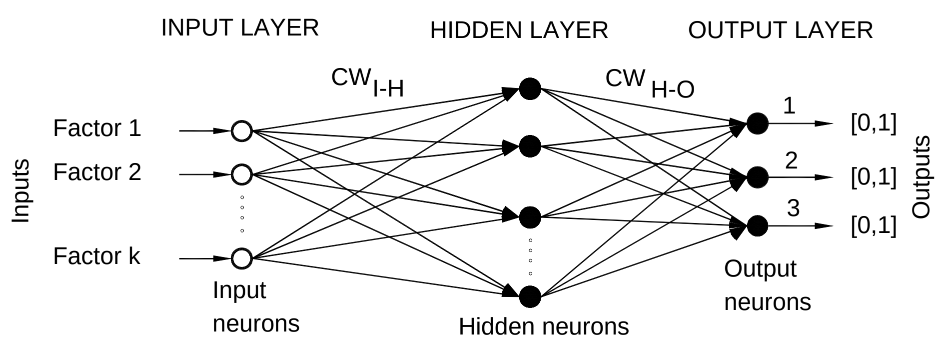

Figure 3-6: Structure of the NNDM

A/ Artificial Neurons and Connection Weights

The biological nervous systems of humans come in various architecture; some are simple, while others are complex. But all these different types are composed of the same type of building blocks, called the neural cells or neurons. A neuron receives signals or inputs, and produces a response or an output. In the biological neuron, the inputs and the response are electrical pulses. The input pulses are passed to the neuron through multiple channels (i.e. dendrites) and the output is passed forward via its only one output channel (i.e. axons). Each dendrite has a contact point (called synapses) which acts as a gate to open or close and thus allow some input signals to flow in or stop some others depending on modes of operation. Figure 3-7 (a) shows the basic structure of a biological neuron.

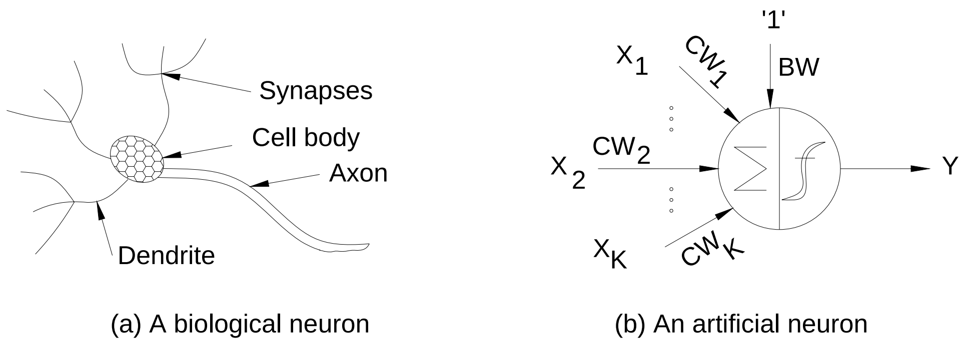

Figure 3-7. Basic structure of a biological neuron and an artificial neuron

In this sense, a biological neuron acts as a function which receives a set of inputs or parameters and produces an output. Analogously to this, an artificial neuron has a multiple-input channel, a cell body and a one-output channel (Figure 3-7 (b)). Usually the input channel (X_1, X_2,…, X_k) has associated weights (called connection weights) which are 'attached' to input signals. These weights (CW_1, CW_2,…, CW_k) allow choosing the important signals among input signals by their large weight values. The neuron has a special input signal whose value is always 1 and the weight attached to this signal is called bias weight (BW as shown in Figure 3-7). This bias weight and the special input signal are not shown in Figure 3-6 for reducing the complexity. The bias weight simulates the function of synapse that can allow (being non-zero value) and stop (being zero-value) the input signals going through. The transmitted signals are integrated (usually just by adding up all input signals) and the mathematical function (also called activation function) in the cell body is evaluated to produce an output signal. The mathematical relationship between input signals and output in an artificial neuron therefore can be formulated as below:

$$Y = f(\sum_{i=1}^{K} X_i \ W_i) \tag{3-21}$$

where: Y is the output signal

X_i is the input signal i

K is the number of input signals

W_i is the weight attached to the input signal i

f is the activation function

B/ Feed-Forward Type

In this study, the 'feed-forward' type of NNs was used for the NNDM to ensure that the network outputs can be calculated as explicit functions of the inputs and the network weights (CWs and BWs). According to Lou *et al.*(2001), the use of this NN type can reduce the unnecessary complexity in determining the structure of NN models whilst the use of 'recurrent' type might affect the predictive capability of the NN models. As can be seen from Figure 3-6, signals travel in the same direction between layers in the 'feed-forward' NN.

C/ Activation functions

Any activation function can be used for the neurons; however, the use of non-differentiable functions such as the step function can be considered a serious limitation. This is because many simple approximation methods where gradient information (i.e. derivatives) plays an essential role are not utilized. Among continuous and differentiable functions, the non-linear sigmoid and hyperbolic tangent functions as shown in Figure 3-8 were often used in most NN models (Moselhi and Shehab-Eldeen 2000; Lou *et al.* 2001; Kingston *et al.* 2006). This is because these non-linear functions allow non-linear mappings between input and output signals. Furthermore, according to Bishop (1995), the use of these two functions with a hidden layer can approximate any non-linear relationships in real world problems.

In this study, the tangent function was chosen for the hidden neurons since this allows a flexible range of input signal values computable. The sigmoid function was used for output neurons since the values of output signal must be between [0, 1] for the classification rule of the NNDM.

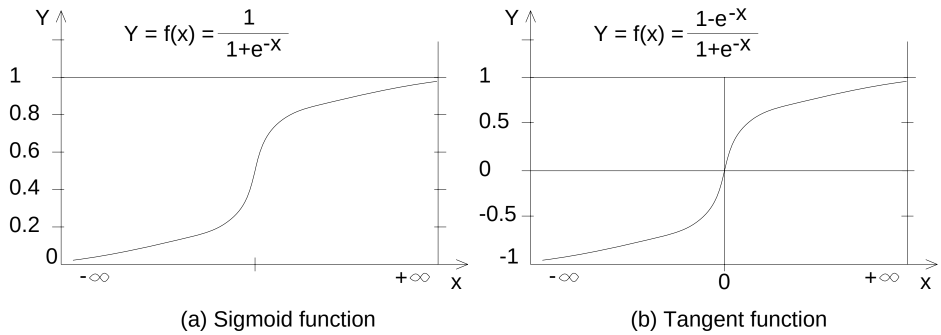

Figure 3-8. Activation functions commonly used in NN models.

D/ Number of hidden layers

In this study, one hidden layer was basically adopted since several studies have shown that an NN with one hidden layer and the sigmoid and tangent activation functions is capable of approximating most non-linear continuous function (Cattan and Mohammadi 1997; Zhao et al. 1998; Lou et al. 2001; Attalla and Hegazy 2003).

E/ Number of hidden neurons

The number of hidden neurons affects how well an NN is able to classify the data (Hassoun 1995). On one hand, an NN with too few hidden neurons is unable to learn sufficiently for making correct predictions. An NN with too many hidden neurons, on the other hand, can become a memory device and thus loses the generalization ability. These two situations are sometimes called under-fitting and over-fitting of NN models respectively.

F/ Supervised Learning and Error Function

NN is attractive because of its ability to learn and generalize like the human brain. In a similar way to how a person develops his knowledge, NN learns by training itself with a set of training data or calibration data. During the training process, the network weights (i.e. connection weights and bias weights) are adjusted. The adjustments of these weights are undertaken by a learning rule.

Among several available learning rules such as supervised learning and unsupervised learning (Samarasinghe 2006), the supervised learning is the most commonly used learning rule in many NN models (Alsugair and Al-Qudrah 1998; Zhao *et al.* 1998; Moselhi and Shehab-Eldeen 2000; Singh and Deo 2007) and was adopted in this study. In this supervised learning, a sample of training data is presented to the NN. The NN then learns by adjusting its weights constantly so that an error function between the predicted data and observed data is minimized. The mean square error (MSE) as given in Equation (3-22) was chosen for the error function in this study.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(predicted_i - observed_i)^2 \qquad (3\text{-}22)$$

where: MSE is the error function.

N is the sample size.

i is count index.

3.3.4.2 Training of NNDM

Training of NNDM was aimed to determine the model parameters which are the number of hidden neurons and the network weights (i.e. connection weights and bias weights) in this study. MSE was used as the criterion in the training process. The problem of over-fitting during the training process was considered by using the early stopping technique (Bishop 1995). The occurrence of local optimum (Gori and Tesi 1992) and the uncertainty of network weights (Kingston *et al.* 2006) are often associated with training of the NN models due to the complexity and the high-dimensionality of the parameter space. These two problems can adversely affect the training of NNDM, and hence the performance of NNDM.

The number of hidden neurons was first determined using the back-propagation training method; the Levenberg-Marquartd algorithm (LMA) was employed and used by trail and error to determine the suitable number of hidden neurons. The trail and error approach had been often used to determine the suitable number of hidden neurons in many NN models (Moselhi and Shehab-Eldeen 2000; Lou *et al.* 2001; Mohammad and Guru 2005). Once the number of hidden neurons was determined, the NNDM was then trained by other two different techniques, namely, genetic algorithm (GA) and Bayesian MCMC method for addressing the problems of local optimum and weight uncertainty as identified in literature (Gori and Tesi 1992; Kingston *et al.* 2006). This is to ensure the best possible solutions are achieved.

A/ Early-stopping technique

The goal of training NN is not to find a model that exactly fits the training data. Such a model often performs poorly on unseen or new data because instead of learning the true underlying function of data, it memorizes or over-fits the training data. As explained earlier, the ability to perform well on new pattern is known as the generalization ability of a NN. One commonly used approach to handle the generalization problem is to stop the training process earlier, before it over-learns the training data (Bishop 1995). This early stopping technique requires an extra data set which is called validation dataset. Note that the validation dataset is different with the train dataset (for training the NNDM) and the test dataset (for testing the NNDM) to ensure effective testing result. These three datasets are often randomly generated from sample data. Figure 3-9 shows a hypothetical illustration of the early stopping technique using the minimum MSE of the validation set. As can be seen from this figure, without early stopping the fitting error on the training dataset continues to decrease after each iteration. However, the fitting error on the validation dataset decreases until a point where it starts to increase. This is the point where training process should be stopped otherwise the NN will perform poorly on unseen data.

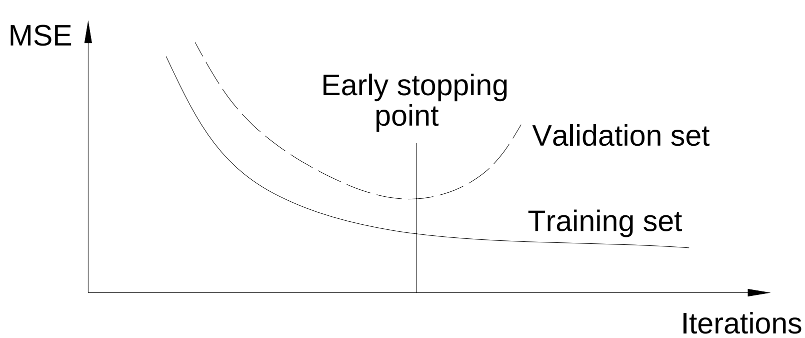

Figure 3-9: Illustration of the early stopping technique

B/ Trial and error approach for the number of hidden neurons

The trial and error approach starts with a minimum number of hidden neurons and increases until the MSE on training and validation datasets show a clear trend. The relationship between MSE values and the number of hidden neurons is plotted so that the appropriate number can be selected. A typical curve is shown in Figure 3-10. Generally, the MSE of the training dataset is smaller than that of the validation dataset.

This is because the validation dataset is not used in the minimizing process of the MSE. Furthermore, as can be seen from this figure, the lowest MSE achieved with 9 hidden neurons does not necessarily means a good generalization (higher MSE of validation dataset). As a result, 12 hidden neurons appear to best compromise between the MSEs of the training and validation datasets.

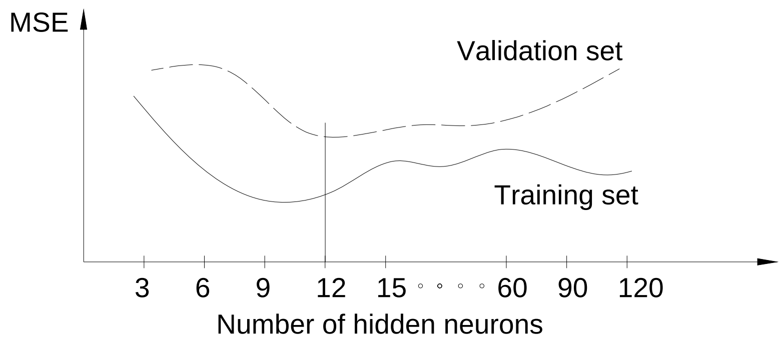

Figure 3-10: Illustration of selection of number of hidden neurons

C/ Back-propagation training using Levenberg-Marquartd algorithm

The back-propagation (BP) training is the commonly used iterative search process which adjusts the weights from the output layer back to the input layer in each run until no further improvement in MSE value is found (Bishop 1995). On one hand, gradient descent and conjugate gradient are among the slow convergence algorithms of the BP training, which were based on the steepest descent optimization using first-order derivatives. On the other hand, Gauss-Newton and Levenberg-Marquartd algorithms are among the fast convergence algorithms of the BP training which use second-order derivatives. In particular, the Levenberg-Marquartd algorithm (LMA) was designed for the error function using sum of square such as MSE (Bishop 1995) and LMA was used in many NN models (Attalla and Hegazy 2003; Najafi and Kulandaivel 2005; Singh and Deo 2007). Therefore, the BP using LMA was used to determine the number of hidden neurons and the network weights of the NNDM in this study.

The LMA often starts with the given initial values of network weights and makes use of the Gauss-Newton method to update the network weights as given in Equation (3-23) (Masters 1995). When μ=0, the LMA becomes the Gauss-Newton method, and for a higher value of μ, the LMA becomes the gradient descent algorithm. The μ in the LMA is always automatically adjusted so that good convergence is ensured. This is achieved by successively reducing the value of μ at each step until there is a reduction in the error function. In this way, the error function is always minimized in each iteration.

$$\mathbf{w}_{k+1} = \mathbf{w}_k - (\mathbf{H} + \mu\mathbf{I})^{-1}\mathbf{J}^T\boldsymbol{\varepsilon}(\mathbf{w}_k) \tag{3-23}$$

where:

$\mathbf{w}_{k+1}$ and $\mathbf{w}_k$	are the network weights at iterations *k+1* and *k* respectively
$\mathbf{J}$	is the Jacobian matrix that contains the first-order derivatives of the error function MSE with regards to network weights
$\mathbf{H}$	is the Hessian matrix that contains the second-order derivatives of the error function MSE with regards to network weights
μ	is learning rate
$\mathbf{I}$	is the identity matrix,
$\varepsilon(\mathbf{w}_k)$	is the value of error function (MSE) with regards to network weights at time steps *k*.

Although the LMA and other back-propagation algorithms (Samarasinghe 2006) would converge to a solution for almost any initial values of connection weights, the 'good' solution depends on the 'properly' given initial values. Since the 'proper' initial values are unknown, they are often randomly generated within a 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 network weights determined by the LMA are considered uncertain with unknown 'true' optimum values. In other words, it is impossible to evaluate how close the estimated weights are to these true optimum weights. It is therefore important to look for weight estimation methods that can reduce the complexity but improve the generality and account for the uncertainty in estimating the weights. The genetic algorithm (GA) and Bayesian Markov chain Monte Carlo simulation are two such methods that were used in this study to address the problem of local optimum and uncertainty of network weights.

D/ Genetic Algorithm (GA)

Genetic algorithm (GA) is a search algorithm that is based on the concepts of natural selection and natural genetics. GA is considered a directed 'global' search algorithm (Goldberg 1989; Ng and Perera 2003) that is especially useful for complex optimization processes where the number of parameters is large and the analytical solutions are difficult to obtain (Pham and Karaboga 2000). The use of GA in neural networks problems has proved efficient and continues to increase a rapid rate in many diverse areas (McInerney and Dhawan 1993; VanRooij *et al.* 1996; Kim *et al.* 2005b; Osman *et al.* 2005).

The key differences between GA and other conventional optimization techniques such as gradient descent and Gauss-Newton are:

- GA searches from a population of points and not from a single point
- GA utilizes the information of the objective function without using the derivatives
- GA uses probabilistic transition rules and not deterministic rules in updating new network weights

GA was used as a competing technique (against the LMA and Bayesian MCMC simulation) for training of the NNDM in this study. The GA used in this study was based on the GA toolbox of MATLAB® which consists of three basic operations: (1) selection, (2) crossover and (3) mutation. The ultimate goal of using the above operations is to generate a population of weight vectors which contain the 'best' weight vector that has the optimum value of fitness function. The fitness function in this study was the MSE of training data as formulated in Equation (3-22) which can be minimized by the GA. A weight vector is a set of network weights and the use of weight vector is because the GA searches from a population instead from a single point (i.e. a set of network weights). One complete cycle of the operations is called a generation. In this study, the initial population was randomly chosen to ensure the diversity in the search space.

The selection process normally chooses two weight vectors that have the lowest values of the error function from the current population and transfers them to next generation without processing. This ensures that the good weight vectors are inherited to the next generation. This selection process also chooses some weight vectors for performing of genetics exchanges (i.e. crossover and mutation). This process can be achieved in many ways; however, the roulette wheel selection (Pham and Karaboga 2000) was used in this study because of its relative ease of implementation. Basically, this method of selection allows weight vectors with low values of error function to have a better chance of moving to the next generation and used in the genetics exchanges. These chosen weight vectors are called 'parents'.

The crossover process combines two parents to form a new offspring or a new weight vector in the next generation. It is carried out among pairs of weight vectors by swapping parts of their set sequences separated at a randomly chosen point, called the crossover point. The role of the crossover process is to generate new weight vectors that did not exist in the current population, so that the solution space is searched thoroughly. The 'scattered' method for crossover was selected in this study due to the ease of implementation. This method creates a random binary vector. It then selects the genes where the vector is a 1 from the first parent, and the genes where the vector is a 0 from the second parent, and combines the genes to form the child.

The mutation process makes small random changes to a single parent or a weight vector to produce a new weight vector. Note that, the mutation process and crossover process of GA toolbox are performed independently with each other. The mutation process provides genetic diversity for the next generation, and thus enables the GA to search a broader space. Among several mutation methods, the Gaussian method (Pham and Karaboga 2000) was chosen in this study due to the ease of implementation. This method adds a random number to the selected weight vector and this random number is taken from a Gaussian distribution centered on zero with the arbitrarily chosen variance.

To effectively carry out these operations in GA, the population size and the crossover fraction are two parameters which should be properly chosen. A too small population size may cause a poor search performance and a too large population size increases the computing time. The crossover fraction is the percentage of offsprings that come from the crossover process and the remaining percentage represents for offsprings that come from the mutation process. For example, if the population size is 20, the crossover fraction is 0.8 and the inherited offsprings are 2, in the new generation, the number of children created from crossover is 0.8 x 18 = 14.4 (or rounded to 14). The number of children created from the mutation process is 18 – 14 = 4. Without mutation offsrpings, the search process of GA may result in poor performance since the diversity in the population is not utilized. Suitable values for the crossover fraction and for the population size were therefore investigated using a trial and error procedure in this study.

E/ Bayesian MCMC

The Bayesian framework for estimating weights of an NN was first introduced by MacKay (1992) and Neal (1992). In their approach, weights were treated as random numbers whose posterior distribution depends on observed data and prior knowledge according to Bayesian theory. Later, Kingston *et al.* (2006) implemented this approach using both simulated data and real data for probabilistic knowledge extraction from the network weights of an NN model in order to reveal the range of relationships between input and output data. This study adopted the Bayesian MCMC approach by Kingston *et al.* (2006) as a competing method for training of the NNDM.

Using the Bayesian theorem, the posterior distribution Q(**W**|**Y**,**X**) of network weights can be extracted from training data as shown in Equation (3-24).

$$Q(\mathbf{W} \mid \mathbf{Y}) = \frac{Q(\mathbf{Y} \mid \mathbf{W})Q(\mathbf{W})}{Q(\mathbf{Y})} \qquad (3\text{-}24)$$

where:

$\mathbf{W}$	is a vector of network weights
$\mathbf{Y}$	is a set of N observations of pipe condition $\{y_n\}$
$Q(\mathbf{W})$	is the prior knowledge about $\mathbf{W}$
$Q(\mathbf{Y})$	is a normalization factor
$Q(\mathbf{Y}\|\mathbf{W})$	is the likelihood function
$Q(\mathbf{W}\|\mathbf{Y})$	is the posterior distribution of network weights

By assuming a Gaussian noise model with the same variance for each observation with regard to the predicted outputs, the likelihood function is expressed in Equation (3-25).

$$Q(\mathbf{Y} \mid \mathbf{W}) = \prod_{i=1}^{N} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2}\left(\frac{Y_i - f(\mathbf{X}_i, \mathbf{W})}{\sigma} \right)^2 \right) \qquad (3\text{-}25)$$

where: $f(\mathbf{X}_n, \mathbf{W})$ is the predicted pipe condition from the NNDM

σ^2 is the variance of the Gaussian distribution

The posterior distribution $Q(\mathbf{W}|\mathbf{Y})$ of the network weights can be estimated from the likelihood function $Q(\mathbf{Y}|\mathbf{W})$ and the prior knowledge $Q(\mathbf{W})$, since the normalization factor $Q(\mathbf{Y})$ is considered as a scale factor and can be cancelled out of the estimation of $Q(\mathbf{W}|\mathbf{Y})$. Furthermore, the prior knowledge $Q(\mathbf{W})$ was assumed to follow a uniform distribution, meaning the $Q(\mathbf{W})$ can be cancelled out of the estimation of $Q(\mathbf{W})$. If a new set of training data can be obtained in the future, the posterior distribution of network weights obtained in this study can become the prior knowledge. Finally, the $Q(\mathbf{W}|\mathbf{Y})$ can be estimated using the $Q(\mathbf{Y}|\mathbf{W})$.

If it is possible to sample the network weights from their posterior distribution as in Equation (3-25), the values of the network weights could be determined from their sample data with a confidence limit. In other words, the uncertainty of the network weights can be accounted for by specifying the confident ranges that contain the 'best' values.

The Metropolis-Hastings algorithm (MHA) as described in Section 3.3.1.4, a member of Bayesian Markov Chain Monte Carlo (MCMC) simulation methods was also used for sampling the posterior distribution $Q(\mathbf{W}|\mathbf{Y})$. The mean values and the confident ranges (or 95% probability limit) of the network weights can be computed from the sample data. The confident ranges of the network weights were then used to compute the network outputs given the inputs from test dataset. Therefore, each predicted output value was expressed by an interval values using 95% probability limit.

3.3.5 Probabilistic Neural Network Deterioration Model (PNNDM)

Probabilistic neural network (PNN) was originally developed by Specht (1990) and is considered a hybrid technique that use a Bayesian classifier (Gelman *et al.* 1995) and a Parzen-Cacoullos theory (Cacoullos 1966) on an NN platform to produce the probability distribution of each pattern or class. Both Bayesian classifier and Parzen-Cacoullos theory are considered statistical technique. PNN were successfully applied on some infrastructure modellings (Sinha and Pandey 2002; Kim *et al.* 2005a). Based on the concept of classifying deterioration patterns of stormwater pipes used by the NNDM in Section 3.3.4, the PNNDM in this study used the PNN to classify a pipe into one three possible conditions.

3.3.5.1 Bayesian Classifier

The Bayesian classifier (Wasserman 1993), as shown in Equation (3-26), was used to classify a pipe into one of the three possible pipe conditions. The purpose of Equation (3-26) is to minimize the expected risk in classification (Kim *et al.* 2005). From the Bayesian theorem, the product of h_c and $f_c(\mathbf{X})$ is a posterior probability that allows the updating of existing knowledge h_c with new information $f_c(\mathbf{X})$. The existing knowledge h_c could be obtained from a previous sample or expert opinion. The loss l_c which is associated with misclassification can be interpreted with following examples. When a pipe in condition 1 is misclassified into condition 3, the loss is just an inspection cost. However, when a pipe in condition 3 is misclassified into condition 1, the loss can be substantially higher. This is because if no inspection or repair is done due to pipe is assumed in good condition, the pipe then fails and incurs repair cost and damage cost.

In this study, the loss l_c was assumed identical between the classes since no data for calculating risk are available. This means that all pipes are treated equally. Furthermore, the prior probability h_c of occurrence in the class c was assumed to a follow uniform distribution which means that a pipe is classified into condition c if its probability distribution in that class has the highest value compared with those in other classes. This is because the effects of l_c and h_c were cancelled by the above assumptions.

$$D(\mathbf{X}) = c \text{ if } l_c h_c f_c(\mathbf{X}) \geq l_j h_j f_j(\mathbf{X}) \ \forall j \in [1,3] \qquad (3\text{-}26)$$

where:

$\mathbf{X}$	is a K-dimensional vector representing a pipe with K contributing factors
D($\mathbf{X}$)	is an image of $\mathbf{X}$ in a set of three classes C_1, C_2 and C_3
l_c	is the loss associated with misclassifying a vector of the class c into other classes
h_c	is the prior probability of occurrence in the class c
$f_c(\mathbf{X})$	is the probability distribution function for class c

3.3.5.2 Parzen-Cacoullos method for estimating PDF

As can be seen in the previous section, the challenge to the Bayesian classifier is the fact that the probability distribution function (PDF) $f_c(\mathbf{X})$ is not usually known. Therefore, it is necessary to derive an estimate of $f_c(\mathbf{X})$ from the training data. This can be done by using the Parzen-Cacoullos method (Kim *et al.* 2005a). The univariate case of PDF was first developed by Parzen and then was extended to the multivariate case by Cacoullos. This method is given in Equation (3-27).

$$f(\mathbf{X}) = \frac{1}{N\sigma_1\sigma_2...\sigma_K}\sum_{i=1}^{N} W\left(\frac{\mathbf{X}-\mathbf{X}_i}{\sigma_i}\right) \tag{3-27}$$

where:

$\mathbf{X}$	is a *K*-dimensional vector representing a pipe with *K* contributing factors
σ_i	is standard deviation of a contributing factor *i*
N	is the number of training data (i.e. number of pipes with known condition and contributing factors)
$f(\mathbf{X})$	is the probability distribution function (PDF) of **X**
W	is (kernel) density function

This study assumed that all smoothing parameters are identical to a smoothing parameter σ and a bell-shaped Gaussian function is used for *W*. Equation (3-27) then reduces to Equation (3-28). The meaning of the smoothing parameter σ in the case of the Gauss kernel, is that the Gaussian curve is sharply peaked with σ smaller than one, and tends to flatten out with increasing σ (Wasserman 1993).

$$f(\mathbf{X}) = \frac{1}{(2\pi)^{K/2}N\sigma^K}\sum_{i=1}^{N}\exp\left(\frac{\|\mathbf{X}-\mathbf{X}_i\|^2}{2\sigma^2}\right) \tag{3-28}$$

where: $\|\mathbf{X}-\mathbf{X}_i\|^2$ is the Euclidean distance from the vector **X** of the query pipe to a training vector $\mathbf{X}_i$

Equation (3-28) was then used to compute the PDF $f_c(\mathbf{X})$ of a pipe represented by a vector **X** of *K*-contributing factors in class *c* given a sample of training data $\{\mathbf{X}_i, Y_i\}$ with inspected (or known) pipe condition and contributing factors. $\mathbf{X}_i$ is called a training vector of *K*-contributing factors. The Bayesian classifier was then applied to classify or predict the pipe into one of the three possible conditions.

3.3.5.3 Topology of the PNNDM

An NN platform was used to implement the Bayesian classifier and the Parzen-Cacoullos method by Specht (1990), which was called PNN. The PNN is composed of many connected processing units or artificial neurons which are laid in four successive and fixed layers, namely input layer, pattern layer, summation layer and output layer as shown in Figure 3-11. For classifying a query pipe into one of the three conditions, the PNNDM computes the posterior probabilities of the query pipe to each of the condition classes. The condition class that the query pipe has the highest posterior probability is then assigned to the query pipe. The functions of four layers in the PNNDM are described below.

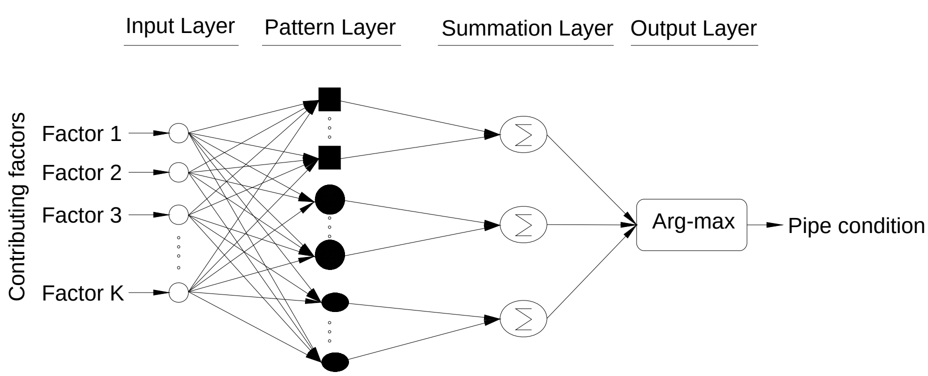

Figure 3-11: Topology of PNNDM

<u>A/ Input layer</u>

In the input layer, the number of neurons is equal to the number of input factors. This layer does not perform any computations and simply distributes the query pipe with a vector of contributing factors to the neurons in the pattern layer.

<u>B/ Pattern layer</u>

Suppose that there are N training data in which N_1, N_2 and N_3 ($N_1 + N_2 + N_3 = N$) training data are for classes C_1, C_2 and C_3 respectively. The total number of neurons in this layer is equal to N and these neurons are divided into three classes with corresponding numbers of neurons N_1, N_2 and N_3 as shown by three sets of neurons of different shapes in Figure 3-11. The neurons with square shape are for training vectors of condition 1. The neurons with circular shape are for training vectors of condition 2. The neurons with elliptical shape are for training vectors of condition 3. This means that each neuron in a class was designed to hold a training vector of contributing factors. When the incoming signal of the query pipe is presented, these neurons compute the exponential part of the Equation (3-28) (i.e. $\exp\left(\frac{\| \mathbf{X} - \mathbf{X}_i \|^2}{2\sigma^2}\right)$) and transfer the values to the summation layer

C/ Summation Layer

The summation layer contains one neuron for each class. The number of neurons in the summation layer is equal to the number of classes. This layer computes the posterior probabilities of a query pipe being into one of the three possible conditions from Equation (3-28) on the incoming signals. The computed probabilities are then sent to the output layer.

D/ Output Layer

There is one neuron in this layer. The 'Arg Max' activation function of this neuron (Kim et al. 2005) simply compares the incoming probabilities and assigns the query pipe into the class that has the highest posterior probability.

3.3.5.4 Training PNNDM

Training of the PNNDM was actually to store the training data in the system by assigning their values into the neurons in the pattern layers. However, there is still one parameter, the smoothing parameter σ of the Gaussian kernel, which needs to be estimated. This can be done by trial and error search so that the MSE of training data has the lowest value, or equivalently, the number of correct predictions on the training data has the highest possible value. A correct prediction is counted if the predicted pipe condition is same as the known pipe condition in the training data. The training of

PNNDM in this study was done by searching for the maximum number of correct predictions.

3.4 Assessing Performance of Deterioration Models

Testing or assessing models is to quantify the model error which relates to the differences between the predicted values and the observed values when a test data set was presented to the model. To effectively test the model, the test dataset should not be used in calibrating or training of the model. One common method to create such a test dataset from a sample of data is to randomly split the sample data into the calibration (or train) dataset and the test dataset. This strategy was often used for testing infrastructure deterioration models (Micevski *et al.* 2002; Baik *et al.* 2006).

This study adopted two scalar performance measures, namely, false negative rate and overall success rate derived from the confusion matrix (Hajmeer and Basheer 2003) 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.

3.4.1 Confusion Matrix

There are always four possible situations between a predicted case and an observed case: (1) true negative (TN) when the model correctly identifies a negative case (i.e. pipe in poor condition), (2) true positive (TP) when the model correctly identifies a positive case (i.e. pipe in good condition), (3) false negative (FN) when the model wrongly identifies a pipe actually in poor condition as in good condition, and (4) false positive (FP) when the model wrongly identifies a pipe actually in good condition as in poor condition. It is obvious that the consequence of an FP case is just the inspection cost. On the other hand, the consequence of an FN case is far more severe since when that pipe fails, all costs including repair, penalty and disruption should be added. In this study, the positive case or the pipe in good condition is defined as the pipe is either in condition 1 or 2. If the pipe condition is 3, it is defined as a negative case.

These four possible situations can be used to assess the predictive performance of a deterioration model by using the confusion matrix or the contingency table (Johnson and Wichern 2002) on a test dataset as given in Table 3-2. For example, the FN21 in this table means the number of pipes in the observed condition 2 which were incorrectly predicted as the condition 1. Furthermore, the total number of pipes which were observed in condition 1, 2 and 3 are O_1, O_2 and O_3 respectively and the total number of pipes which was predicted in condition 1, 2 and 3 are P_1, P_2 and P_3 respectively.

Table 3-2: Confusion matrix

		Predicted condition			Total
		1 (good)	**2 (fair)**	**3 (poor)**	
Observed condition	**1 (good)**	TP_{11}	FP_{12}	FP_{13}	O_1
	2 (fair)	FP_{21}	TP_{22}	FP_{23}	O_2
	3 (poor)	FN_{31}	FN_{32}	TN_{33}	O_3
Total		P_1	P_2	P_3	

The overall success rate (OSR) and false negative rate (FNR) can be used to assess the predictive performance of the four deterioration models (i.e. MDDM, OPDM, NNDM and PNNDM) which were developed to predict the condition changes of individual pipes in this study. The OSR and FNR cannot be used for assessing the Markov model since this model was not able to predict the condition changes of a particular pipe due to the lack of longitudinal data. The OSR and FNR can be computed from the confusion matrix using Equations (3-29) and (3-30) respectively.

$$OSR = \frac{TP_{11} + TP_{22} + TN_{33}}{O_1 + O_2 + O_3} \tag{3-29}$$

$$FNR = \frac{FN_{31} + FN_{32}}{FN_{31} + FN_{32} + TN_{33}} \tag{3-30}$$

The OSR indicates how well the deterioration models predict the condition of individual pipes for all cases. The FNR indicates the risk associated with the use of the models. It is obvious that a ‘good’ deterioration model requires high OSR and low FNR.

3.4.2 Goodness-of-Fit Test

The goodness-of-fit test using Pearson chi-squared test statistic (χ^2) is based on a null hypothesis that the observed frequency is matched with the estimated (or predicted) frequency (Micevski *et al.* 2002). This test can be used for the five deterioration models developed in this study. It is often required a 95% or 99% confidence level to conclude the fitness of a model (Montgomery *et al.* 2004). The test statistic χ_M^2 for the deterioration models in this study can be calculated using equation (3-31).

$$\chi_M^2 = \sum_{c=1}^{3} \frac{(O_c - P_c)^2}{P_c} \tag{3-31}$$

where: O_c is the observed number of pipes in condition *c*

P_c is the predicted number of pipes in condition *c*

If the test statistic χ_M^2 is larger than the critical $\chi_{0.05,2}^2$ (95% confidence level and 2 degree of freedom), the hypothesis is rejected. The goodness-of-fit test shows how confidently a model fit with a set of observations. To ensure the accuracy of χ_M^2, one rule of thumb should be enforced. That is the predicted number of pipes in any condition *c* must be at least 5 (Montgomery *et al.* 2004).

For the Markov model, test statistic χ_M^2 can be computed using the predicted proportions of pipe P_1, P_2 and P_3 in each condition over a time interval (by Equation (3-2) in Section 3.3.1.3) and the computed proportions of pipes observed O_1, O_2 and O_3 in condition 1, 2 and 3 from the test dataset. For the remaining four deterioration models, the test statistic χ_M^2 can be computed by using P_1, P_2 and P_3 (which are the column sums) and O_1, O_2 and O_3 (which are the row sums) in Table 3-2.

3.5 Identification of Significant Factors

Identification of significant factors to the underlying process is one of the important tasks in the construction of engineering models. This is also the case with developed deterioration models of stormwater pipes. There are many methods that can be used for carrying out this task (Saltelli *et al.* 2000), which are classified into local and global sensitivity analysis and. These methods were discussed in Section 2.4.5.

In this study, the most commonly used methods were used for identifying significant factors for both structural and hydraulic deterioration models. They are forward stepwise method (Nakashima *et al.* 1997; Leung and Tran 2000; Barendregt and Bio 2003) for the MDDM, Wald test (Madanat *et al.* 1995; Baik *et al.* 2006) for the OPDM, connection weight analysis (Olden *et al.* 2004) for the NNDM and backward stepwise method (Emery Coppola *et al.* 2003; Ha and Stenstrom 2003) for the PNNDM. However, since the Markov model uses only one input factor (i.e. pipe age), the identification of significant factors is not applied to the Markov model.

3.5.1 Forward Stepwise Method

The forward stepwise method involves entering the contributing factors into the MDDM one at a time and assessing its classifying power. The classifying power is the proportion of variance in the output of the MDDM that may be attributed to the factor of interest. The classifying power can be described by the test statistic F_{ratio}, which can be computed using Equation (3-32) (Tabachnick and Fidell 2001). The F_{ratio} is assumed to follow an F-distribution and thus the P-value of the F_{ratio} can be computed. If the P-value is smaller than 0.05 (equivalent to 95% confidence level), the factor is considered significant (Tabachnick and Fidell 2001). Although it seems complicated, the computing process is obtainable via computer software such as SPSS® and Stata®.

$$F_{ratio} = \frac{SSE_{\text{regression}} / df_{\text{regression}}}{(SSE_{\text{regression}} + SSE_{\text{constant}}) / df_{\text{residual}}} \tag{3-32}$$

where:

$SSE_{\text{regression}}$	is sum of square errors due to contributing factors.
SSE_{constant}	is sum of square errors using only a constant value.
$df_{\text{regression}}$	is degree of freedom equal to the number of is contributing factors.
df_{residual}	is degree of freedom equal to the sample size minus the number of contributing factors and the constant value.

3.5.2 Wald Test

For the OPDM, the significant factors can be identified using the Wald test in which a Z statistics is calculated using the ratio of estimated mean value to standard error (Tabachnick and Fidell 2001). The square of this Z statistic yields the Wald statistic, which follows a Chi-squared distribution. By using a 95% confidence level, the contributing factors with the P-value of the Wald statistic less than 0.05 are considered significant factors to the output of the OPDM.

3.5.3 Backward Stepwise Method

This method (Tabachnick and Fidell 2001) involves using all input factors and recording the predictive performance of the PNNDM on the test dataset as a reference predictive performance. Then, each input factor is subsequently withdrawn from the PNNDM and the predictive performance of the PNNDM with the remaining factors is recorded which indicates the influence of that particular factor to the PNNDM. The ranking of input factors is based on the largest percentage influences which are the relative differences between the predictive performances of individual input factors with the reference predictive performance.

3.5.4 Connection weight analysis

Olden *et al. (*2004) introduced the connection weight analysis (CWA) for identifying the significant inputs to the output with one neuron of an NN model. The magnitude and direction of the connection weights can decide how much each input variable affects the output of an NN model (Olden and Jackson, 2002). Input variables with large connection weights play greater roles in transferring signals to output neurons and thus can be considered more important in the operation of NN models. Positive and negative connection weights, respectively, increase and decrease the value of predicted response at the hidden or output neurons and therefore affect the final outcomes. Since input factors are measured in different scales, they must be standardized to the same range such as [0, 1] for proper comparison of importance.

Table 3-3 shows illustrated steps of the CWA which was used in this study for computing the overall significance measure of the input factor j to the NNDM. Since the number of hidden neurons in the NNDM can only be determined upon a case study, for illustration purposes, it is assumed that the NNDM had three hidden neurons. Furthermore, it is proposed in this study that the overall significance measure (OZ_c) of the factor j is the average of three local significance measures ($Z_{j,c}$) which can be computed according to the original CWA developed by Olden *et al. (*2004). Then, the ranking from the most to least significant factors can be established by sorting the overall significance measure (OZ_c) of each factor in a descending order.

Table 3-3: Computing steps to measure overall significance of an input factor in the NNDM (example with 3 hidden neurons)

Step	Factor X_j	Hidden neurons		
		1	2	3
1	Connection weights between the input factor X_j and hidden neurons	A_1	A_2	A_3
2	Connection weights between hidden neurons and the output neuron *c*	B_1	B_2	B_3
3	Local significance measure $Z_{j,c}$ of input factor X_j to the output neuron *c*	$Z_{j,c} = \sum_{i=1}^{3} A_i * B_i$		
4	Overall significance measure OZ_c of input factor X_j to the NNDM model (proposed step in this study)	$OZ_j = \frac{1}{3}\sum_{c=1}^{3} abs(Z_{j,c})$		

3.6 Summary

The structural and hydraulic deterioration of stormwater pipes have been the major cause for the interrupted service of stromwater drainge systems. However, maintaining the intended performance of stormwater pipes is not an easy task because of the limited budget and the massive lengths of pipes. The need for deterioration models, which can predict current and future condition of pipes, is intensifying. This is the primary aim of this study. Once the models are developed, they can be used to identify the significant factors that affect the model output and hence the deterioration process of stormwater pipes.

The ideal deterioration model (IDM) was first considered using assumed curves for both structural and hydraulic deterioration of stormwater pipes. The IDM defines each pipe by a different deterioration curve because pipes in reality deteriorate differently from one to another due to many contributing factors. From this IDM, the estimation of the condition changes over time for the pipe population and the estimation of the condition changes overtime for individual pipes are the model outputs for the development of practical deterioration models. A list of potential contributing factors was also mentioned.

Based on the IDM, conclusions in Chapter 2 and the availability of the snapshot data, five practical deterioration models including Markov model, multiple discriminant deterioration model (MDDM), ordered probit deterioration model (OPDM), neural network deterioration model (NNDM) and probabilistic neural network deterioration model (PNNDM) were developed. The Markov model, MDDM and OPDM are considered the statistical deterioration models while the NNDM and PNNDM are considered the artificial intelligence deterioration models. The predictive performances of these models were compared on a case study (detailed in Chapter 4) so that the best possible deterioration model can be identified. These five deterioration models used contributing factors as model inputs for predicting pipe conditions. Furthermore, they are considered generic models because they can be applied to both structural and hydraulic deterioration of stormwater pipes in this study and can also be used for sewers.

The Markov model was developed to predict the condition changes of pipe population and it cannot be used to predict the condition changes of individual pipes due to the lack of regular (or longitudinal) data. The four remaining deterioration models were developed to predict the condition changes of individual pipes. They can also be used for predicting the condition changes of pipe population by summing up the predicted conditions of individual pipes and computing the proportions.

Training or calibration of the deterioration models was done using trial and error approaches and advanced optimization methods. They are listed below:

- For the Markov model, the transition probabilities were the model parameters, which can be estimated by two different techniques namely, the Bayesian MCMC simulation using Metropolis-Hastings algorithm (MHA) and a non-linear optimization technique.

- For the MDDM, the factor coefficients are the model parameters, which can be estimated by maximizing Fisher's criterion.

- For the OPDM, the factor coefficients and two thresholds are the model parameters, which can be estimated by two different techniques namely, maximum likelihood (ML) and the Bayesian MCMC simulation using Gibbs sampler.

- For the NNDM, the number of hidden neurons and the network weights are the model parameters. They can be estimated by three different methods namely, Back-propagation using Levenberg-Marquartd (LMA), Genetic algorithm (GA) and the Bayesian MCMC simulation using MHA. Furthermore, the effects of the population size and the crossover fraction on the performance of the GA also need to be investigated.

- For the PNNDM, the smoothing parameter was the only model parameter, which can be estimated by the trial and error approach.

The predictive performances of the five developed deterioration models can be assessed by the goodness-of-fit test using Pearson Chi-squared test statistic and two scalar performance measures namely, the overall success rate (OSR) and the false negative rate (FNR) which can be derived from the confusion matrix.

The significant factors that affect the structural and hydraulic deterioration can be identified by using several analysis methods on these deterioration models (except the Markov model). The forward stepwise method, the Wald-test, the connection weight analysis (CWA) and the backward stepwise method can be used for the MDDM, OPDM, NNDM and PNNDM respectively. The identification of significant factors is not applied to the Markov model since the Markov model uses only one input factor (i.e. pipe age).

One application of this study is to infer or extrapolate the condition of those pipes that were not CCTV-inspected. Therefore, it is better to have a representative sample data. This means the oldest and newest pipes in the network should be in the training data. For testing future condition (i.e. beyond maximum age in the data), a repeated inspection is recommended. Unfortunately, such repeated data are not available for proper testing as can be seen in the Chapter 4 (case study). Except for the structural and hydraulic condition, the remaining contributing factors such as pipe size and pipe depth were assumed to be time-independent due to limited data. When applied, the predictive result must be checked by field experts.

CHAPTER 4 CASE STUDY

4.1 Overview

This chapter presents the application of deterioration models developed in Chapter 3 of this thesis to a case study with a sample of real data collected from a stormwater pipe system in City of Greater Dandenong, Australia. Section 4.2 presents a description of the case study. Section 4.3 explores the structures of data and the relationships between contributing factors and between contributing factors with hydraulic and structural conditions by conducting standard statistical analysis on the sample data. Sections 4.4 and 4.5 calibrated and tested the developed structural and hydraulic deterioration models of stormwater pipes using the supplied sample data of stormwater pipes. The significant factors were also identified in these two sections. Section 4.6 discusses the findings of the Sections 4.4 and 4.5 in comparisons with the results of Section 4.3 and the literature. Section 4.7 presents a summary of this chapter.

4.2 Case Study Description

4.2.1 Data Source

This case study used a data set supplied by City of Greater Dandenong (CGD) in Victoria. CGD is responsible for 806 kms of a stormwater pipe system in which there are 801 kms of buried pipes and 4 kms of culverts of various sizes (Burkhardt and Hananto 2004). In addition to the underground system, there are also over 80 kms of open drains which are generally located in the rural portion of the municipality. There are over 27,800 side entry pits and approximately the same number of easement pits. The underground pipes range in diameter from 150 mm to 2100 mm, with the majority being between 150 mm to 450 mm. The location of CGD with respect to Melbourne metropolitan area is shown in Figure 4-1, while a typical suburb in CGD (where stormwater pipes run through) is shown in Figure 4-2.

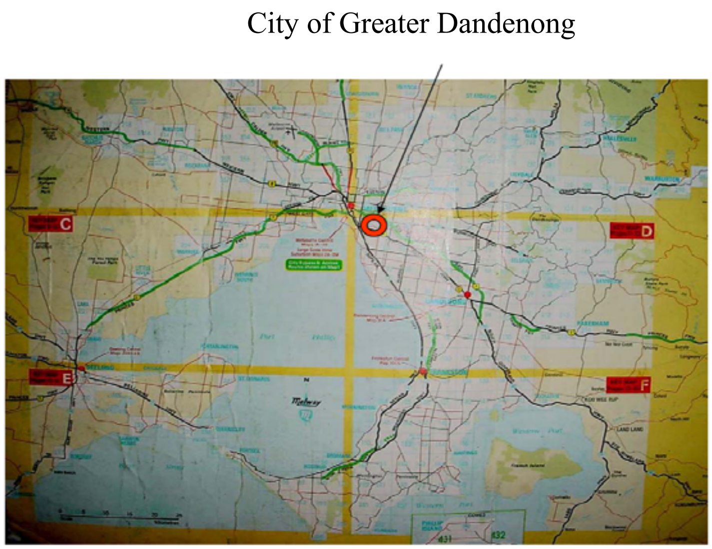

Figure 4-1: Location of CGD

Figure 4-2: An aerial photograph of CGD's suburb and stormwater pipes (dark lines)

The age profile of the underground stormwater pipe system is given in Figure 4-3. It can be seen from this figure that nearly 67% of the system has been in service for more than 20 years and nearly 23% of the system for more than 40 years. The replacement value of the stormwater pipe system at 2004 is $84.5 million. The CGD's annual budget for its stormwater pipe system is approximately $650,000 representing an expenditure of only 0.6% of the existing replacement value. Until 1999, there had been no comprehensive physical or visual inspection of any part of the stormwater pipe system and therefore there was no basis on which to prepare or implement a proactive maintenance and rehabilitation program.

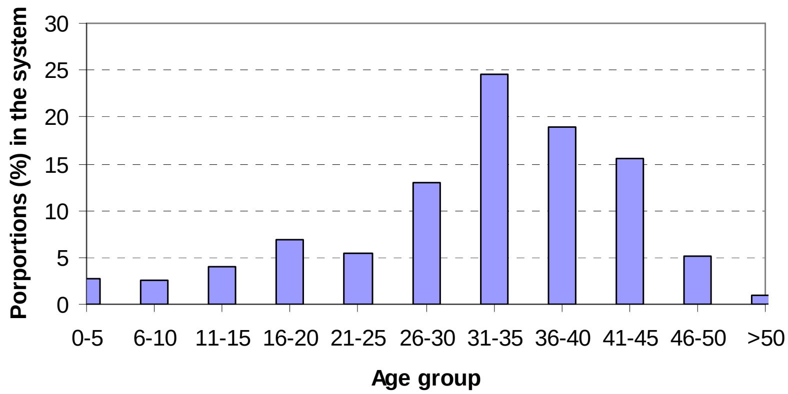

Figure 4-3: Age profile of pipes in the system

4.2.2 City Improvement Program

The City Improvement Program as part of Local Government Act (1993) is a continuing process used to identify and prioritise municipal public capital works within cities in Victoria. This process significantly assisted CGD to make investment decisions by targeting resources and funds to areas of greatest needs. The City Improvement Program plans projects for the next five years and the program is reviewed annually to ensure priorities are current.

Funding was allocated from the City Improvement Program for each of five consecutive years starting from 1999-2003 to conduct CCTV inspection programs to monitor and assess the internal condition of the stormwater pipe system. The inspection schedule was set out as given in Table 4-1 which shows that the older pipes were the priority.

Table 4-1: CCTV inspection scheduling

Age Group	% to be inspected	Pipes to be inspected over 5 years
>45 years	20% per year	All pipes
30-45 years	10% per year	Sample pipes in this group
15-30 years	5% per year	Identified problem pipes

This means the collected data set was biased and thus is less valid for a research study. In order to support the research work in this study, CGD has used additional funding to conduct further CCTV inspections between 2006 and 2007. In this additional inspection program, a set of 200 pipes were randomly selected throughout the whole catchment of CGD, which were not previously inspected.

4.2.3 Description of Data Set

4.2.3.1 Sample Size

As mentioned in Section 4.2.2, there were two inspection programs with the first one in between 1999-2003 (considered biased) and the second one in between 2006-2007 (less biased). Both programs resulted in 695 pipes in which 495 pipes were from the first program and 200 pipes were from the second program. Each pipe in the sample was described by structural and hydraulic conditions together with contributing factors such as pipe size, pipe age and pipe location (to be detailed in Section 4.2.3.3). However, only a smaller data set of 417 data points, representing a sample size of 2.2% of the pipe population, was valid for analysis and modelling due to the following reasons.

- One third of inspections were abandoned (or not completed) because of obstructions, root masses, high water level and defective connections, which blocked the CCTV camera.
- A number of pipes had missing contributing factors.
- Some inconsistent data and outliers were found because three different contractors were employed for CCTV inspections.

4.2.3.2 Inspected Condition of Pipes

The Sewer Inspection Reporting Code of Australia (WSAA 2002) was used for grading deterioration condition of the inspected pipes. The structural and hydraulic conditions of each pipe in the data set were provided by CGD and the condition takes the value between 1-3 with one being perfect, two being fair and three being poor.

A/ Structural Condition

The distribution of structural conditions of inspected pipes in the supplied dataset is shown in Figure 4-4. It can be seen that the majority (67%) of pipes are in condition state 3 while there is only 7.7% of pipes are in condition state 2.

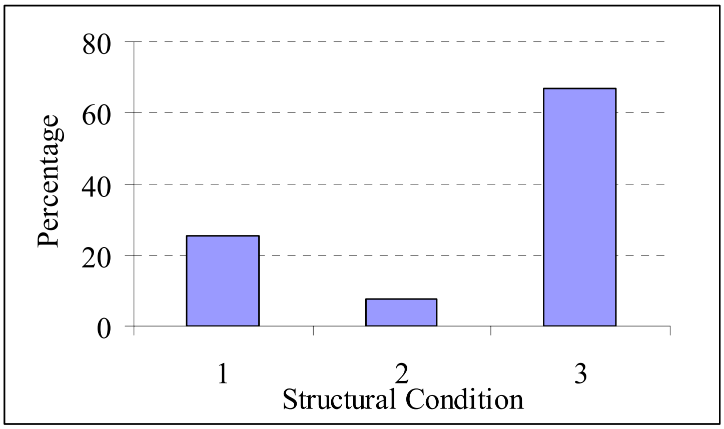

Figure 4-4: Distribution of structural conditions in the sample

B/ Hydraulic Condition

The distribution of hydraulic conditions of inspected pipes in the supplied dataset is shown in Figure 4-5. It can be seen that an approximately equal distribution of three pipe conditions across the sample data. This may indicate that the average rate of hydraulic deterioration seems to be slower than that of the structural deterioration.

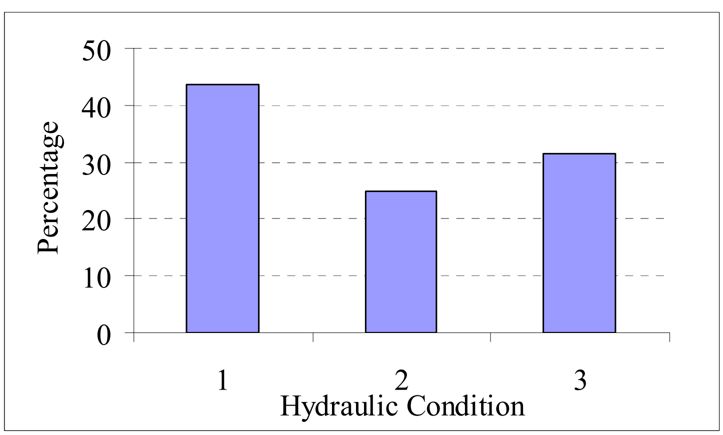

Figure 4-5: Distribution of hydraulic conditions in the sample

4.2.3.3 Contributing Factors

Each pipe in the dataset also has the following contributing factors: pipe material, pipe size, construction year (or pipe age), pipe depth, pipe slope, pipe location and tree count. However, all pipes in the data set are of reinforced concrete type (i.e. pipe material). The literature suggested two other potential factors should be considered with respect to pipe deterioration, namely, soil type (WRC 1983) and climatic conditions (Hahn *et al.* 2002), since these factors may affect the growth of tree roots and soil movement, which could eventually contribute to the structural and hydraulic deterioration. Hence, soil type and Thornthwaite Moisture Index (TMI), which is a representative of climatic conditions, were added into the list of pipe factors by inferring them from soil maps of Victoria and pipe depth respectively.

For contributing factors with continuous values such as pipe size and pipe depth, the distribution of the factor value is of interest because it can be used for simulation study and generation of artificial data. Therefore, the popular normal distribution curve is shown on histogram of each factor for comparing. Due to limited data, the distribution found can only be used as a reference.

A/ Pipe Size

Pipe sizes were collected from the design drawings which showed the nominal size (or diameter). The pipe size range is 225 – 1950 mm; the distribution of pipe size is shown in Figure 4-6. As can be seen from this figure, the distribution of pipe size appears not to be of normal distribution with a peak frequency of 11% at size 300 mm.

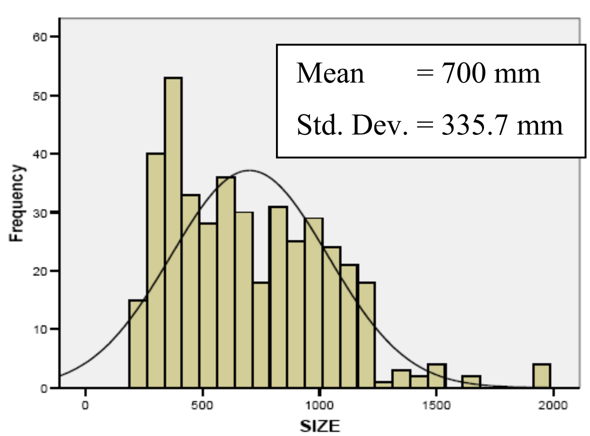

Figure 4-6: Distribution of pipe size (mm)

B/ Pipe Age

The pipe age was computed by referring the construction year (collected from the construction documents) to the years of inspection. The age range is 0 – 65 with mean age of 38.3 and standard deviation of 0.8. The distribution of pipe age is shown in Figure 4-7. As can be seen from this figure, the distribution of pipe age does not appear to be normal distribution.

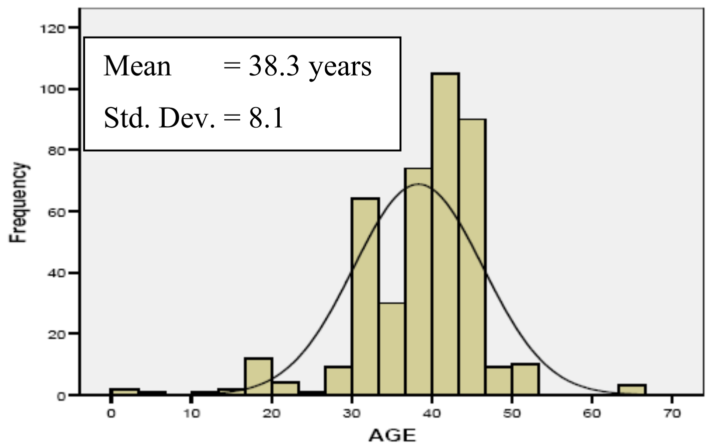

Figure 4-7: Distribution of pipe age (years)

C/ Pipe Depth

The pipe depth represents the distance from the pipe crown to the ground surface and was collected from the construction drawings since the records of actually installed depths were not available. The depth range is 0 - 8.99 m; the distribution of pipe depth is shown in Figure 4-8.

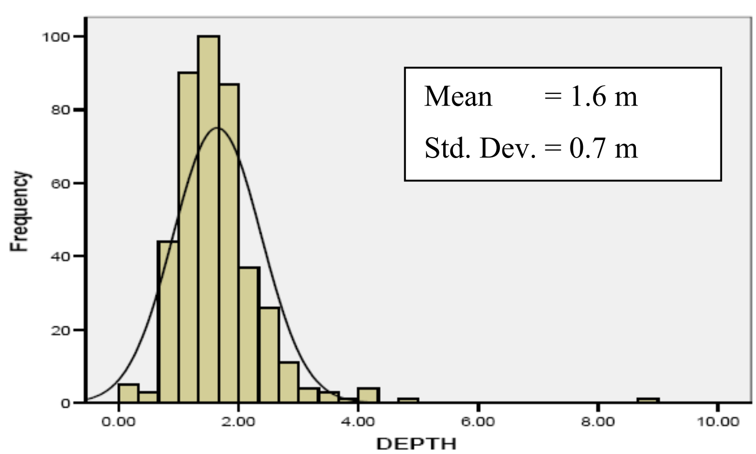

Figure 4-8: Distribution of pipe depth (m)

As can be seen from this figure, the distribution of this factor can be approximated with a normal distribution. A mean depth value of 1.6 m and a standard deviation value of 0.8 m indicate that pipes are not deeply buried and hence, the effects of load and tree roots must be considered in the development of deterioration models.

D/ Pipe Slope

The pipe slope was computed for each pipe by considering pipe invert levels and pipe length from construction drawings as the records of actually installed slopes were not available. The slope range is 0 - 22.9 % and a slope of 0 % means the pipe is horizontal. The histogram of pipe slope is shown in Figure 4-9, which shows that the distribution of the pipe slope does not appear to be normal distribution.

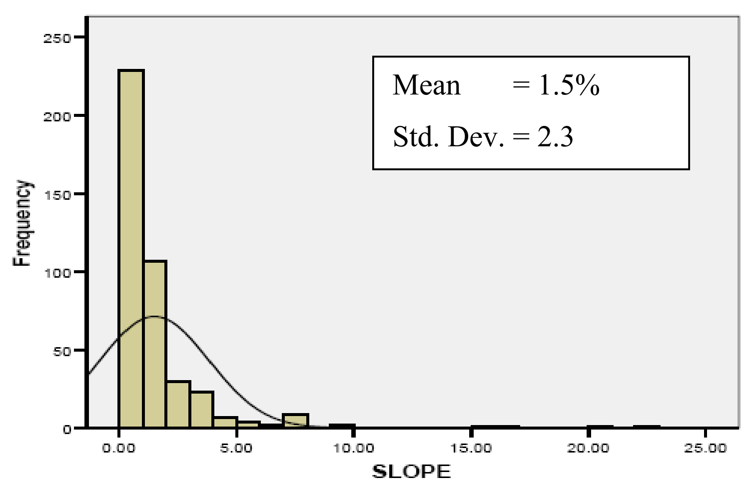

Figure 4-9: Distribution of pipe slope (%)

E/ Tree-Count

The tree-count represents the number of trees found within 3 meters on either side of the pipe and thus shows the likelihood of tree-root attack. The tree-count was collected using the satellite photographs in 2005. The histogram of tree-count is shown in Figure 4-10, which shows that the distribution of tree-count appears not to follow a normal distribution.

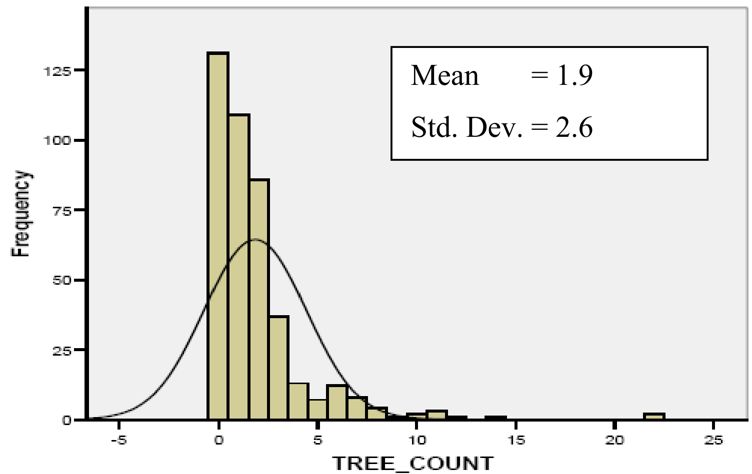

Figure 4-10: Distribution of tree-count

F/ Pipe Location

The pipe location was defined in terms of the following four categories: under easement (i.e. under private properties), under road, under nature strip and under reserve (e.g. park, protected area). The pipe location information was collected and recorded during the CCTV inspection. The distribution between the four categories in the sample is shown in Figure 4-11. It can be seen from this figure that nearly 40% of pipes in CGD appears to be under roads, where the structural deterioration due to traffic load is more likely to be dominant. The remaining pipes are either under easement, nature strip or reserve which means that there are possible tree roots going into pipes.

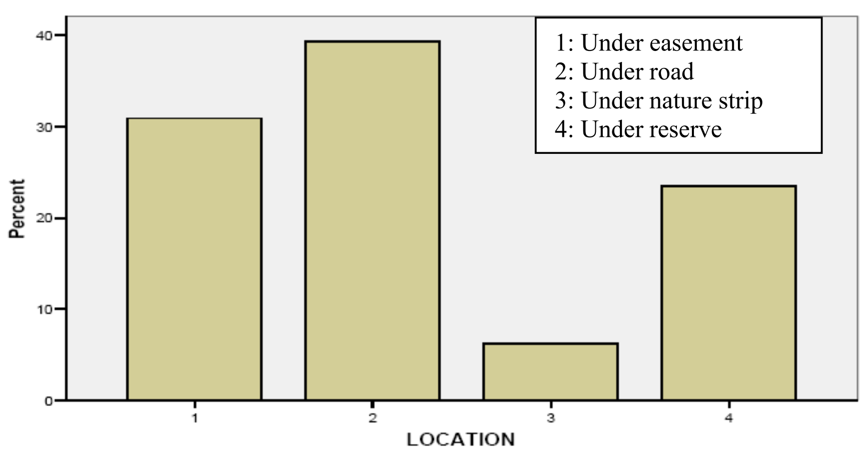

Figure 4-11: Distribution of pipe location

G/ Soil Type

Soil type is classified according to four types of soil layers (i.e. dark grey sand, light grey sand, clay and mix) which were found from soil maps of Victoria and these soil layers were identified by distance to the surface. The layer of dark grey sand was defined for the depths between 0 - 0.3 m; the layer of light grey sand was defined for the depths between 0.3 - 0.5 m. The layer of clay was defined for the depths between 0.5 - 1.5 m and beyond that was the layer of mixed soil types.

The distribution of different soil layers in the supplied dataset is shown in Figure 4-12. It can be seen from this figure that the layer of clay soil (44%) and the layer of mix soil (54%) were dominant, while the layers of sandy soil (type 1 and 2) were rare in CGD. This high percentage of the clay soil layer presented a high risk environment for structural condition and a low risk for hydraulic condition since clay soil may cause unstable bedding but reduce the development of tree root and deposits (Bashir 2000).

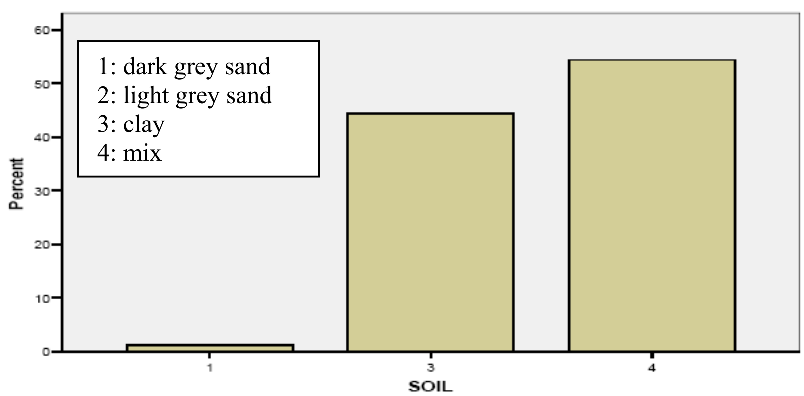

Figure 4-12: Distribution of soil type

H/ TMI

The Thornwaite Moisture Index (TMI) is a climatic classification that categorizes the soil into wet and dry layers according to depth (McManus *et al.* 2004). According to McManus *et al.* (2004), the six layers of different TMI in Victoria were wettest (depth<1.5m), wetter (1.5 - 1.8 m), wet (1.8 - 2.3 m), dry (2.3 - 3.0 m), drier (3.0 - 3.5 m) and driest (depth>4m).

The distribution of TMI layers in the supplied dataset is shown in Figure 4-13, respectively. It can be seen from this figure that the majority (85%) of pipes works in wet condition which could favor the hydraulic deterioration due to tree root intrusion.

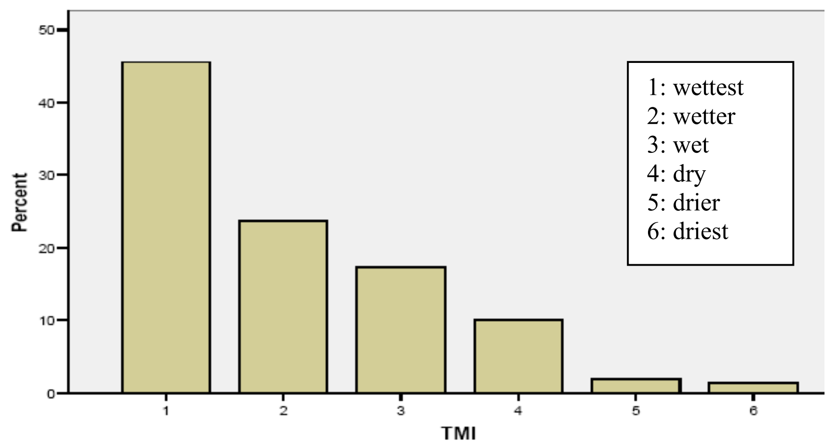

Figure 4-13: Distribution of TMI

4.2.4 Example of Data Set

A portion of the supplied data set is presented in Table 4-2. This table shows each pipe segment has information on both condition assessment and corresponding contributing factors.

Table 4-2: A portion of the supplied dataset

No.	Structural Condition	Hydraulic Condition	Pipe Size (m)	Pipe Age (years)	Pipe Depth (m)	Pipe Slope (%)	Tree-count	Pipe Location	Soil Type	TMI
1	2	2	375	42	1.15	7.80	0	2	3	1
2	2	2	900	44	1.40	1.04	1	1	3	1
3	1	3	750	39	1.30	1.11	0	2	3	1
4	1	3	600	30	1.30	1.00	2	4	3	1
5	3	3	525	32	1.70	0.51	0	4	4	2

Note:
Structural condition: 1 = good 2 = fair 3 = poor
Hydraulic condition: 1 = good 2 = fair 3 = poor
Pipe location: 1 = under easement 2 = under road
3 = under nature strip 4 = under reserve
Soil type: 1 = dark grey sand 2 = light grey sand
3 = clay 4 = mix
TMI: 1 = wettest 2 = wetter 3 = wet
4 = dry 5 = drier 6 = driest

4.3 Preliminary Data analysis

Several basic statistical techniques including correlation tests and univariate analysis of variance (Oneway-ANOVA) were used to study the relationships between contributing factors, and relationships between structural/hydraulic conditions and contributing factors. One important aspect in most statistical techniques is the classification of variables into scale variables and categorical variables. Some techniques such as correlation test can only be applied to the scale variables, whilst others such as the cross table analysis can only be applied to the categorical variables.

Scale variables represent ordered categories with a meaningful metric, so that distance comparisons between values are appropriate. Examples of scale variables include age in years and income in thousands of dollars. In this study, scale factors are pipe size, pipe age, pipe depth, pipe slope and tree-count.

Categorical variables are classified as nominal variables and ordinal variables. Nominal variables represent categories with no intrinsic ranking. Examples of nominal variables include region, zip code, or religious affiliation. Ordinal variables represent categories with some intrinsic ranking. Examples of ordinal variables include attitude scores representing degree of satisfaction or confidence and preference rating scores. In this study nominal factors are pipe location, soil type and TMI. Ordinal factors are the structural and hydraulic conditions.

The SPSS software package can be used to perform the analysis and was used in this study.

4.3.1 Correlation Tests

The correlation test measures show how two variables are linearly related (Dasu and Johnson 2003). The Pearson's correlation coefficient is a measure of linear association between two scale variables (Johnson and Wichern 2002). The correlation coefficient takes values between [0, 1]. Generally, strong and weak linear relationships would take values between [0.85-1] and [0-0.5] respectively; the mild or moderate linear relationships would take values between 0.5 and 0.85. The *t*-test (Montgomery *et al.* 2004) can be used for the correlation tests to specify whether the linear relationships are statistically significant by considering the *P*-value. If the *P*-value of the *t*-statistic is smaller than a critical value of 0.05 for 95% confidence level, the linear relationship is considered statistically significant (Montgomery *et al.* 2004).

The correlation test was applied only to scale factors including pipe size, age, depth, slope and tree-count. The results are given in Table 4-3, which shows that there is a statistically significant correlation between pipe size and pipe depth. This correlation was mild since the correlation coefficient of 0.517 was between 0.5 and 0.85. In short description, this correlation was called statistically significant and mild. In a similar description, there are statistically significant and weak correlations between pipe size and age, pipe size and slope, pipe age and depth, and depth and slope. However, the 'tree-count' factor has no statistically significant correlation with other scale factors.

The positive (+) correlation indicates a value of one variable increases with increase in the value of the other variable. Similarly, the negative (-) correlation indicates a value of one variable increases with decrease in the value of the other variable. The positive correlation between pipe size and depth is reasonable since the large size pipes are often used as the main pipes which must be buried deeper because of cover requirements. Similarly, the positive correlation between pipe size and age can be viewed in a sense that larger size pipes are often laid first followed by smaller size pipes which are often added later with urban development. On the other hand, the negative correlation between pipe size and slope could relate to design or construction practices in which large pipes can have smaller slopes (to reduce cost) because they typically are designed for larger minimum flows, which can provide the minimal required flow velocity (typically 0.75 m/s) to avoid settling of solids.

Table 4-3: Results of Pearson's correlation tests

	Pipe Size	Pipe Age	Pipe Depth	Pipe Slope	Tree-count
Pipe Size	1	0.106(*)	0.517(**)	-0.165(**)	0.058
Pipe Age		1	0.102(*)	0.034	0.024
Pipe Depth			1	-0.101(*)	0.079
Pipe Slope				1	-0.008
Tree-count					1

(**): Correlation is statistically significant at the 0.01 level from *t*-test.
(*): Correlation is statistically significant at the 0.05 level from *t*-test.

4.3.2 One-way ANOVA and Cross-Table analysis

Besides the correlation tests, the analysis of variance (one-way ANOVA) and cross-table analysis (Hair et al. 1998) can be used to detect associations between two variables.

The one-way ANOVA technique compares a scale variable across two or more groups of a categorical variable with a hypothesis of equality of group means. If the hypothesis is rejected, the scale variable has different effects on each group. For stormwater pipes, the common hypothesis is whether scale factors (i.e. pipe size, age, depth, slope, tree-count) have significantly different effects on three groups of pipes corresponding to three pipe (structural and hydraulic) conditions. On the other hand, the cross-table analysis technique assesses whether a category factor has an association with another category factor using the hypothesis of equality of cell counts across the table of two factors. If the hypothesis is rejected, the association or effect exists. For stormwater pipes, this test is carried out for categorical factors (i.e. pipe location, soil and TMI) on the pipe (structural and hydraulic) conditions.

The symmetric measure (Hair et al. 1998) is a statistical indicator that can be used to determine the degree of association in the cross-table analysis. The symmetric measure ranges between 0 and 1, with 0 indicating no association between the row and column variables and values close to 1 indicating a high degree of association between the variables.

Similar to the *t*-test in the correlation tests in Section 4.3.1, the *F*-test can be used for the oneway-ANOVA and the Pearson Chi-square test can be used for the cross-table analysis in order to test whether the association is statistically significant by considering the *P*-values (Hair et al. 1998). If the *P*-value is smaller than a critical value of 0.05 for 95% confidence level, the hypothesis is rejected (Hair *et al.* 1998).

4.3.2.1 Structural Condition versus Contributing Factors

The results of performing one-way ANOVA and cross-table analysis on structural condition are given in Table 4-4 and Table 4-5 respectively. It can be seen From Table 4-4, all *P*-values are larger than the critical value which means that the structural condition did not have associations with the five scale factors as substantiated by. It can be seen from Table 4-5, only the hydraulic condition was found to have statistically significant effect on the structural condition as substantiated by its *P*-value of 0.002. However, the symmetric measure shows a low degree of association between them.

Table 4-4: One-way ANOVA on structural condition

Factors	Mean Square	*F*-statistic	*P*-value
Pipe Size	247200.9	2.205	0.112
Pipe Age	18.6	0.286	0.751
Pipe Depth	0.086	0.157	0.855
Pipe Slope	6.8	1.277	0.280
Tree-count	3.9	0.584	0.558

Table 4-5: Cross-table analysis on structural condition

Factors	Pearson Chi-square	Symmetric measure	*P*-value
Pipe Location	5.099	0.084	0.531
Soil Type	3.925	0.01	0.416
TMI	10.638	0.04	0.386
Hydraulic Condition	17.075	0.132	0.002*

*statistically significant at 0.05 significance level

4.3.2.2 Hydraulic Condition versus Contributing Factors

Similar to Section 4.3.2.1, the results of performing one-way ANOVA and cross-table analysis on the hydraulic condition are given in Tables 4-6 and 4-7 respectively. It can be seen that the pipe age and pipe slope were found to have statistically significant effect on the hydraulic condition. The structural condition and pipe location were found to have statistically significant effects on the hydraulic condition as substantiated by the *P*-values in Tables 4-6 and 4-7 respectively. However, the symmetric measure using contingency coefficient provides weak association between the pipe location and the hydraulic condition.

Table 4-6: One-way ANOVA on hydraulic condition

Factors	Mean Square	*F*-statistic	*P*-value
Pipe Size	124129.042	1.102	0.333
Pipe Age	518.017	8.261	0.000*
Pipe Depth	.734	1.349	0.261
Pipe Slope	34.704	6.597	0.002*
Tree-count	13.412	2.020	0.134

*statistically significant at 0.05 significance level

Table 4-7: Cross-table analysis on hydraulic condition

Factors	Pearson Chi-square	Symmetric measure	*P*-value
Pipe Location	16.012	0.196	0.014*
Soil Type	5.521	-0.034	0.238
TMI	17.510	-0.034	0.064

*statistically significant at 0.05 significance level

4.4 Application of Structural Deterioration Models

Five deterioration models (i.e. Markov model, MDDM, OPDM, NNDM and PNNDM) developed in Section 3.3 were applied to model the structural deterioration of stormwater pipes of CGD. The Markov model was used for predicting the condition changes of pipe population; this model was not able to be used for individual pipes due to the lack of longitudinal pipe condition data. The predicted information on the condition changes of pipe population can be used for budget planning. The remaining four models (MDDM, OPDM, NNDM and PNNDM) were used for predicting the condition changes of individual pipes and pipe population. The predicted information on the condition changes of individual pipes can be used for prioritizing repair works. Except for the Markov model, nine contributing factors provided were used as inputs to the remaining four deterioration models. Inputs to the Markov model were the pipe age. The output of the four models was the pipe condition at different ages and the output of the Markov model was the number of pipes in each of three structural conditions at different ages. The five deterioration models were calibrated by different techniques as shown in Figure 3-1, the details of these calibration techniques were given throughout Section 3.3.

As outlined in Section 3.4, the fitness of five deterioration models for modelling structural deterioration of stormwater was tested by the goodness-of-fit test using Pearson Chi-square statistic. Except for the Markov model, the predictive performance of the remaining four deterioration models in predicting condition changes of individual pipes was also assessed by two scalar performance measures, namely, the overall success rate (OSR) and the false negative rate (FNR). The OSR indicates how well the deterioration models predict condition changes of individual pipes and the FNR shows the risk associated with the use of the models.

As outlined in Section 3.5, the significant input factors to four deterioration models MDDM, OPDM, NNDM and PNNDM were identified by the forward stepwise method, Wald test, connection weight analysis and the backward stepwise method respectively.

The SPSS® software package was used to perform computational tasks for the MDDM and OPDM. The MATLAB® software package and its toolboxes (i.e. NN toolbox and GA toolbox) were used to perform computational tasks for the Markov model, the NNDM and the PNNDM.

Section 4.4.1 presents the data preparation for the models. Section 4.4.2 describes the results of calibration or training while section 4.4.3 describes the testing results. Section 4.4.4 presents the significant input factors identified from four deterioration models MDDM, OPDM, NNDM and PNNDM.

4.4.1 Data preparation

As outlined in the development of the five deterioration models in Sections 3.3.1-3.3.5, first the model parameters need to be estimated using a calibration dataset, and the predictive performances of these models need to be tested using a test dataset which is different to the calibration dataset. However, the calibration and test datasets required for the Markov model are different from that of the remaining four deterioration models (i.e. MDDM, OPDM, NNDM and PNNDM). This is because the inputs of the Markov model were only the pipe age.

4.4.1.1 Data for the Structural Markov Model

The entire dataset was randomly split into the calibration dataset containing approximately 75% of the entire dataset and the test dataset containing the remaining 25%. The calibration and test datasets are given in Table 4-8. This table was constructed by assigning the pipes of different ages randomly into the calibration and test datasets to get 75/25% split. Pipes are assigned at a certain age only to one dataset. This condition was required to test the Markov model.

4.4.1.2 Data for the Structural MDDM, OPDM, NNDM and PNNDM

Since the MDDM, OPDM, NNDM and PNNDM used similar inputs factors; the entire dataset was randomly split into the calibration dataset containing approximately 75% of the entire dataset and the test dataset containing the remaining 25%. A part of the dataset is shown in Table 4-9. As can be seen from this table, there are totally nine input factors (from the pipe size to the Thornwaite Moisture Index (TMI)). The hydraulic condition was used as one of the inputs to the MDDM, OPDM, NNDM and PNNDM for structural condition because this factor could be associated with structural deterioration. For example, a poor hydraulic condition caused by tree roots and sediment deposition may be a result due to a hole or fracture (structural defects) along the pipe. The last column shows how the pipe has been assigned to either the calibration dataset (code=1) or the test dataset (code=0) based on randomly generated numbers and a threshold value. The calibration dataset used for the NNDM was randomly split into a train dataset containing 60% of the entire dataset and the validation dataset containing 15% of the entire dataset (i.e. 75%=60%+15%). This is because the NNDM needs the validation dataset in the training process to avoid the problem of over-fitting, as outlined in Section 3.3.4.2/B. Furthermore, values of all the input factors used for the NNDM were scaled between 0 and 1 in order to identify the significant factors using the connect weight analysis (Section 3.5.4).

Table 4-8: Details of calibration and test datasets for the Markov model

Calibration Dataset				
Age	Structural Condition			Total
	1	2	3	
0	0	0	1	1
2	0	0	1	1
10	1	0	0	1
17	0	0	11	11
18	0	0	1	1
25	0	0	1	1
27	0	0	1	1
30	5	5	23	33
31	1	0	0	1
32	6	1	21	28
33	0	0	2	2
35	4	0	10	14
36	2	1	1	4
37	14	2	11	27
39	6	3	18	27
40	1	1	25	27
41	4	2	13	19
43	10	2	23	35
44	11	8	29	48
45	8	2	16	26
47	0	0	4	4
48	1	0	3	4
50	0	0	4	4
51	0	0	1	1
65	0	0	3	3
Total	74	27	223	324

Test dataset				
Age	Structural Condition			Total
	1	2	3	
5	0	0	1	1
14	2	0	0	2
21	3	0	1	4
29	7	0	1	8
34	1	0	11	12
38	3	4	13	20
42	10	1	13	24
46	4	0	12	16
49	0	0	1	1
52	2	0	3	5
Total	32	5	56	93

Table 4-9: A part of calibration of and test datasets for MDDM, OPDM, NNDM and PNNDM

No.	Output	Input Factors									Code
	St. Cond.	Pipe Size (m)	Pipe Age (years)	Pipe Depth (m)	Pipe Slope (%)	Tree-count	Hy. Cond.	Pipe Location	Soil Type	TMI	
1	2	2	375	42	1.15	7.80	0	2	3	1	1
2	3	2	900	44	1.40	1.04	1	1	3	1	0
3	1	3	750	39	1.30	1.11	0	2	3	1	1
4	1	3	600	30	1.30	1.00	2	4	3	1	1
5	3	3	525	32	1.70	0.51	0	4	4	2	0
6	3	525	44	0.65	1.43	1	2	4	3	1	1
7	3	1425	32	2.4	0.21	2	3	1	4	4	1
8	3	450	35	1.60	0.55	2	3	2	4	2	0
9	1	225	39	0.85	1.13	2	1	3	3	1	1
10	1	825	47	1.67	0.67	0	2	2	4	2	0

Note:
St. Cond.: structural condition 1 = good 2 = fair 3 = poor
Hy. Cond.: hydraulic condition 1 = good 2 = fair 3 = poor
Pipe location: 1 = under easement 2 = under road
3 = under nature strip 4 = under reserve
Soil type: 1 = dark grey sand 2 = light grey sand
3 = clay 4 = mix
TMI: 1 = wettest 2 = wetter 3 = wet
4 = dry 5 = drier 6 = driest

4.4.2 Calibration (or Training) of Structural Deterioration Models

Section 3.3 dealt with model calibration (or training of model) which was aimed at estimating the model parameters from the sample data. One major issue in the calibration process is to produce local optimum model parameters instead of global optimum parameters. The occurrence of local optimum model parameters could adversely affect the calibration performance leading to poor model performance. This was addressed in this study by using different calibration techniques for the Markov model, OPDM and NNDM. The calibration of the MDDM and PNNDM, on the other hand, can be done without any concern for the local optimum due to their model structures.

4.4.2.1 Structural Markov Model

The transition probabilities were the model parameters in the structural Markov model. The Metropolis-Hastings algorithm (MHA) of the Bayesian MCMC simulation and the standard optimization technique were two calibration techniques used in this study. Initially the calibration and test dataset were used to calibrate and test the Markov model respectively. Once the model was tested, then the entire dataset was used for constructing the condition changes of pipe population as the transition probabilities estimated with the entire dataset (large sample size) would be better than that with the calibration dataset (small sample size).

The MHA was performed on the MATLAB® platform and the programming codes for the MHA are given in the Appendix C.1. The MHA was run with 13,000 iterations for the calibration dataset and entire dataset to achieve convergence of the chain to stationary distributions. An acceptance rate of 0.34 was found in the runs, which is not far from the suggested value of 0.234 (Roberts and Rosenthal 2001) for checking the suitability of the variance-covariance matrix of the MHA (Section 3.3.1.4). The last 3,000 results were kept to estimate the mean and confidence ranges of the transition probabilities. The Excel Solver® optimization tool was used to implement the standard optimization technique for maximizing the likelihood on the calibration dataset.

The mean values of the transition probabilities estimated by the MHA with the calibration dataset were given in Table 4-10. Similarly, the values of the transition probabilities estimated by the optimization technique with the calibration dataset are given in the Table 4-11. It can be seen from these two tables, the estimated transition probabilities by two calibration techniques are slightly different. The performances of each calibration technique are shown in Section 4.4.2.

Table 4-10: MHA estimated transition probabilities with the calibration dataset

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

The mean values of the transition probabilities and their 95% confidence intervals (values within brackets) estimated by the MHA on the entire datasets are given in Table 4-12. The 95% confidence limits of the transition probabilities give an indication of the uncertainty of the model parameters. In other words, since the true values of transition probabilities are unknown, the mean values within 95% confidence limits can be used to approximate the true values. This is the advantage of the MHA over the standard optimization technique which cannot provide the confidence limits of the transition probabilities.

Table 4-11: Optimization estimated transition probabilities with the calibration dataset

Optimization		Future Condition State		
		1	2	3
Current Condition State	1	0.9426	0.0196	0.0378
	2	0	0.9998	0.0002
	3	0	0	1

Table 4-12: MHA estimated transition probabilities with the entire dataset

MHA		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

4.4.2.2 Structural Multiple Discriminant Deterioration Model (MDDM)

The calibration of the structural MDDM was to estimate the model parameters which were the factor coefficients of the two discriminant functions as outlined in Section 3.3.2.3. The calibration of the MDDM was done using the SPSS® software. The estimated factor coefficients are given in Table 4-13. The estimated coefficients as shown in Tables 4-13 are of little interest because they are just a transformation from a set of axis to another set of axis in the same factor space in order to better separate the pipe condition.

Table 4-13: Factor coefficients for discriminant functions of structural MDDM

Factors	Discriminant Function	
	1	2
Pipe Size (m)	.002	.001
Pipe Age	.002	-.034
Pipe Depth (m)	-.551	-1.142
Pipe Slope	-.116	.176
Tree-count	.183	-.030
Hydraulic Condition	.607	.318
Pipe Location	-.294	.408
Soil Type	-.784	.396
TMI	.320	.792

4.4.2.3 Structural Ordered Probit Deterioration Model (OPDM)

The calibration of the structural OPDM was to estimate the model parameters which are two thresholds (θ_1 and θ_2) and the factor coefficients (Section 3.3.3.3). The Maximum Likelihood (ML) and Bayesian MCMC using Gibb sampler were two alternative calibration techniques used in this study. The ML technique is a frequently used technique in calibration of statistical models (Greene 1990). Its solution was counterchecked in this study by the Bayesian MCMC as local optimum may occur. The ML and the Gibb sampler were implemented using the SPSS® software and the WINBUGS® software respectively. Table 4-14 shows estimated values for the model parameters. It can be seen that the estimated values of model parameters by both techniques are not much different. The magnitude of the factor coefficients as shown in Table 4-14 was reasonable with the value range of contributing factors. The positive sign of the factor coefficient means that the larger the value of the factor (or covariates) the poorer the condition. The negative sign shows the inverse effect. All contributing factors except the tree-count had positive factor coefficients. This means pipes will have poorer condition with aging and larger size. This is consistent with other study by Baik *et al*. (2006) and Ariaratnam *et al*.(2001).

4.4.2.4 Structural Neural Network Deterioration Model (NNDM)

As outlined in Section 3.3.4.2, the number of hidden neurons in the structural NNDM was first determined using the Levenberg-Marquardt algorithm (LMA). This also means that with the chosen number of hidden neurons, the structural NNDM was already trained by the LMA. Genetic algorithm (GA) and Bayesian MCMC using Metropolis-Hastings algorithm (MHA) were then used to train the NNDM as the LMA may not handle well the problems of local optimum and the uncertainty of network weights.

Table 4-14: Estimated thresholds and factor coefficients for the structural OPDM

Input Factors	ML	Bayesian MCMC
θ_1	2.532	2.745
θ_2	2.795	2.992
Pipe Size	0.001	0.002
Pipe Age	0.001	0.003
Pipe Depth	0.672	0.658
Pipe Slope	0.045	0.055
Tree-count	-0.056	-0.063
Hydraulic Condition	0.399	0.400
Pipe Location	0.041	0.049
Soil Type	3.011	3.005
TMI	2.208	2.309

A/ Training of NNDM using LMA and determine the number of hidden neurons

The NN toolbox of MATLAB® was used to perform computational tasks. The suitable number of hidden neurons for the NNDM was searched using the LMA and mean square error (MSE) criterion. The results are given in Figure 4-14 which shows the changes of MSE computed from the train and validation datasets against the number of hidden neurons. The validation dataset was used to avoid over-fitting the NNDM

(Section 3.3.4.2). The training of the NNDM should stop whenever the MSE of the validation dataset starts to increase. As can be seen from this figure, the best possible number of hidden neurons was 18 as the MSE values had the lowest values of 0.04 and 0.08 respectively on the train and validation datasets at this point. The NNDM for structural deterioration had 9 input neurons, 18 hidden neurons and 3 output neurons with a total of 237 network weights (including connection weights and bias weights). The values of network weights estimated by the LMA can be used in the NNDM to compute the predicted output values given any input values.

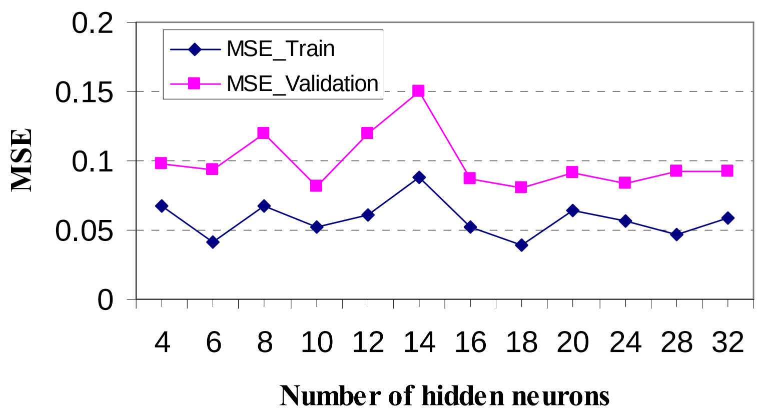

Figure 4-14: MSE of structural NNDM with different number of hidden neurons

B/ Training of structural NNDM using GA

This task was performed using the GA Toolbox of MATLAB software package and the programming code was given in Appendix C.3. The population size and the crossover fraction were two GA parameters that could affect the GA performance and therefore required investigation as outlined in Section 3.3.4.2. The suitable value of the population size was determined by changing its value while keeping crossover fraction at the average value of 0.5. Similarly, the suitable value of the crossover fraction was determined by changing its values while keeping the population size at the determined value. Figure 4-15 shows the effects of population size and the effect of crossover fraction on the MSE of training dataset which was the fitness value of GA. As can be seen in this figure, the suitable value of population size was 230 with an MSE value of 0.026 since the other values caused an increase in the MSE of GA. The suitable value of crossover fraction appeared to be 0.8 with an MSE value of 0.02. Beyond 0.9 for crossover fraction, the MSE value increases rapidly since less mutation occur. This was expected as explained in Section 3.3.4.2 since the variability in population members is reduced. With these optimum values for the population size and crossover fraction, GA was used again to determine the network weights. The MSE value of 0.018 was found with GA training which is smaller than the MSE value of 0.04 found with LMA training. The estimated network weights by GA were then used in the structural NNDM to compute the predicted output values given any input values.

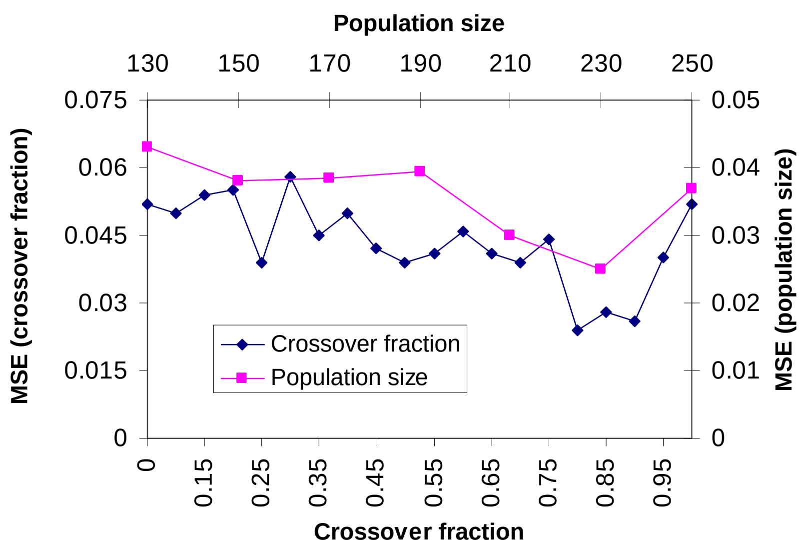

Figure 4-15: Effect of crossover fraction and population size on MSE of GA training for structural NNDM

C/ Train NNDM using MHA of Bayesian MCMC

Similar to the Metropolis-Hastings algorithm (MHA) used in the calibration of the structural Markov model, the MHA used for training of the structural NNDM was run on the MATLAB® platform and the programming code was given in Appendix C.2. The last 3000 values of network weights were kept to compute the mean values and 95% confidence limits. The average MSE value found with the MHA was 0.009 which is smaller than both the MSE values found with LMA and GA. One typical distribution of a network weight (among 237 network weights) is given in Figure 4-16. From this figure, the mean value of the network weight was computed as 0.45 and the 95% confidence interval was [0.21, 0.62]. This implies that in a considerable uncertainty exists in estimating the network weights. The values with 95% confidence limit of network weights were then used in the NNDM to produce the corresponding predicted structural condition with 95% confidence limit (or interval prediction) given any input values.

4.4.2.5 Structural Probabilistic Neural Network Deterioration Model (PNNDM)

The NN toolbox of MATLAB® was used to perform the computational tasks. The training of the PNNDM was almost instantaneous since the PNNDM simply stored the training data into the pattern layer as explained in Section 3.3.5.3. The smoothing parameter (or standard deviation) of the Gaussian kernel was searched based on the trial and error approach. The value of 0.5 was found since other values caused a reduction on the number of correct predictions in the training dataset.

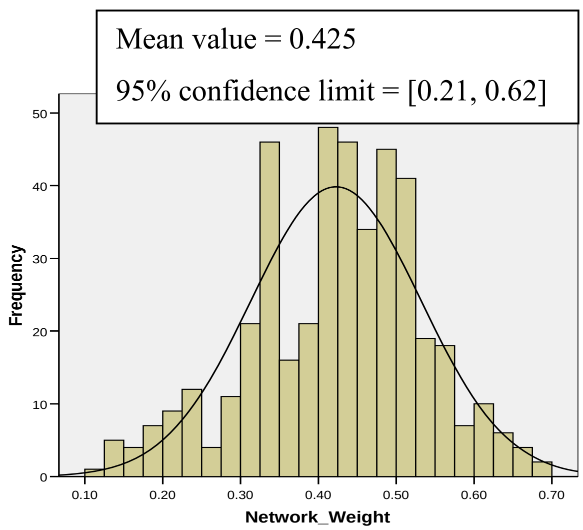

Figure 4-16: Histogram of a network weight

4.4.3 Testing Five Structural Deterioration Models

As outlined in Section 1.3, the primary aim of this study was to develop deterioration models which can predict the condition changes of pipe population and the condition changes of individual stormwater pipes. An essential part of this development is the testing of the developed models, once the model parameters were estimated. As described in Section 3.4, the fitness of the five deterioration models for predicting structural condition changes of pipe population can be tested by the goodness-of-fit test using Pearson Chi-square statistic. The predictive performance of the remaining four deterioration models (i.e. MDDM, OPDM, NNDM and PNNDM) in predicting condition changes of individual pipes can be assessed using two scalar performance measures, namely, the overall success rate (OSR) and the false negative rate (FNR). The OSR indicates how well the deterioration models predict condition changes of individual pipes, while the FNR shows the risk associated with the use of the models. These performance measures (i.e. goodness-of-fit test, OSR and FNR) were used to select the best deterioration models to predict the condition changes of pipe population and the condition changes of individual stormwater pipes for the case study.

4.4.3.1 Best Suitable Structural Deterioration Model for Predicting Condition Changes of Pipe Population

Table 4-15 shows the computed Chi-square values for the calibration and test datasets for testing the fitness of five deterioration models. As expected, the Chi-square value for the test dataset is larger than that for the calibration dataset for each of the models since the model parameters were determined by minimizing the MSE on the calibration dataset. As can be seen from this table, the Markov model, NNDM and PNNDM passed the goodness-of-fit test for both calibration and test datasets as substantiated by the small Chi-square values which were lower than the critical Chi-square value of 5.99 for this case study. This means that these deterioration models are suitable models for structural deterioration of stormwater pipes. Furthermore, among suitable deterioration models, the Markov model had the lowest Chi-square value which suggested the Markov model was the best model to predict the condition changes of the pipe population for stormwater pipes in this case study. The MDDM and OPDM failed the goodness-of-fit test.

The Bayesian MCMC technique provided the better performance for model calibration for the Markov model over the standard optimization. This is substantiated by the lower Chi-square values found with this technique on both calibration and test datasets as shown in Table B-1 (Appendix B). This suggested that the Bayesian MCMC technique was the best calibration technique for the Markov model. The Bayesian MCMC also provided the better performance for the NNDM in comparison with LMA and GA. This is substantiated by the lowest MSE value during training of the structural NNDM and the lowest Chi-square values for both calibration and test dataset. GA was found better than the LMA in training the NNDM as expected.

Since the Markov model was the best model for predicting the condition changes of the pipe population, it was then used to predict the condition changes of pipe population for the stormwater pipes of CGD at different ages. The proportions of the three structural conditions belonging to each structural condition over time were computed using Equation (3-2) with the transition probabilities estimated from the entire dataset (as shown in Table 4-12). The prediction of the structural deterioration of the stormwater pipes is shown in Figure 4-17.

Table 4-15: Chi-square values of five structural deterioration models

Structural Deterioration Models	Calibration Techniques	Chi-square values $\chi^2_M \, (\le \chi^2_{2,0.05} = 5.99)$	
		Calibration dataset	Test dataset
Markov Model	Bayesian MCMC simulation (MHA)	0.22	0.34
	Standard optimization	1.38	1.53
MDDM	Maximizing Fisher's criterion	12.9	14.5
OPDM	Maximum Likelihood	7.21	7.35
	Bayesian MCMC simulation (Gibb sampler)	7.21	7.35
NNDM	LMA	2.95	4.16
	GA	2.44	3.28
	Bayesian MCMC simulation (MHA)	2.13	2.57
PNNDM	Trial and error approach	1.97	4.21

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 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 poor structural condition.

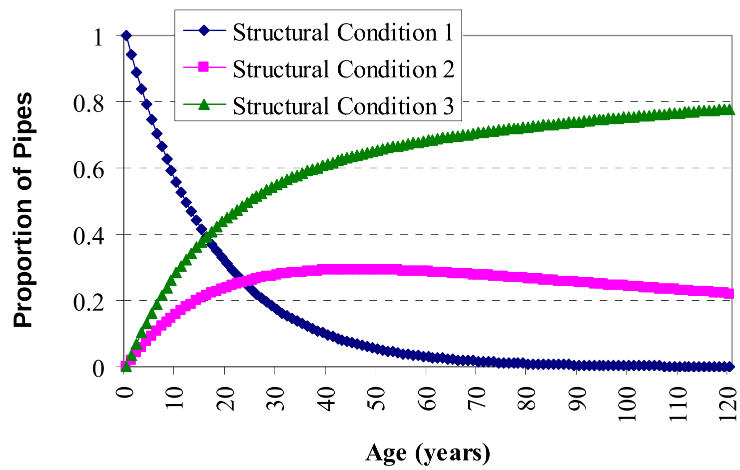

Figure 4-17: Structural condition changes of pipe population

4.4.3.2 Best Suitable Structural Deterioration Model for Condition Changes of Individual Pipes

The confusion matrixes of four deterioration models (MDDM, OPDM, NNDM and PNNDM) are given in Tables B-2 to B-7 (Appendix B). The computed overall success rate (OSR) and the false negative rate (FNR) are shown in this section for determining the best suitable structural deterioration model, the primary aim of this study. Figure 4-18 shows the computed OSRs (in percentages) for the calibration and test datasets for four deterioration models (MDDM, OPDM, NNDM and PNNDM). Furthermore, the effects of different calibration techniques on the OSR of each deterioration model are also shown in this figure. As expected, the OSR for the calibration (or train) dataset is higher than for the test dataset. As can be seen form this figure, the NNDM and PNNDM outperformed the MDDM and OPDM in predicting the structural condition of individual pipes. This was substantiated by the higher values of OSR for the NNDM and PNNDM for both calibration and test datasets. Furthermore, the PNNDM had the highest OSR in the calibration dataset and the NNDM had the highest OSR in the test dataset.

Similar results were found when comparing these four deterioration models in terms of the FNR as shown in Figure 4-19. As expected, the FNR for the calibration (or train) dataset is lower than for the test dataset. As can be seen from this figure, the NNDM and PNNDM again outperformed the MDDM and OPDM as substantiated by the lower FNRs for both calibration and test datasets. The PNNDM had the lowest FNR on the calibration dataset and the NNDM had the lowest FNR on the test dataset.

Based on the performances found with OSR and FNR on the test dataset this study therefore decided to consider the NNDM as the best model for predicting the structural condition of individual stormwater pipes (for this case study).

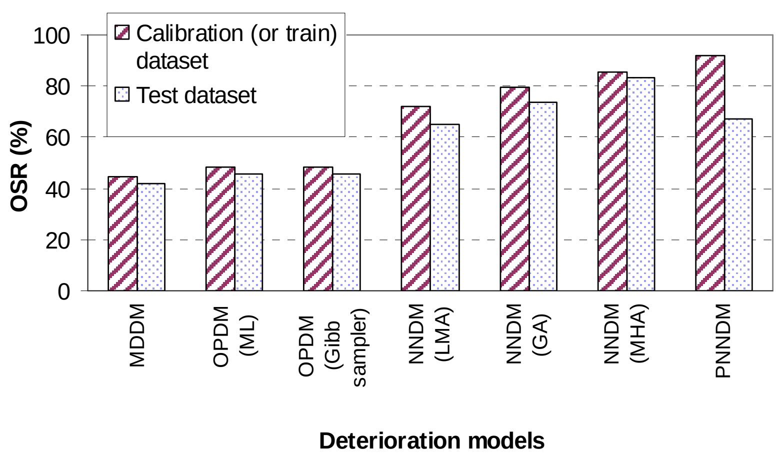

Figure 4-18: Values of OSR for MDDM. OPDM, NNDM and PNNDM

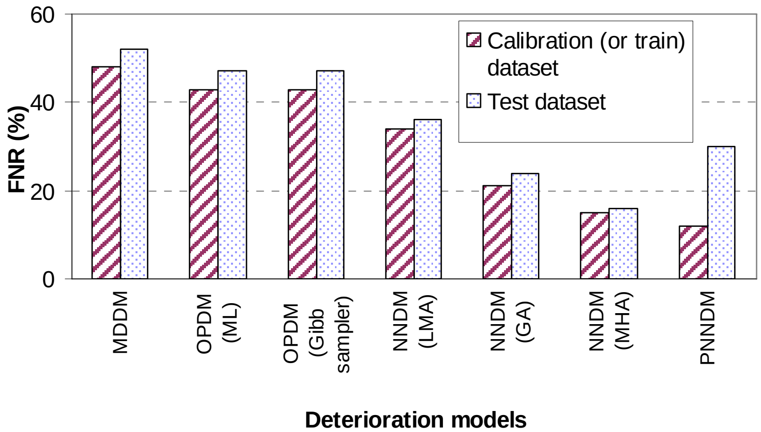

Figure 4-19: Values of FNR for MDDM. OPDM, NNDM and PNNDM

The NNDM trained with GA had higher OSR and lower FNR than those of the NNDM trained with the LMA on both calibration and test dataset. However, the MHA of Bayesian MCMC technique outperformed both GA and LMA techniques in producing the best predictive performances for NNDM for both calibration and test datasets. This implies that the Bayesian MCMC technique was considered as the best calibration technique for the NNDM in this case study. The superiority of the Bayesian MCMC simulation technique over the LMA was shown in Figure 4-20 which illustrates the predictions by the NNDM for the first 25 data points in the test dataset. The point prediction was obtained by using the point values of network weights which were estimated from the calibration of the NNDM by the LMA. The interval prediction was obtained by using the 95% confidence limits of network weights which were estimated from the calibration of the NNDM by the MHA of Bayesian MCMC. The interval prediction indicated the 95% confidence range of structural condition that could contain the observation. As can be seen from this figure, the interval prediction of structural conditions had a better fitting to the observed structural condition than that of the point prediction.

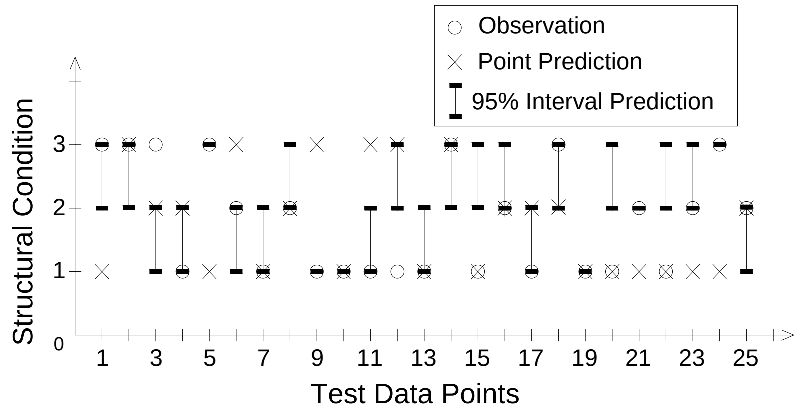

Figure 4-20: point and interval predictions versus observations of structural condition on a portion of test dataset

4.4.4 Identification of Significant Input Factors of Structural Models

As outlined in Section 1.3, the secondary aim of this study was the identification of significant input factors that affect the predicted condition of individual stormwater pipes. By paying attention to the identified significant input factors, the design and operation of pipes could be improved towards fewer pipe failures and longer service lifetimes.

The significant input factors of the structural MDDM and OPDM were identified by the forward stepwise method and the Wald-test respectively described in Sections 3.5.1-3.5.3. The common aspect of these two statistical methods is that if the *P*-value for the computed test statistic (*F*-value for the structural MDDM and Wald statistic for the structural OPDM) is smaller than the value of 0.05 or 0.1 (equivalent to 95% and 90% confidence level respectively), the corresponding input factor can be considered statistically significant.

The significant input factors of the structural NNDM were identified using the connection weight analysis described in Section 3.5.4 while the significant factors of the structural PNNDM were identified using the stepwise backward method described in Section 3.5.3. The common aspect of these two methods is that the input factors can be ranked in significance order according to the magnitudes of their significance values. The significance values of an input factor in the structural NNDM can be computed from its connection weights. The significance values of an input factor in the structural

PNNDM is the decrease in the overall success rate (OSR) on the test dataset when comparing the structural PNNDM using all input factors and the structural PNNDM without the input factor of interest.

Table 4-16 shows the computed *F*-values and *P*-values for the 9 input factors of the structural MDDM. As can be seen from this table, only the hydraulic condition was found to be the statistically significant factor at 0.05 level.

Table 4-16: F-value and P-value of input factors in structural MDDM

Factors	*F*-value	*P*-value
Pipe Size	1.47	0.230
Pipe Age	0.12	0.879
Pipe Depth	.30	0.739
Pipe Slope	1.52	0.219
Tree-count	1.35	0.259
Hydraulic condition	3.36	0.053*
Pipe Location	1.55	0.214
Soil Type	0.43	0.649
TMI	0.24	0.787

* significant input factor at 0.05 level

Similarly, Table 4-17 shows the Wald statistic and corresponding *P*-values. It is seen from this table that pipe size, tree-count, hydraulic condition and pipe location were found to be statistically significant at 0.05 or 0.1 levels as substantiated by the *P*-values.

Figures 4-21 to 4-23 show the significance values of input factors found by three different train techniques (i.e. LMA, GA and MHA respectively) for the NNDM. As can be seen from these figures that pipe size, pipe location, hydraulic condition and soil type stood out as the top four ranked factors. On the other hand, pipe age and TMI were bottom ranked factors across the three training techniques. Furthermore, tree-count was ranked high only in the NNDM trained by the MHA. Figure 4-24 shows the significance values of input factors of the PNNDM. As can be seen from this figure, the top four ranked factors were pipe size, tree-count, hydraulic condition and pipe location. Bottom ranked factors were Pipe age and TMI. By comparing the significant factors found in MDDM, OPDM, NNDM and PNNDM, it was concluded that pipe size, pipe location and hydraulic condition can be considered as significant factors that affect the structural condition of pipes. Pipe age, TMI, pipe slope and pipe depth were considered as insignificance factors for the case study. Tree-count and soil type were inconclusive since the analysis produced inconsistent results.

Table 4-17: Wald-statistic and *P*-value of input factors in structural OPDM

Input Factors	Wald-Statistic	P-value
Pipe Size	3.254	.071**
Pipe Age	.003	.959
Pipe Depth	2.390	.122
Pipe Slope	1.282	.257
Tree-count	3.212	.073**
Hydraulic condition	4.280	.039*
Pipe Location	2.222	.070**
Soil Type	1.821	.177
TMI	3.287	.174

*statistically significant factors at 0.05 level

** statistically significant factors at 0.10 level

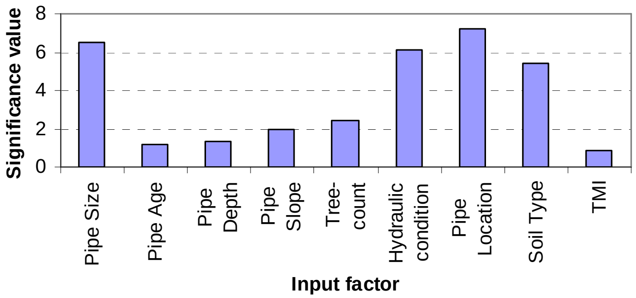

Figure 4-21: Significance values of input factors of NNDM (LMA)

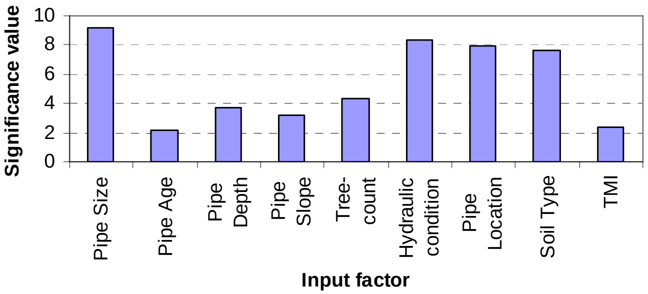

Figure 4-22: Significance values of input factors of NNDM (GA)

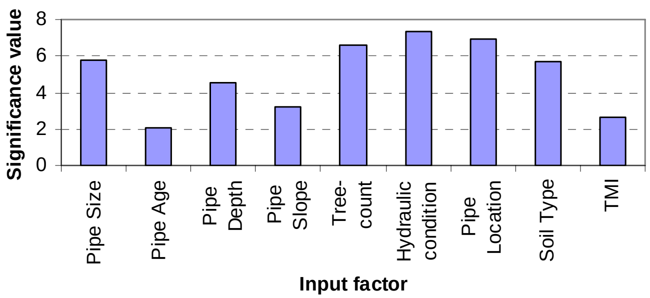

Figure 4-23: Significance values of input factors of NNDM (MHA)

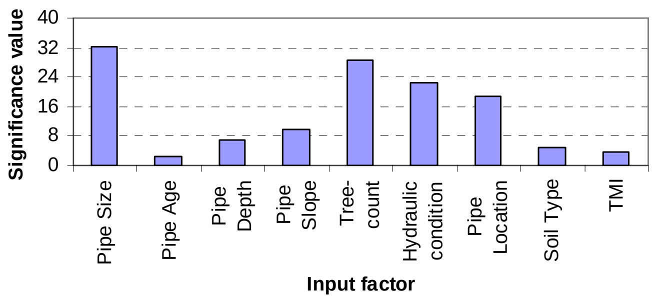

Figure 4-24: Significance values of input factors of PNNDM

4.5 Hydraulic Deterioration Models for Stormwater Pipes of CGD

All five deterioration models (i.e. Markov model, MDDM, OPDM, NNDM and PNNDM) developed in Section 3.3 and applied for modelling structural deterioration of stormwater pipes of CGD in Section 4.4 were also applied for modelling hydraulic deterioration of stormwater pipes of CGD. Methods for calibration and testing of the models, and methods for identifying significant input factors for each model are the same for both structural and hydraulic deterioration. Therefore, only the results are shown in this section with relevant comments.

4.5.1 Data preparation

4.5.1.1 Data for the Hydraulic Markov Model

Similar to the data for the Markov model for structural deterioration, pipe age was the only input factor used for the Markov model for hydraulic deterioration. Table 4-18 shows the calibration and test datasets for the hydraulic Markov model. The method for construction of this table was similar to the method for construction of Table 4-8 which (Section 4.4.1.1). The calibration (approximately 75%) and test (25%) datasets were generated by randomly splitting the entire dataset.

4.5.1.2 Data for the Hydraulic MDDM, OPDM, NNDM and PNNDM

The data format used by four hydraulic deterioration models MDDM, OPDM, NNDM and PNNDM are similar to the data used for four structural deterioration models described in Section 4.4.1.2. That is the calibration dataset of approximately 75% and the test dataset of 25% were generated by randomly picking from the entire dataset. The calibration dataset of the hydraulic NNDM was randomly divided into the train dataset (approximately 60%) and the validation dataset (15%). The use of validation dataset was to avoid over-fitting during the training of the hydraulic NNDM. The input factors of the four hydraulic deterioration models were pipe size, pipe age, pipe depth, pipe slope, tree-count, structural condition, pipe location, soil type and TMI. These input factors were the same as the input factors of four structural deterioration models except that the structural condition was used as an input factor for the hydraulic deterioration models whereas the hydraulic condition was used as an input factor for the structural deterioration models.

Table 4-18: Details of Calibration and test datasets for the hydraulic Markov model

Calibration Dataset						Test dataset				
Age	Hydraulic Condition			Total		Age	Hydraulic Condition			Total
	1	2	3				1	2	3	
0	0	0	1	1		10	1	0	0	1
2	0	0	1	1		21	1	2	1	4
5	1	0	0	1		29	2	0	6	8
14	0	0	2	2		34	4	5	3	12
17	0	0	11	11		39	18	3	6	27
18	0	0	1	1		42	13	6	5	24
25	1	0	0	1		45	12	6	8	26
27	0	0	1	1		Total	51	22	29	102
30	12	7	14	33						
31	1	0	0	1						
32	12	7	9	28						
33	2	0	0	2						
35	4	2	8	14						
36	3	1	0	4						
37	13	10	4	27						
38	13	5	2	20						
40	12	8	7	27						
41	5	7	7	19						
43	11	11	13	35						
44	25	19	4	48						
46	5	5	6	16						
47	3	0	1	4						
48	1	0	3	4						
49	0	0	1	1						
50	3	0	1	4						
51	0	0	1	1						
52	2	0	3	5						
65	2	0	1	3						
Total	131	82	102	315						

4.5.2 Calibration (or Training) of the Hydraulic Deterioration Models

Similar to the calibration or training of five structural deterioration models in Section 4.4.2, the major issue in calibration process was to determine the global optimum parameters instead of local optimum parameters which could adversely affect the calibration performance leading to poor model performance. The methods used were similar to those used for the structural deterioration models of Section 4.4.2.

4.5.2.1 Hydraulic Markov Model

The transition probabilities were the model parameters of the hydraulic Markov model. They were estimated using the Metropolis-Hastings algorithm (MHA) of the Bayesian MCMC and the standard optimization technique. As was in Section 4.4.2.1, the calibration dataset and the entire dataset were also used in the calibration of the Markov model for hydraulic deterioration. The calibration dataset was used so that the Markov model can be tested with the test dataset. The entire dataset was used for constructing the condition changes of pipe population as the transition probabilities estimated with the entire dataset would be better than that with the calibration dataset.

The mean values of the transition probabilities estimated by the MHA with the calibration dataset are given in Table 4-19. As can be seen from this table, the probability of 0.0173 for the transition from current condition 1 to future condition 3 is larger than that of 0.01 for the transition from current condition 1 to future condition 2. This implies that the multi-state transition from the current condition 1 to the future condition 3 is more likely to occur than the transition from the current condition 1 to the future condition 2.

Table 4-19: MHA estimated transition probabilities with the calibration dataset

MHA		Future Condition State		
		1	2	3
Current Condition State	1	0.9727	0.01	0.0173
	2	0	0.9996	0.0004
	3	0	0	1

The values of the transition probabilities estimated by the standard optimization technique with the calibration dataset are given in Table 4-20. These values of transition probabilities are again slightly different to those estimated by the MHA as encountered with the structural Markov model (Section 4.4.2.1).

The mean values of the transition probabilities estimated by the MHA using the entire dataset are given in Table 4-21. The values within the bracket of the Table 4-21 are the 95% confidence limits of the transition probabilities, which indicate the uncertainty of the model parameters for the hydraulic Markov model.

Table 4-20: Optimization estimated transition probabilities with the calibration dataset

Optimization		Future Condition State		
		1	2	3
Current Condition State	1	0.9726	0.01	0.0174
	2	0	0.9999	0.0001
	3	0	0	1

Table 4-21: MHA estimated transition probabilities with the entire dataset

MHA		Future Condition State		
		1	2	3
Current Condition State	1	0.9732 (0.9730-0.9734)	0.0109 (0.0108-0.011)	0.0159 (0.0158-0.0160)
	2	0	0.9950 (0.9948-0.9952	0.0005 (0.0048-0.0052)
	3	0	0	1

4.5.2.2 Hydraulic Multiple Discriminant Deterioration Model (MDDM)

The factor coefficients of the two discriminant functions as described in Section 3.3.2.3 were the model parameters to be estimated during the calibration. The estimated factor coefficients are given in Table 4-22.

4.5.2.3 Hydraulic Ordered Probit Deterioration Model (OPDM)

Two thresholds and the factor coefficients described in Section 3.3.3.3 were estimated by two different calibration techniques, Maximum Likelihood (ML) and Bayesian

MCMC using Gibb sampler, similar to the structural OPDM. Table 4-23 shows estimated values for the model parameters of the hydraulic OPDM. It can be seen that both techniques provided similar results. Pipe size, pipe depth and pipe slope had negative factor coefficients. This means large, deep and more sloped pipes tend to have better hydraulic condition. This is reasonable since it take time for tree roots to reach deep pipes. However, the finding is not conclusive because pipe age also had negative factor coefficient which is not reasonable. A larger and less biased sample data could produce different outcomes.

Table 4-22: Factor coefficients for discriminant functions in the hydraulic MDDM

Factors	Discriminant Function	
	1	2
Pipe Size	0.525	-0.307
Pipe Age	0.457	-0.247
Pipe Depth	0.455	-0.257
Pipe Slope	0.581	-0.092
Tree-count	0.036	-0.399
Structural Condition	0.264	0.528
Pipe Location	0.396	0.385
Soil Type	-0.071	-0.183
TMI	-0.471	0.93

4.5.2.4 Hydraulic Neural Network Deterioration Model (NNDM)

The number of hidden neurons and the network weights were the model parameters of the NNDM (Section 3.3.4.2). Similar to the calibration of structural NNDM in Section 4.4.2.4, the number of hidden neurons in the hydraulic NNDM was first determined using the Levenberg-Marquardt algorithm (LMA). This also meant that with the chosen number of hidden neurons, the NNDM was already trained by the LMA. As mentioned with the training of the structural NNDM, there is a possibility that with LMA, the solution might be trapped in a local optimum point. Furthermore, LMA does not produce any indication of uncertainty of network weights. Hence, GA and Bayesian MCMC using MHA were then used to train the hydraulic NNDM to handle the problem of local optimum and the uncertainty of network weights respectively.

Table 4-23: Estimated thresholds and factor coefficients for the hydraulic OPDM

Input Factors	ML	Bayesian MCMC
θ_1	-2.6762	-2.852
θ_2	-2.0364	-2.2274
Pipe Size	-0.0003	-0.0003
Pipe Age	-0.0224	-0.0232
Pipe Depth	-0.3881	-0.4393
Pipe Slope	-0.0932	-0.0948
Tree-count	0.0382	0.0379
Structural Condition	0.3573	0.3583
Pipe Location	0.1898	0.1938
Soil Type	1.5432	1.4904
TMI	0.7047	0.6771

A/ Training of NNDM using LMA

The suitable number of hidden neurons for the NNDM was searched using the LMA and mean square error (MSE) criterion as was done for the structural NNDM. The results are given in Figure 4-25 which shows the best possible number of hidden neurons was 12 as the MSE values of 0.04 and 0.072 respectively are the lowest values on the train and validation datasets at this point. The hydraulic NNDM then consistsed of 9 input neurons, 12 hidden neurons and 3 output neurons with a total of 159 network weights (including connection weights and bias weights). The values of network weights estimated by the LMA can be used in the NNDM to compute the predicted hydraulic condition given any input values for individual pipes.

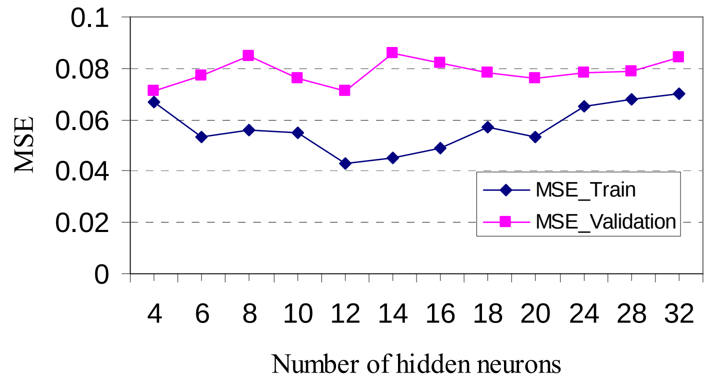

Figure 4-25: MSE with different number of hidden neurons – hydraulic NNDM

B/ Training of Hydraulic NNDM using GA

The hydraulic NNDM has similar forms of inputs, outputs and structures with that of the structural NNDM. Therefore, the population size of 230 and the crossover fraction of 0.8 as optimized during the training of structural NNDM with GA were used for GA for training of the hydraulic NNDM. The MSE value of 0.032 was achieved on the calibration dataset which is smaller than that of the LMA.

C/ Train NNDM using MHA of Bayesian MCMC

The Metropolis-Hastings algorithm (MHA) used for training of the hydraulic NNDM was the same with the MHA used in the calibration of structural NNDM in Section 4.4.2.4 C/. The MSE value of 0.018 was achieved with the calibration dataset. This MSE value is smaller than those obtained by the LMA (0.04) and GA (0.032). In a similar manner with that of structural NNDM, the last 3000 values of network weights were kept to compute the mean values and 95% confidence limits for individual network weights of the hydraulic NNDM. The 95% confidence limits were then used to compute the 95% confidence limits for the predicted hydraulic conditions in the test dataset.

4.5.2.5 Hydraulic Probabilistic Neural Network Deterioration Model (PNNDM)

The training of the hydraulic PNNDM was similar to that of the structural PNNDM described in section 4.4.2.5. However, the suitable smoothing parameter (or standard deviation) of the Gaussian kernel was found as 0.4 since other values caused a reduction on the number of correct predictions in the training dataset.

4.5.3 Testing of Hydraulic Deterioration Models

The goodness-of-fit test and two scalar performance measures, namely, overall success rate (OSR) and false negative rate (FNR) derived from the confusion matrix were used to test the five structural deterioration models in Section 4.4.2. These methods were also used to test the five hydraulic deterioration models. The results of these testings were used to identify the best hydraulic deterioration model for both pipe population and individual pipes.

4.5.3.1 Best Suitable Hydraulic Deterioration Model for Predicting Condition Changes of Pipe Population

Table 4-24 shows the computed Chi-square values for the calibration and test datasets for testing the fitness of five deterioration models. Except for the hydraulic MDDM and PNNDM, the remaining hydraulic deterioration models, Markov model, OPDM and NNDM, were calibrated by different calibration techniques. Similar to the structural deterioration models (Section 4.5.2.1), the Chi-square values for different models under different calibration techniques are shown in Table 4-24. As can be seen from this table, the Markov model, NNDM and PNNDM consistently passed the Goodness-of-fit test on both calibration and test datasets. This was substantiated by the small Chi-square values which were lower than the critical Chi-square value of 5.99 for the case study. This means that these models are suitable to model the hydraulic deterioration of stormwater pipes at least for the case study. Furthermore, among the suitable deterioration models, the hydraulic Markov model had the lowest Chi-square values on both calibration and test datasets. This suggested that the Markov model was the best model to predict the hydraulic condition changes of stormwater pipe population in this case study. The MDDM failed the goodness-of-fit test on both calibration and test datasets. The OPDM passed the goodness-of-fit test on the calibration dataset and failed on the test dataset. Therefore, it was decided that both MDDM and OPDM were not suitable models for the hydraulic deterioration of stormwater pipes in this case study.

As found with the structural Markov model, the Bayesian MCMC simulation technique again provided the better performance for model calibration for the hydraulic Markov model over the standard optimization. This is substantiated by the lower Chi-square values found with this technique on both calibration and test datasets as shown in Table B-8 (Appendix B). This suggested that the Bayesian MCMC technique was the best calibration technique for the hydraulic Markov model. The Bayesian MCMC simulation also provided the better performance for the NNDM in comparison with LMA and GA. This is substantiated by the lowest MSE value during training of the structural NNDM and the lowest Chi-square values for both calibration and test dataset. GA was also found to be better than the LMA in training the NNDM as in the case of structural NNDM.

Table 4-24: Chi-square values of five hydraulic deterioration models

Hydraulic Deterioration Models	Calibration Techniques	Chi-square values $\chi^2_M \, (\le \chi^2_{2,0.05} = 5.99)$	
		Calibration dataset	Test dataset
Markov Model	Bayesian MCMC simulation (MHA)	0.06	0.09
	Standard optimization	0.16	0.21
MDDM	Maximizing Fisher's criterion	6.01	6.92
OPDM	Maximum Likelihood (ML)	5.89	6.36
	Bayesian MCMC simulation (Gibb sampler)	5.89	6.36
NNDM	LMA	5.59	5.89
	GA	2.83	3.05
	Bayesian MCMC simulation (MHA)	2.24	2.55
PNNDM	Trial and error approach	2.17	3.34

Since the Markov model was the best model for predicting the hydraulic condition changes of the pipe population, the Markov model was then used to predict the hydraulic condition changes of stormwater pipe population of CGD. The proportions of the three hydraulic conditions belonging to each hydraulic condition over time were computed by applying Equation (3-2) to the Markov model with the estimated transition probabilities from the entire dataset (as shown in Table 4-21). The results are shown in Figure 4-26. 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 mild upwards slope for distribution curves of structural condition 2 and 3 with a peak at the age of 60 years for condition grade 2. As can be seen from this figure, the proportions of conditions 1 and 3 continuously decreased and increased respectively. If M&R actions are not carried out until the age of 120 year, about 70% of pipes would be predicted to be in poor hydraulic condition.

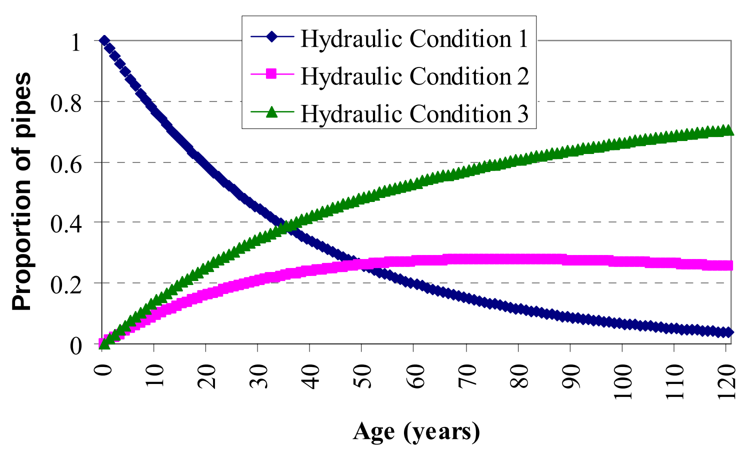

Figure 4-26: Hydraulic condition changes of pipe population

4.5.3.2 Best Suitable Hydraulic Deterioration Model for Predicting Condition Changes of Individual Pipes

The confusion matrixes of four hydraulic deterioration models (MDDM, OPDM, NNDM and PNNDM) are given in Tables B-9 to B-14 (Appendix B). The computed overall success rate (OSR) and the false negative rate (FNR) are shown in this section for determining the best suitable hydraulic deterioration model, the primary aim of this study. Figure 4-27 shows the computed OSRs (in percentage) on the calibration and test datasets for four hydraulic deterioration models, MDDM, OPDM, NNDM and

PNNDM. Furthermore, the effects of different calibration techniques on the OSR of each deterioration model were also shown in this figure. As expected, the OSR for the calibration (or train) dataset is higher than for the test dataset. As can be seen form this figure, the NNDM and PNNDM outperformed the MDDM and OPDM in predicting the hydraulic condition of individual pipes. This was substantiated by the higher values of OSR for the NNDM and PNNDM for both calibration and test datasets. Furthermore, the PNNDM had the highest OSR in the calibration dataset and the NNDM had the highest OSR in the test dataset.

Similar results were found when comparing these four deterioration models in terms of the FNR, as shown in Figure 4-28. As expected, the FNR for the calibration (or train) dataset is lower than for the test dataset. As can be seen from this figure, the NNDM and PNNDM again outperformed the MDDM and OPDM as substantiated by the lower FNRs for both calibration and test datasets. The PNNDM had the lowest FNR on the calibration dataset and the NNDM had the lowest FNR on the test dataset.

Based on the performances found with OSR and FNR on the test dataset, the NNDM was considered as the best model for predicting hydraulic condition of stormwater pipes in this case study.

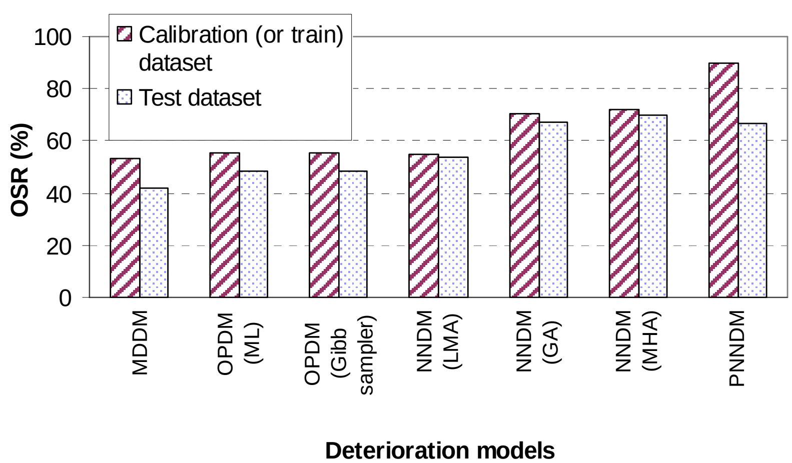

Figure 4-27: Values of OSR for hydraulic MDDM. OPDM, NNDM and PNNDM

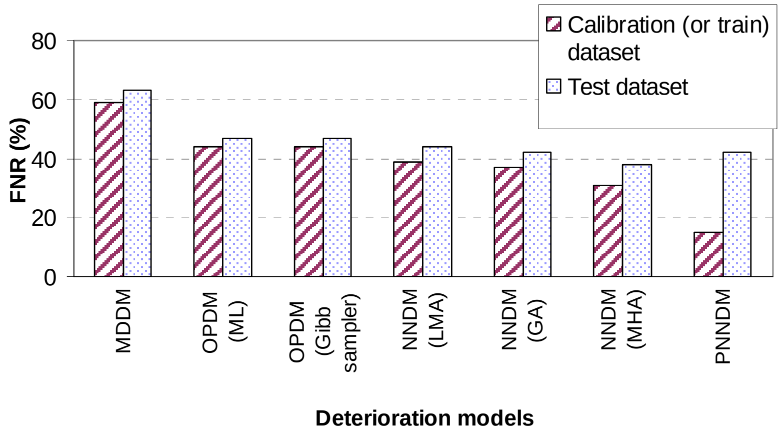

Figure 4-28: Values of FNR for hydraulic MDDM. OPDM, NNDM and PNNDM

As found with the training of the structural NNDM, the NNDM trained with GA had higher OSR and lower FNR than those of the NNDM trained with the LMA for both calibration and test dataset. However, the MHA of Bayesian MCMC technique outperformed both GA and LMA techniques in producing the best and consistent predictive performances for NNDM for both calibration and test datasets. This implies that the Bayesian MCMC technique was again considered as the best calibration technique for the hydraulic NNDM.

4.5.4 Identification of Significant Input Factors

Methods for identifying the significant input factors to the structural deterioration models in Section 4.4.3 were also used for the hydraulic deterioration models. The significant input factors of the hydraulic MDDM were identified by using the forward stepwise method (Section 3.5.1). The significant input factors of the hydraulic OPDM were identified using the Wald test (Section 3.5.2). The common aspect of these two statistical methods is that if the *P*-value for the computed test statistic (*F*-value for the hydraulic MDDM and Wald statistic for the hydraulic OPDM) is smaller than the value of 0.05 or 0.1 (equivalent to 95% and 90% confidence level respectively), the corresponding input factor can be considered statistically significant at that level.

The significant input factors of the NNDM were identified using the connection weight analysis (Section 3.5.4). The significant factors in the PNNDM were identified using the backward method (Section 3.5.3). The common element of these two methods is that the input factors can be ranked in significance order according to the magnitudes of their significance values. The significance values of an input factor in the NNDM can be computed from its connection weights. The significance values of an input factor in the PNNDM is the decrease in the overall success rate (OSR) on the test dataset when comparing the PNNDM using all input factors and the PNNDM without the input factor of interest.

Table 4-25 shows the computed *F*-values and *P*-values for the nine input factors of the hydraulic MDDM. As can be seen from this table, pipe age, pipe slope, structural condition and pipe location were found to be the statistically significant factor at a 0.05 level. Similarly, Table 4-26 shows the computed Wald statistics and corresponding *P*-values for the input factors of the hydraulic OPDM. As can be seen from this table, pipe size, pipe age, pipe slope, structural condition and pipe location were found to be the statistically significant as substantiated by their *P*-values which are smaller than 0.05.

Figures 4-29 to 4-31 show the significance values of input factors obtained by three different training techniques (i.e. LMA, GA and MHA respectively) for the hydraulic NNDM. As can be seen from these figures, the pipe size, pipe age, structural condition, pipe slope and pipe location stood out as the top five ranked factors. On the other hand, pipe depth, tree-count and TMI were bottom ranked factors across the three training techniques.

Table 4-25: F-value and P-value of input factors in MDDM

Factors	*F*-value	*P*-value
Pipe Size	2.736	.16
Pipe Age	6.716	.001*
Pipe Depth	2.107	0.123
Pipe Slope	6.118	0.002*
Tree-count	2.144	0.119
Structural condition	6.716	0.01*
Pipe Location	5.710	0.004*
Soil Type	.837	0.434
TMI	2.907	0.156

*statistically significant factor at 0.05 level

Table 4-26: Wald-statistic and *P*-value of input factors

Input Factors	Wald-Statistic	P-value
Pipe Size	5.267	0.022*
Pipe Age	7.511	0.006*
Pipe Depth	2.390	0.122
Pipe Slope	7.592	0.006*
Tree-count	2.212	0.273
Structural condition	5.509	0.019*
Pipe Location	5.801	0.016*
Soil Type	0.497	0.698
TMI	0.69	0.46

*statistically significant factors at 0.05 level

Figure 4-32 shows the significance values of input factors of the hydraulic PNNDM. As can be seen from this figure, the top four ranked factors were pipe size, pipe age, structural condition and pipe location. Bottom ranked factors were tree-count, soil type and TMI.

By comparing the significant factors found in the hydraulic MDDM, OPDM, NNDM and PNNDM, it was concluded that the significant input factors were pipe size, pipe age, pipe slope, pipe location and structural condition. The insignificance input factors were tree-count and TMI. Soil type and pipe depth were inconclusive.

4.6 Discussion

4.6.1 Statistical Models versus Neural Network Models

Three statistical models (Markov model, MDDM and OPDM) and two neural network models (NNDM and PNNDM) were developed for modelling structural and hydraulic deterioration of stormwater pipes, as the primary aim of this study. The statistical models can be classified as the model driven type because the model structure is decided by experts (Dasu and Johnson 2003). The neural network models on the other hand, can be classified as the data driven type because the model structure is decided by the data (Dasu and Johnson 2003). The attributes of these two types as outlined in Section 2.4.2.4 and 2.4.3.4 were considered for finding the best suitable model.

The expected outcomes of these deterioration models were the prediction for the condition changes of pipe population and the prediction for the condition changes of individual pipes. However, the Markov model was used to predict only the condition changes of pipe population and was not able to be used for predicting the condition changes of individual pipes due to the lack of regular data (or longitudinal data over time). The other four models were designed to predict the condition changes of individual pipes, but they can then be applied to pipe population considering the predictions across all individual pipes within the pipe population. These five models were applied to a case study which contained the structural and hydraulic condition data of snapshot type.

The predictive performances of these models for the case study were compared against each other so that the best suitable models for modelling structural and hydraulic deterioration of stormwater pipes can be determined. Based on the results of goodness-of-fit test, the Markov model was found conclusively to be the most appropriate choice for predicting both structural and hydraulic condition changes of pipe population. The assumption of homogenous Markov model was found adequate when considering the acceptable results of the goodness-of-fit test. A homogenous Markov model means that the transition probabilities are time-independent. This is consistent with the finding of a study using the homogenous Markov model for modelling structural deterioration of the stormwate pipe system in Newcastle in New South Wales (Australia) by Micevski *et al.* (2002). Their finding was that the use of homogeneous Markov model was appropriate and the use of a non-homogenous Markov model could adversely reduce the predictive performance of the Markov model. This is because a greater uncertainty of parameter estimation can occur due to the increased number of model parameters associated with the use of the non-homogenous Markov model. Although it appears that older pipes tend to deteriorate faster than the new pipes (i.e. non-homogenous deterioration), this assumption may no hold due to other contributing factors or covariates such as pipe size and pipe location. This was supported by this study and the study of Micevski *et al.* (2001). Other research papers concerned with bridges and sewers whose deterioration properties are considered different with stormwater pipes in Australia. Furthermore, the assumption of probabilistic and multi-state condition changes were found appropriate in this study and in a study by Micevski *et al.* (2002).

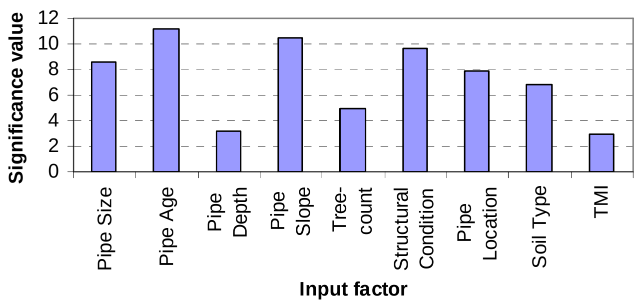

Figure 4-29: Significance values of input factors of NNDM (LMA)

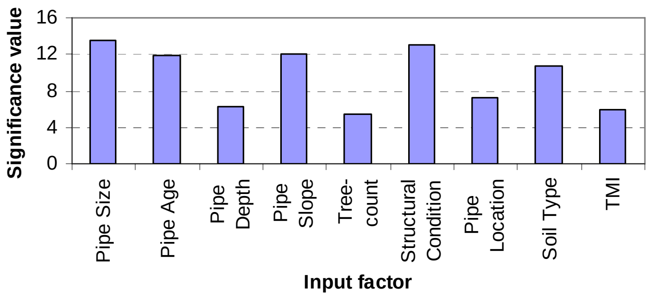

Figure 4-30: Significance values of input factors of NNDM (GA)

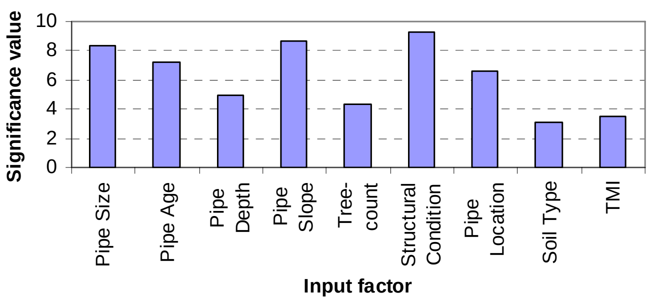

Figure 4-31: Significance values of input factors of NNDM (MHA)

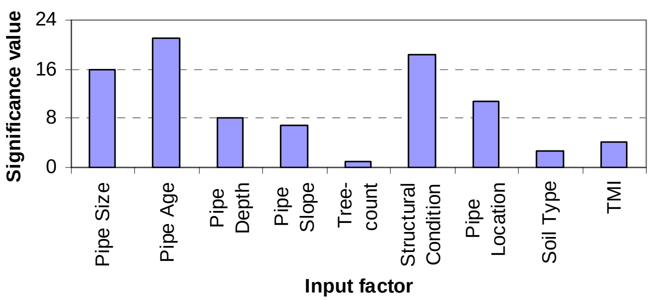

Figure 4-32: Significance values of input factors of PNNDM

Based on the overall success rate (OSR) and the false negative rate (FNR), the NNDM was found to outperform all the remaining deterioration models (MDDM, OPDM and PNNDM) in predicting the structural and hydraulic condition changes of individual pipes as shown in Figures 4.18 and 4.19 (page 126 of Section 4.4.2.2) and Figures 4.27 and 4.28 (page 141 of Section 4.5.2.2). This is consistent with the theoretical capability and practical performance of NN found in previous studies (Marquez et al. 1991). Although the NNDM showed a promising capability for predicting individual pipes, the FNRs of 18% and 38% for the structural and hydraulic conditions respectively were still of great concern. This means that a misclassification can occur. Therefore expert opinion should be sought to reconfirm the predicted outcomes of the NNDM prior to conducting any M&R actions. Increasing the number of input factors such as backfill material, ground water table as listed in Table 3-1 in the NNDM could be a practical solution to increase the predictive performance of the NNDM and to significantly reduce the FNR. By doing so, each pipe deterioration curve has more attributes to uniquely describe pipe deterioration and increase the classification power of the NNDM.

The low predictive performance and the failure of the goodness-of-fit tests of both MDDM and OPDM for modelling the structural and hydraulic conditions found in the case study could be explained by one important reason. That is the statistical assumptions such as normality of the input factors in MDDM and normal distribution of the random error in OPDM could greatly reduce the predictive capability of these two models. These statistical assumptions have been recognized in a number of studies involving prediction models in various fields where NN models were alternatively used and produced a much better outcome (Leung and Tran 2000; Hajmeer and Basheer 2003; Ermini et al. 2005). Furthermore, in predicting individual pipe conditions, MDDM and OPDM have done poorly compared to neural networks. That is two are linear models and neural networks (NNDM) capture nonlinear relationships. MDDM is the poorest because it is strictly linear. OPDM is slightly better because it has more flexibility as it incorporates the error distribution left over by a linear model. The fact that the results from these two and neural networks are different is an indication that the contributing factors are nonlinearly related to the deterioration. This is also supported by the linear statistical correlation not being able to indicate some of the significant contributing factors.

PNNDM appeared to be the best balance between two opposite model types: model driven type (i.e. MDDM and OPDM) and data driven type (i.e. NNDM) because PNN models do not require complex training process as found with the NN models and are based on the well established Parzen-Cacoullos theory and Bayesian decision theory. These advantages can be seen in the predictive performance of PNNDM which passed the goodness-of-fit test. Furthermore, the OSR of PNNDM on the calibration dataset was consistently better than that of the NNDM using a sophisticated training algorithm (i.e. Bayesian MCMC) for both structural and hydraulic deterioration. However, the poorer predictive performance of the PNNDM on the test dataset found in modelling both structural and hydraulic deterioration 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).

4.6.2 Calibration techniques

As explained in Section 4.6.1, the Markov model and the NNDM were found to be the best suitable models for predicting the structural and hydraulic condition changes of pipe population and individual pipes respectively. Both models relied on the sophisticated training method, the Bayesian MCMC simulation to avoid the problem of local optimum and uncertainty in the estimation of model parameters. In this study, it was found that the Bayesian MCMC simulation consistently outperformed the conventional non-linear optimizations and genetic algorithm as found in the calibration of the Markov model, OPDM and NNDM.

Although the conventional non-linear optimization techniques such as the first or second order derivative (LMA) would converge to a solution, their search methods are well known for being easily trapped iat a local optimum (Gori and Tesi 1992). This is the major disadvantage in finding solutions in a complex and high-dimensional space with many local optima like the parameter space of the NNDM (Gori and Tesi 1992).

GA is considered a directed 'global' search algorithm with probabilistic search rules (Goldberg 1989) that is especially useful for such parameter space. However, unlike the conventional optimization techniques, GA does not make use of local knowledge of parameter space. Therefore, the convergence of GA may take a long time in the large solution space of NN parameters. The Bayesian MCMC simulation, on the other hand, also used probabilistic search rules and the 'global' knowledge of parameter space via updating the variance-covariance matrix as outlined in Section 3.3.1.4. This could be the reason that the Bayesian MCMC technique outperformed all other calibration techniques used in this study.

4.6.3 Structural Deterioration and Hydraulic Deterioration

From the results of the structural and hydraulic Markov models in the Figure 4-17 and Figure 4-26, if no maintenance and rehabilitation (M&R) actions are carried out, almost 80% and 70% of the stormwater pipe system would be in poor structural and hydraulic conditions respectively at the age of 120 years. Therefore, the structural deterioration rate was faster than that of the hydraulic deterioration rate in this case study. This was substantiated by comparing the proportional structural and hydraulic conditions 3 of pipes, as shown in Figure 4-33. Furthermore, this was also consistent with the preliminary analysis of structural and hydraulic conditions in the case study which shows that more pipes are in structural condition 3 (66.9%) than in hydraulic condition 3 (31.4%).

4.6.4 Significant input factors

The significant and insignificant input factors that affect the structural and hydraulic condition as determined in Section 4.4.3 and 4.5.3 are summarized in Table 4-27. The results of one-way ANOVA and cross-table analysis for the structural and hydraulic conditions in Section 4.3.2 are also shown in this table. Input factors with '*' mark were found to have statistical associations with the structural and hydraulic conditions. As can be seen from this table, significant input factors found from the one-way ANOVA or the cross-table analysis were also found significant by the four deterioration models.

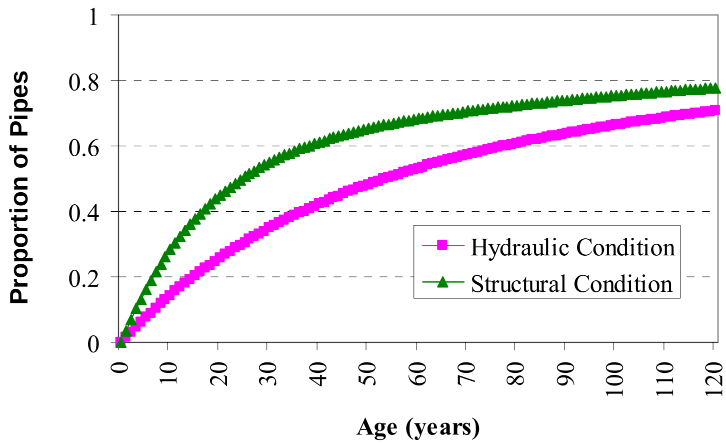

Figure 4-33: Comparison between structural and hydraulic deterioration rates (condition 3 only) predicted by the Markov model

Table 4-27: Significant input factors to structural and hydraulic condition

Input factor	Structural condition	Hydraulic condition
Significant	Pipe Size	Pipe Size
	Hydraulic Condition*	Structural Condition*
	Pipe Location	Pipe Location*
		Pipe Age*
		Pipe Slope*
Insignificant	TMI	TMI
	Pipe Age	Tree-count
	Pipe Depth	
	Pipe Slope	
Undecided	Soil type	Soil type
	Tree-count	Pipe Depth

Input factors with '*' mark were found to have statistical associations with the structural and hydraulic conditions.

Although several factors out of the nine input factors considered in the case study were found to be significant (or important) to the prediction of the deterioration of stormwater pipes, the remaining factors are still useful since the deterioration process is still not fully understood and the collected data of the case study just represents a fraction of the whole pipe population. Hence, the findings of significant factors in the case study should not be considered as totally conclusive.

Pipe size: Pipe size was found to be a significant factor that affects both structural and hydraulic conditions. Pipe size is an important factor in the structural design of stormwater pipes. As outlined in Section 2.2.1, Micevski *et al.* (2002) mentioned that pipe designers may underestimate the traffic loads or the cover requirements for small size pipes. Furthermore, It may be the case that larger sewers are laid with more care and precision by more experienced personnel (Davies *et al.* 2001b). Pipe size is also an important factor to the hydraulic design of stormwater pipes. Pipes of larger size tend to have low fluid velocity which could not flush away all sediments. Pipes of smaller size are close to the ground surface and therefore are likely subjected to tree root intrusion.

Pipe age: Pipe age was not a significant factor to the structural condition but was a significant factor to the hydraulic condition. This could be explained by the fact that the structural deterioration seems to be the result of the combined effects of various factors. Furthermore, considering the results found in the study that the rate of structural deterioration is greater than the hydraulic deterioration, it is surprising that the age or a directly age related variable did not become a prominent factor for structural condition. This may have something to do with the data. Judging the structural condition of pipes using only pipe age is therefore not appropriate. On the other hand, the tree root intrusion and sediment accumulation appear a time consuming process.

Pipe depth: This factor was not significant to the structural deterioration and its effect on the hydraulic deterioration was not strong enough to be considered significant in this study. However, it should be noted that pipe depth had mild correlation with pipe size (as described in Section 4.3.1.1) which was also the strongest correlation found among other correlations between input factors in the case study. Therefore, it can be considered that the effects of pipe depth on the structural and hydraulic deterioration models were already explained by the pipe size.

Pipe slope: Similar to the pipe age, pipe slope was not a significant factor to structural condition but was a significant factor to the hydraulic condition. Pipes with steeper slope allow higher gravity flow rate, which can remove the sediments and small obstructions. However, in the case of unstable backfill or subsoil, the pipes tend to move relatively to each other, which may damage the joint section and thus, allow tree root intrusions.

Tree-count: This factor was not a significant factor that affects the hydraulic deterioration of stormwater pipes. Furthermore, the effect of tree-count was not strong enough to be considered significant to the structural deterioration in this study. It implies that more related factors such as tree age, height and tree type may be more appropriate since these factors have a direct relationship with the coverage of tree roots which in turn affect the structural and hydraulic condition.

Structural condition and hydraulic condition: The structural condition was found to be a significant input factor to the hydraulic deterioration. This could be explained by the fact that structural defects allow surrounding soil and tree roots to enter the pipes. Similarly, the hydraulic condition was found to be significant to the structural condition. This finding was contradicted by the study of Micevski *et al.* (2002). They assumed that hydraulic condition was based on hydraulic defects that did not affect the structural condition. However, a different point of view could be that because the poor structural condition may lead to the poor hydraulic condition, the hydraulic condition can act as an 'indicator' or predictor to predict the structural condition of pipes.

Pipe location: This factor was found to be significant to both structural and hydraulic conditions. In this case study, four different pipe locations (i.e. under roads, nature strips, reserves and easements) were considered. Pipes under roads are more likely to be structurally damaged due to road repair, construction and dynamic loads associated with heavy traffic. Pipes under nature strips, reserves and easements are associated with root intrusion, illegal household connections and garden waste.

Soil type: The effect of soil type to the structural and hydraulic condition was not consistently found between the four deterioration models. However, in other studies by Micevski *et al.* (2002) and Davies *et al.* (2001a), soil type was found to be important factor that affect the structural deterioration of stormwater pipes and sewers. A larger sample size or a more detailed investigation of soil type around each pipe could provide more information on the effect of the soil type.

TMI: This factor was seen as an indirect factor that could affect both structural and hydraulic deterioration. However, TMI was found as an insignificant factor in this case study.

4.7 Summary

This chapter presented the application of deterioration models that were developed in Chapter 3 to a case study with a sample of real data collected from a stormwater pipe system in City of Greater Dandenong (CGD), Australia. The supplied dataset consisted of 417 concrete pipes which accounted for 2.2% of the whole stormwater pipe system of CGD. Each pipe in the dataset was described by the structural condition, hydraulic condition and eight input factors (i.e. pipe size, pipe age, pipe depth, pipe slope, tree-count, soil type and TMI). The structural and hydraulic conditions of pipes were graded using CCTV inspected data and Sewer Inspection Reporting Code of Australia (WSAA, 2002).

The preliminary analysis of the supplied dataset revealed a number of interesting results. More of inspected pipes were in structural condition state three than in hydraulic condition state three. Based on the correlation tests, a mild correlation was found between pipe size and pipe depth. There were weak correlations found between pipe size and the factors, pipe age and pipe slope. Furthermore, pipe depth had weak correlations with pipe age and pipe slope. Based on one-way ANOVA and cross-table analysis, the statistical associations were found between structural and hydraulic conditions, between hydraulic condition and the following factors: pipe age, pipe slope and pipe location.

The supplied dataset was randomly split into calibration (75%) and test datasets (25%) which were used for calibrating and testing the structural and hydraulic deterioration models. The data format used for the Markov model was different with those used for the remaining four deterioration models. Furthermore, the NNDM required an extra dataset (called validation dataset) which was randomly generated from the calibration dataset. This means the NNDM used a train (or calibration) dataset of 60% and a validation dataset of

15% for the training (or calibration) of the NNDM and the test dataset of 25% for testing the NNDM.

Based on the goodness-of-fit test, the Markov model was consistently found to be the best suitable model for predicting the condition changes of pipe population for both structural and hydraulic deterioration. The NNDM and PNNDM ranked second and third, while the MDDM and OPDM failed the test for both structural and hydraulic deterioration. It was predicted from the structural and hydraulic Markov models, that if no maintenance and rehabilitation (M&R) actions are to be carried out, almost 80% and 70% of the CGD stormwater pipe system would be in poor structural and hydraulic conditions respectively at the age of 120 years. Furthermore, the structural deterioration rate was found to be faster than that of the hydraulic deterioration rate in this case study.

Based on the overall success rate (OSR) and the false negative rate (FNR), the NNDM was consistently found to be the best suitable model in predicting the condition changes of individual pipes for both structural and hydraulic deterioration. The PNNDM ranked second, the OPDM ranked third and the MDDM ranked fourth for both structural and hydraulic deterioration. However, the NNDM still had relatively high FNR, which means that misclassifications may occur and thus expert opinions should be sought to reconfirm the predicted outcomes of the NNDM prior to conducting any M&R actions.

The Bayesian Markov chain Monte Carlo (MCMC) simulation was found to be the best calibration method for the Markov model over the standard optimization method. This calibration method was also found to be the best training method for the NNDM over the Levenberg-Marquardt algorithm (LMA) and genetic algorithm (GA). GA was also found to outperform the LMA in training of the NNDM.

Hydraulic condition, pipe size and pipe location were found to be the significant factors for structural deterioration, while structural condition, pipe age, pipe size and pipe location were found to be the significant factors for the hydraulic deterioration.

CHAPTER 5 SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary and Conclusions

Deterioration of stormwater pipes can cause pipe failures with catastrophic consequences to socio-environment. Monitoring and assessing the condition of stormwater pipes throughout their service life are important in ensuring that stormwater pipes perform adequately. However, it is not feasible to monitor all stormwater pipes due to the limited budget, massive number of pipes and technical constraints. Alternatively, deterioration models can be used to predict current and future condition of pipes and based on the predicted information, 'optimal' decision can be made regarding when and how to repair, overhaul or replace pipes in poor condition.

In many cases, the stormwater pipes systems have been maintained using a crisis-based (or reactive) approach. One major reason for use of the reactive approach is the lack of deterioration models. As a result of poor maintenance and rehabilitation associated with reactive approach to stormwater pipe management, the Australian Infrastructure Report Card (2001) rated the stormwater pipe systems in Australia as in 'poor condition'. Because of the increasing importance being placed on asset management strategies and the increasing awareness on pipe ageing together with pipe failures, asset managers need to change from reactive to proactive approach in managing stormwater pipe systems.

The challenge of this study reported in the thesis was to utilize the available but limited snapshot closed circuit television (CCTV) data of stormwater pipes and the surrounding environment (i.e. contributing factors) to develop deterioration models. The developed models were then used for identifying significant factors that affect stormwater pipe deterioration. Over the past decades, several statistical methods and techniques have been developed to model the deterioration of sewers which can be applied to model the deterioration of stormwater pipes. Recognizing the important differences between the deterioration of sewers and stormwater pipes as well as the increasing need to support the proactive management of stormwater pipe systems, this study was undertaken with the following two objectives:

- The primary objective was to develop structural and hydraulic deterioration models to predict current and future condition of stormwater pipes. The outcomes of the deterioration models were the condition changes of pipe population and individual pipes. The condition changes of pipe population show the predicted proportions of the pipe population in each condition state in each year; this predicted information can be used for planning annual budget required for maintenance and rehabilitation of pipes. The condition changes of individual pipes, on the other hand, show the predicted condition of any particular pipe, as compared to the 'like new' condition, given the contributing factors (e.g. pipe size and pipe age) of the individual pipes; this predicted information can be used to identify pipes that are in poor condition and considered for repair works.

- The secondary objective was to identify significant input factors that affect the output of deterioration models and hence the deterioration process of stormwater pipes. By paying attention to these significant factors, the design and operation of stormwater pipes could be improved in order to reduce pipe failures and increase service life.

A case study with data from City of Greater Dandenong (CGD) in Melbourne (Australia) was used to demonstrate the applicability of the developed models. The dataset consisted of 417 concrete pipes which accounted for 2.2% of the whole stormwater pipe system of CGD. Each pipe in the dataset was described by the structural condition, hydraulic condition and eight input factors (i.e. pipe size, pipe age, pipe depth, pipe slope, tree-count, soil type and Thornwaite moisture index (TMI)). The structural and hydraulic conditions of the pipes were graded using CCTV inspection data and Sewer Inspection Reporting Code of Australia (WSAA, 2002).

The following conclusions were drawn from the development of deterioration models in this study and the application to the case study. However, these conclusions cannot be considered as representative for stormwater pipes across Australia, since it is the only study of pipe deterioration models of this magnitude.

1. The preliminary analysis of the supplied dataset revealed a number of interesting results. Based on the correlation tests, a mild correlation was found between pipe size and pipe depth. There were weak correlations found between pipe size and the factors of pipe age and pipe slope. Furthermore, pipe depth had weak correlations with pipe age and pipe slope. Based on one-way ANOVA and cross-table analysis, the structural condition has a statistical association with the hydraulic condition. Furthermore, the hydraulic condition has statistical associations with the following factors: pipe age, pipe slope and pipe location.

2. Literature review undertaken in this study showed that rigid pipes (e.g. concrete and vitrified clay) are still dominantly used in sewer and stormwater pipe systems. The deterioration of rigid pipes is affected by various factors and probabilistic damage events. Currently, the assessment of deterioration is often observed using the popular CCTV inspection technique. The deterioration of rigid sewers and stormwater pipes can be divided into structural and hydraulic deterioration. Development of deterioration modes that can predict the current and future condition of infrastructure assets has received increased attention. Although there are some disadvantages associated with the statistical models (such as sensitivity to noisy data and assumed model structure), these models are still better than the deterministic models in handling integer valued outputs (i.e. pipe conditions) and the probabilistic nature of the pipe deterioration. There are several advantages in artificial intelligence models to deal with the major issues such as data scarcity, probabilistic deterioration process and noisy data. In the artificial intelligence models, neural network (NN) and probabilistic NN models emerge as a powerful and flexible tool for modeling infrastructure facilities. Nevertheless, the NN and PNN models have not been used for stormwater pipes. The goodness-of-fit test and the confusion matrix analysis used in this study are the only available methods for assessing the performance of deterioration models with the output of ordinal pipe condition.

3. The ideal deterioration model (IDM) using assumed curves for both structural and hydraulic deterioration of individual stormwater pipes can be used to show that pipes in reality deteriorate differently from one to another due to many contributing factors. From this IDM, the estimation of the condition changes over time for the pipe population and the estimation of the condition changes overtime for individual pipes can be constructed and then used as the model outputs for the development of practical deterioration models. A list of potential contributing factors such as pipe size, pipe age, and soil type was found. The full list of contributing factors is shown in Table 3-1 of this thesis.

4. Based on the IDM, literature review and the availability of the snapshot data of the case study, five practical deterioration models, Markov model, multiple discriminant deterioration model (MDDM), ordered probit deterioration model (OPDM), neural network deterioration model (NNDM) and probabilistic neural network deterioration model (PNNDM), were developed in this study. These five deterioration models used contributing factors as model inputs for predicting pipe conditions. The Markov model, MDDM and OPDM are the statistical deterioration models while the NNDM and PNNDM are artificial intelligence deterioration models. The Markov model was developed to predict the condition changes of pipe population and cannot be used to predict the condition changes of individual pipes due to the lack of regular (or longitudinal) data. The four remaining deterioration models were developed to predict the condition changes of individual pipes. They can also be used for predicting the condition changes of pipe population by summing up the predicted conditions of individual pipes and computing the proportions. Furthermore, the five deterioration models are considered as generic models because they can be applied to model both structural and hydraulic deterioration of stormwater pipes. In training or calibrating the five deterioration models, the advanced optimization methods including genetic algorithm (GA) and Bayesian Markov Chain Monte Carlo (MCMC) simulation were used as the effective methods as compared to the standard optimization methods such as the Levenberg-Marquardt algorithm (LMA) in handling the local optimum of complex parameter spaces.

5. The structural and hydraulic deterioration models for the stormwater pipes of CGD were implemented using the five deterioration models: Markov model, MDDM, OPDM, NNDM and PNNDM developed in this study. The supplied dataset was randomly split into the calibration (75%) and test (25%) datasets which were then used for respectively calibrating and testing the structural and hydraulic deterioration models. The predictive performances of these models were compared against each other so that the best possible deterioration model can be identified.

For the structural deterioration models of CGD stormwater pipes, the Markov model was found to be the best suitable model in predicting the condition changes of the pipe population. This was based on the acceptable results of the goodness-of-fit test with the smallest Chi-square values of 0.22 and 0.34 as compared to the critical value of 5.99 on the calibration and test datasets respectively. The NNDM and PNNDM ranked second and third, while the MDDM and OPDM failed the test for both structural and hydraulic deterioration. In predicting the condition changes of individual pipes, the NNDM was found to be the best suitable model based on the overall success rate (OSR) and the false negative rate (FNR). The NNDM achieved the highest value (82%) of OSR and the lowest value (16%) of FNR on the test dataset. Although the PNNDM ranked second, it got the highest value (95%) of OSR and lowest value (9%) of FNR on the calibration dataset. The OPDM ranked third and the MDDM ranked fourth. The Bayesian MCMC simulation was found to be the best calibration method for the Markov model over the standard optimization method. This calibration method was also found to be the best training method for the NNDM over the LMA and genetic algorithm (GA). GA was also found to outperform the LMA in training the NNDM. Hydraulic condition, pipe size and pipe location were found to be significant factors that affect the outputs of structural deterioration models and hence the structural deterioration of stormwater pipes.

For the hydraulic deterioration models of CGD stormwater pipes, the Markov model was also found to be the best suitable model in predicting the condition changes of pipe population as found by the acceptable results of the goodness-of-fit test with the best Chi-square values of 0.06 and 0.09 on the calibration and test datasets respectively. Again, the NNDM and PNNDM ranked second and third, while the MDDM and OPDM failed the goodness-of fit test. In predicting the condition changes of individual pipes, the NNDM was consistently found to be the best suitable model with the highest value (74%) of OSR and lowest value (38%) of FNR on the test dataset. The PNNDM repeatedly ranked second with the highest value (88%) of OSR and lowest value (15%) of FNR on the calibration dataset. The OPDM ranked third and the MDDM ranked fourth. Similar to the structural deterioration models, the Bayesian MCMC simulation was consistently found to be the best calibration method for the Markov model and the NNDM. GA was also found to outperform the LMA in training the NNDM. Structural condition, pipe age, pipe size and pipe location were found to be significant factors that affect the outputs of hydraulic deterioration models and hence the hydraulic deterioration of stormwater pipes.

6. It was predicted from the structural and hydraulic Markov models, that if no maintenance and rehabilitation (M&R) actions are to be carried out, almost 80% and 70% of the CGD stormwater pipe system would be in poor structural and hydraulic conditions respectively at the age of 120 years. Furthermore, the structural deterioration rate was found to be faster than the hydraulic deterioration rate in this case study. The FNRs of NNDM for both structural and hydraulic deterioration models are still considered as relatively high, which means misclassifications may occur and thus expert opinion should be sought to reconfirm the predicted outcomes of the NNDM prior to conducting any M&R actions on individual pipes.

5.2 Recommendations for future work

As stated in the conclusions, different case studies should be used to verify the findings of this study and to make general comclusions for stormwater pipes across Australia.

The deterioration process of rigid stormwater pipes was investigated via the development of deterioration models in this study. The Markov model was found to have the highest performances for prediction of condition changes of pipe population for both structural and hydraulic conditions. This indicates that the Markov model may provide a better predictive performance for individual pipes than the NNDM and other models. Therefore, a regular inspection program is recommended in future data collection so that the Markov model can be calibrated and tested for prediction of individual pipes.

Nevertheless, the NNDM can still improve its predictive performance on the condition that more factors (as listed in Table 3-1) should be collected. On the other hand, the PNNDM also has proven a promising candidate that can replace the statistical models and avoid the complexity associated with the training process of the NNDM. Therefore, it is also recommended that more investigation on improving the PNNDM should be carried out in the future.

This study is limited to stormwater rigid pipes and therefore, it is recommended to extend the work to the stormwater flexible pipes which are increasingly used in buried infrastructure facilities. The significant factors found within this study may provide a starting point for the future work with flexible pipes.

It is also recommended to use the predicted hydraulic conditions of stormwater pipes for evaluating the changes of pipe flow capacity due to hydraulic deterioration in comparison with the increasing runoff volume due to climatic change and urban development.

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APPENDIX A: INSPECTION TECHNIQUES

A.1 Level 1-techniques

A.1.1 Manual Manhole surveys

Accessible manholes and pits can be physically surveyed to identify the position of all structures, flow direction, segment length and connecting pipes. The information of position contains depth and geo-coordinators to a standard referent point. This is also a preparation step for level 2 of inspection. Safety should be carefully considered. Gas reading must be measured and recorded prior to opening covers.

A.1.2 Sonde Locator

Sonde locators use radio frequency to locate the non-metallic pipes. A sonde locator is a small radio transmitter inserted into a pipe. A radio receiver on the surface will move along as the sonde is pushed farther in the pipe. At every pace of sonde, pipe's position is marked. Alternatively, a plumber‘s snake can be used to emit the signal to the surface.

A.1.3 Global Positioning System (GPS)

The GPS is a world-wide radio-navigation system using a constellation of satellites and ground stations. GPS uses the satellite as reference point to calculate ground position within the accuracy of meters. Hand-held GPS units become a common mapping tool in infrastructure information management.

A.2 Level 2-techniques

A.2.1 Man Walk-through (Manual) Inspection

This type of inspection can be used only in circumstances where the pipe diameters are over 1.2 meters and safety precautions are ensured before and during inspection. This method has a series of disadvantages such as low productivity and high subjectivity. Other manual inspection techniques are smoke testing and dye testing. Smoke testing is performed to detect lateral defects, illegal connection and buried manholes. Dye testing can be used to detect overflow into river, creek and infiltration/exfiltration.

A.2.2 CCTV Inspection

Mobile or robotic CCTV systems are the most common means of inspecting sewer and stormwater pipelines. This robotic CCTV system uses a CCTV camera mounted on an electric-driven robot that enters a pipe segment. The camera generally looks forward as the robot moves along the pipe axis, allowing the field operators to examine and evaluate the entire segment via a TV monitor. The field operators exercise subjective judgment when identifying and classifying pipe defects in the filed. This judgment is affected by many factors such as experience, mental awareness and equipment capability. When the operator finds a defect, he then stops the robot, zooms in the defect, records images of the defect and codes the defect. The process starts again and repeats until the end of the segment. After defect coding, computer software is used to do defect scoring and condition grading. It is obviously that the subjectivity of CCTV inspection occurs before defect scoring.

Several techniques and accessories have been developed to improve the subjectivity during CCTV inspections. Examples are:

- Pan and tilt head – allowing the camera to look sideways around the pipe wall.
- Zoom lens – the latest high-powered tele-objective zoom lens (Lee 2005) allows viewing upto 150 meters in large size pipes.
- Lighting – High intensity lighting is also adopted to enhance the image quality.
- Inclinometer – to show the instantaneous gradient of the pipe; integration software can calculate the overall gradient for the whole segment.
- Sonde - a radio transmitter built into the camera allows tracing the position of the camera.
- Multiplex control - only one cable is used to carry both power and data lines.
- Automated defect classifying – recorded images are automatically scanned to spot defects and code them.

A.2.3 Sewer Scanner and Evaluation Technology (SSET)

The development of the SSET in Japan is considered an improvement to the standard CCTV inspection. It houses a CCTV camera, a fish-eye, digital and high-resolution scanner and a fiber optic gyroscope that allows an engineer to see the total pipe surface in 360 degree forward view from one end to other, along with vertical and horizontal alignment data. The scanned image is digitized so that a color-coded computer image can be viewed on a computer screen. The key advantage is that the field operator does not need to stop the robot when a defect is found and assessed.

A.2.4 Multi-Sensor Pipeline Inspection System (KARO, PIRAT)

KARO is a robot multi-sensor inspection system developed in Germany which attempts to automatically detect the type, location and size of defects in sewers. It consists of a 3D optical sensor, ultra-sonic sensors and microwave sensors. KARO applies a sensor fusion fuzzy logic system for conducting damage diagnosis. KARO can work with pipe size of 20-cm, travel up to 400 meters, measure obstacles, and cracks even under the cover of mud.

Similarly, PIRAT developed in Australia uses semi-independent systems. The instrument system which houses a sensor system, a laser scanner for dry pipes and a sonar scanner for flooded pipes, collects the geometry data. This data is input into the interpretation system to detect, identify and rate each defect.

A.2.5 Laser Scanning System

This type of inspection utilizes a laser as a light source to scan the geometric shape of a pipe's interior wall and detects variation in shape and type of cracks as small as 0.3 mm. It is done by narrowing a ring of light at the pipe wall in order to profile the pipe interior at any cross section. One critical limit of this method is above water line.

A.2.6 Sonar (Ultrasonic Inspection)

Ultrasonic inspection is performed using a beam of very high frequency which is many orders of magnitude higher than a human being can hear. The sound wave travels into the object being inspected and reflects whenever a change in density occurs. A sonar head which is mounted on a tractor or crawler sends out a 360 degree sound wave. The sonar head picks up the signal reflected from various surfaces with different depths and objects within the pipes, and calculate the delaying time to generate a profile of the pipe surface.

This technique can detect pits, voids and cracks although certain crack orientations are more difficult to detect.

A.2.7 Eddy Current Testing

This is an electromagnetic technique that can detect surface and sub-surface discontinuities in tube walls up to 10 mm thick in conductive material. When an energized coil is brought near to the surface of metal component, eddy currents are induced into the specimen. The eddy current sets up a magnetic field that tends to oppose the original magnetic field (from coil). The impedance of coil is influenced by the presence of eddy currents. When the eddy currents in the specimen are distorted by defects, the impedance in the coil is altered and this variation is measured and display in a way that indicates the type of defect.

A.2.8 Focus Electrode Leak Location (FELL)

FELL is used for leak detection and is based on the simple principle that water offers less resistance to the transmission of electrical energy than a non-metallic pipe wall. Consequently, an electrical field generated inside a surcharged pipe will be stronger at locations where water can escape to the surrounding surface. FELL uses a special electrode, named 'sonde' that generates an electrical field. When this sonde is pushed moving inside a pipe and approaches a defect that allows fluid flowing in or out, the current between the sonde and the surface electrode increases until they are radially aligned.

A.3 Level 3-techniques

A.3.1 Impact Echo and Spectral Analysis of Surface Waves (SASW)

The impact echo technique is based on the use of impact-generated stress (sound) waves that propagate through the sewer and are reflected by internal defects and external surfaces. The apparatus consists of a source of controlled impacts such as a falling weight, a pneumatic hammer and one or more geophones that are mounted against the pipe wall. Waves are produced when the pipe is struck by the weight or the hammer. These waves are detected by geophones. The impact echo technique looks at the actual waveform produced by the impact, whereas SASW uses more geophones to separate the waves into different frequency components (i.e. effect from pipe defects and from soil condition). These different components travel at different speeds and penetrate to different depth in the soil beyond the pipe.

A.3.2 Ground Penetrating Radar (GPR)

GPR can detect subsurface voids and defects in concrete pipe. GPR emits electromagnetic pulses into the ground, and measures the reflection and refraction by sub-layers or buried objects. The effective depth can be up to 100 meters depending on soil type. However, it has little effectiveness on clay or soil with high conductivity.

A.3.3 Infrared Thermography

This technique can be used to detect void locations in large areas and GPR can then be employed to identify the thickness and depth of voids. It measures a slight variation in temperature and produces thermographic images of objects rather than their optical values. An infrared scanner head and a detector are used to capture the thermal data which are converted into color images for display on monitor.

A.3.4 Micro Deflection

This technique was developed to investigate the structural integrity of rigid pipes. It measures the change in position (micro deflection) where a pressure is applied. The result is then compared with a measured response from a structurally sound rigid pipe. Any deviation is an indication of a weakness in the pipe.

A.3.5 Wave Impedance Probe

This technique developed in Australia successfully detected voids, loose soil and man-made structure outside the sewers. This is a hybrid of GPR and electromagnetic techniques that can detect differences in electromagnetic impedance of the material.

APPENDIX B: CONFUSION MATRIX FOR PREDICTIONS OF STRUCTURAL AND HYDRAULIC CONDITIONS

Table B-1: Goodness-of-fit test for structural Markov model

Dataset	Structural Condition	Observed Number	Predicted Number	
			MHA	Optimization
Calibration	1	74	73	78
	2	27	25	22
	3	223	226	224
Test	1	32	34	35
	2	5	4	7
	3	56	55	51

Table B-2: Confusion Matrix for predictive performance of the structural MDDM

Observed structural condition		Predicted structural condition (%)			Total (%)
		1	2	3	
Calibration dataset	1	31	17	52	100
	2	2	62	36	100
	3	43	5	52	100
Test dataset	1	26	45	29	100
	2	2	52	46	100
	3	42	10	48	100

Table B-3: Confusion Matrix for predictive performance of the structural OPDM

Observed structural condition		Predicted structural condition (%)			Total (%)
		1	2	3	
Calibration dataset	1	38	16	47	100
	2	55	40	5	100
	3	38	5	57	100
Test dataset	1	32	23	45	100
	2	41	43	15	100
	3	36	11	53	100

Table B-4: Confusion Matrix for predictive performance of BP trained structural NNDM

Observed structural condition		Predicted structural condition (%)			Total (%)
		1	2	3	
Train dataset	1	74	2	24	100
	2	14	50	36	100
	3	17	11	72	100
Test dataset	1	61	6	32	100
	2	5	80	15	100
	3	30	6	64	100

Table B-5: Confusion Matrix for predictive performance of GA trained structural NNDM

Observed structural condition		Predicted structural condition (%)			Total (%)
		1	2	3	
Train dataset	1	83	7	10	100
	2	6	58	36	100
	3	18	3	79	100
Test dataset	1	84	6	10	100
	2	33	37	31	100
	3	16	8	76	100

Table B-6: Confusion Matrix for predictive performance of Bayesian MCMC trained structural NNDM

Observed structural condition		Predicted structural condition (%)			Total (%)
		1	2	3	
Train dataset	1	87	3	10	100
	2	3	75	23	100
	3	10	5	85	100
Test dataset	1	84	6	10	100
	2	15	77	8	100
	3	5	11	84	100

Table B-7: Confusion Matrix for predictive performance of the structural PNNDM

Observed structural condition		Predicted structural condition (%)			Total (%)
		1	2	3	
Train dataset	**1**	96	2	2	100
	2	8	78	14	100
	3	9	0	91	100
Test dataset	**1**	58	19	23	100
	2	8	76	15	100
	3	25	5	70	100

Table B-8: Goodness-of-fit test for hydraulic Markov model

Dataset	Hydraulic Condition	Observed Number	Predicted Number	
			MHA	Optimization
Calibration	1	131	132	134
	2	82	83	79
	3	102	100	102
Test	1	32	34	35
	2	5	4	7
	3	56	55	51

Table B-9: Confusion Matrix for predictive performance of the Hydraulic MDDM

Observed Hydraulic condition		Predicted Hydraulic condition (%)			Total (%)
		1	2	3	
Calibration dataset	**1**	48	14	38	100
	2	11	81	8	100
	3	49	10	41	100
Test dataset	**1**	59	24	18	100
	2	62	16	22	100
	3	54	9	37	100

Table B-10: Confusion Matrix for predictive performance of the Hydraulic OPDM

Observed Hydraulic condition		Predicted Hydraulic condition (%)			Total (%)
		1	2	3	
Calibration dataset	**1**	48	13	39	100
	2	29	67	4	100
	3	34	10	56	100
Test dataset	**1**	59	14	27	100
	2	71	22	7	100
	3	25	22	53	100

Table B-11: Confusion Matrix for predictive performance of BP trained hydraulic NNDM

Observed Hydraulic condition		Predicted Hydraulic condition (%)			Total (%)
		1	2	3	
Train dataset	1	56	9	35	100
	2	44	45	11	100
	3	15	24	61	100
Test dataset	1	57	24	20	100
	2	50	42	7	100
	3	32	13	56	100

Table B-12: Confusion Matrix for predictive performance of GA trained hydraulic NNDM

Observed Hydraulic condition		Predicted Hydraulic condition (%)			Total (%)
		1	2	3	
Train dataset	1	70	9	21	100
	2	10	79	11	100
	3	23	14	63	100
Test dataset	1	90	4	6	100
	2	51	34	15	100
	3	26	16	58	100

Table B-13: Confusion Matrix for predictive performance of Bayesian MCMC trained hydraulic NNDM

Observed Hydraulic condition		Predicted Hydraulic condition (%)			Total (%)
		1	**2**	**3**	
Train dataset	**1**	77	3	21	100
	2	26	67	7	100
	3	22	9	69	100
Test dataset	**1**	90	4	6	100
	2	55	41	4	100
	3	16	22	62	100

Table B-14: Confusion Matrix for predictive performance of the hydraulic PNNDM

Observed Hydraulic condition		Predicted Hydraulic condition (%)			Total (%)
		1	**2**	**3**	
Train dataset	**1**	98	1	1	100
	2	12	81	7	100
	3	7	8	85	100
Test dataset	**1**	75	12	14	100
	2	33	59	7	100
	3	33	9	58	100

APPENDIX C: PROGRAMMING CODES

C.1 Bayesian MCMC for Calibration of Markov Model

```
%MATLAB programming codes
Function y=MCMC_Markov(x,aa)
%x: the number of iteraion
%aa: number of last data taken from the sampling
Data = [to be inserted here];
% generate initial values of Pij
        count=0;
        cpos=1;
        % data matrix setup
        [nrows,ncols]=size(data);
        age=data(:,1);
        number_pjt=data(:,2:ncols-1);
        sumrow=data(:,ncols);
        % assign initial value to Pij from random number generator.
        %Sum of Pij must be equal 1 and each Pij must be in the range [0,1]
        N12=0.1+0.8*rand(1); %rand(1);
        temp12=1-(exp(N12)/(1+exp(N12)));
        N13=-1*log(1/temp12-1)*(1+rand(1));
        N23=randn(1);
        p12=exp(N12)/(1+exp(N12))
        p13=exp(N13)/(1+exp(N13))
        p23=exp(N23)/(1+exp(N23))
         p11=1-(p12+p13);
        p22=1-p23;
        %Initiate variance-covariance matrix with arbitrary values
        cova1=[0.2 0 0;0 0.1 0;0 0 0.15];
        cova=cova1;
```

```
%Initiate iteration start value
ite=2;
while ite<=x
    if ite>(x-aa)
    %cova=cova2;
    end
% record old values of Pij
 oldN11=N11;
oldN12=N12;
oldN13=N13;
oldN23=N23;
oldp11=p11;
oldp12=p12;
oldp13=p13;
oldp22=p22;
oldp23=p23;
% generate new values of Pij
NN=randn(3);
NN=NN(1,:);
N12=oldN12+cova(1,:)*NN';
N13=oldN13+cova(2,:)*NN';
N23=oldN23+cova(3,:)*NN';
p12=exp(N12)/(1+exp(N12));
p13=exp(N13)/(1+exp(N13));
 p23=exp(N23)/(1+exp(N23));
p11=1-(p12+p13);
p22=1-p23;
% check that sum of Pij must be 1
if `p11<0
    prob_value=0; %reject new sample
else
```

```
        r_new=logpost(nrows,age,number_pjt,p11,p12,p13,p22,p23);
        r_old=logpost(nrows,age,number_pjt,oldp11,oldp12,oldp13,oldp22,oldp23);
        prob_value=exp(r_new-r_old);
end %if p11
%Generate a random uniform number in [0,1] to check the new Pij
Ucheck=rand(1);
 if (prob_value > 1)|(prob_value>Ucheck) % accepted
        count=count+1;
last_accept=ite;
        if (count/x)>0.234
        % stoploop=ite
         ite=x;
        end    % increase index of result matrix
else % Not accepted and return to old values Pij
N11=oldN11;
N12=oldN12;
N13=oldN13;
N23=oldN23;
p11=oldp11;
p12=oldp12;
p13=oldp13;
p22=oldp22;
p23=oldp23;
end % check accepatnce
if ite>(x-aa)
        pp11(cpos)=p11;
         pp12(cpos)=p12;
        pp13(cpos)=p13;
        pp22(cpos)=p22;
         pp23(cpos)=p23;
        cpos=cpos+1;
```

```
        end %if ite
        ite=ite+1;
        end % while ite
        yy=[pp11' pp12' pp13' pp22' pp23'];
        [row_y,col_y]=size(yy);
        number_of_acceptance=count
        acceptance_rate=count/x
        disp('the last accepted is: ')
        disp(last_accept);
        %kk=yy(row_y-5:row_y,:)
        for kk=1:col_y % compute mean value
                y(kk)=sum(yy(:,kk))/(row_y);
        end % for kk
        % display the calculated values of Pij
        disp(y);
        y=yy;%(row_y-100:row_y,:);
end % main function
% function to calculate the loglikelihood
Function y=logpost(nrows,age,number_pjt,p11,p12,p13,p22,p23)
        p33=1;
        for i=1:nrows %nrows
  p1t(i,1)=1;
  p2t(i,1)=0.0;
  p3t(i,1)=0.0;
  for j=1:(age(i))
    p1t(i,j+1)=p11*p1t(i,j);
    p2t(i,j+1)=p12*p1t(i,j)+p22*p2t(i,j);
    p3t(i,j+1)=p13*p1t(i,j)+p23*p2t(i,j)+p33*p3t(i,j);
  end  % j
  log_pjt(i,1)=log(p1t(i,age(i)+1));
  log_pjt(i,2)=log(p2t(i,age(i)+1));
```

```
   log_pjt(i,3)=log(p3t(i,age(i)+1));
   loglike(i)=number_pjt(i,:)*log_pjt(i,:)';
end % i,nrows
y=sum(loglike);
end % logpost
```

C.2 Bayesian MCMC Calibration for NNDM

```
%MATLAB programming codes
function y=MCMC_NN(no_hn,x,aa)
%no_hn: number of hidden neurons
%x: the number of iteraion
%aa: number of last data taken from sampling
data =[ to be inserted here];
% generate Init value of Pi-j
count=0;
cpos=1;
last_accept=0;
 %warm_c=round(aa*x);
 % matrix setup
[da_row,da_col]=size(data);
da_in=[ones(da_row) data(:,1:da_col-1)];
da_ou=data(:,da_col);
%assign init values for weight
 no_hw=no_hn*da_col; %number of weight (bias included) in hidden layer
no_ow=no_hn+1; %number of weight (bias included),connecting hidden to output, in output layer
total_wei=no_hw+no_ow; % tatal variables of weight
 % generate initial values for all weights by using normal distribution
old_wei=randn(total_wei,1);
 cova_wei=1+rand(1,total_wei); % make sure positive variance
cova_wei=diag(cova_wei);
```

```
row_yy=total_wei;
% record old values of network weights
update_cova=1;
ite=2;
while ite<=x
   if ite > x/3 & update_cova==1
      [row_yy,col_yy]=size(yy);
      mean_yy=sum(yy)/row_yy;
      cova_wei=(yy-repmat(mean_yy,row_yy,1))/sqrt(row_yy-1);
      cova_wei=cova_wei';
      update_cova=0; %stop
   end
   if ite==round(2*x/3)
      update_cova=1; %stop
   end
% generate new values of network weights
       ZZ=randn(row_yy,1); % generate new sample from multi-Gaussian pdf
       new_wei=old_wei+cova_wei*ZZ; % apply 8.1.4 Tong (multivariate normal)
       r_new=logpost(data,no_hn,new_wei);
      r_old=logpost(data,no_hn,old_wei);
      prob_value=r_new/r_old;
      Ucheck=0.95+0.05*rand(1); %reduce acceptance rate since prop-valur is too small
    if (prob_value > 1)|(prob_value>Ucheck) % accpeted
      count=count+1;
      last_accept=ite;
      % update new value
      old_wei=new_wei;
      yy(count,:)=old_wei';
 end % check acceptance
ite=ite+1;
end % while ite
```

```
  [row_yy,col_yy]=size(yy);
number_of_acceptance=count;
acceptance_rate=count/x;
 if row_yy > aa
    yy=yy(row_yy-aa:row_yy,:);
    [row_yy,col_yy]=size(yy);
end
[te_row,te_col]=size(data_test);
 disp('the accepted rate is: ')
disp(acceptance_rate);
disp('MSE of calibration test: ')
cal_mse(data,no_hn,yy(row_yy,:)') % mse of calibration
  for i=1:row_yy
mm(i,:)=cal_test(data_test,no_hn,yy(i,:)'); %cal culate test data
end
disp('the mean output test is: ')
sum(mm)'/row_yy
std_err=sqrt((row_yy*sum(mm.^2)-(sum(mm).^2))/(row_yy*(row_yy-1)))'
 kk=sum(mm)'/row_yy - data_test(:,te_col);
for j=1:te_row
        if abs(kk(j,1))<=0.17
            kk(j,1)=1;
        else
            kk(j,1)=0;
        end
end
disp('the performance test is: ')
100*sum(kk)/te_row %wei matrix
 y=yy; %wei matrix
 end % main fucntion
 function z=logpost(data_inou,number_hn,matrix_wei)
```

```
 [da_row,da_col]=size(data_inou);
 da_in=[ones(da_row,1) data_inou(:,1:da_col-1)];
 da_ou=data_inou(:,da_col);

 matrix_wei=matrix_wei'; %transform to one row format
 [mawei_row,mawei_col]=size(matrix_wei);
 output_wei=matrix_wei(number_hn*da_col+1:mawei_col)' ;
% extract from last segment & convert in one column format
 hidden_wei=matrix_wei(1,1:number_hn*da_col);
 hidden_wei=reshape(hidden_wei,da_col,number_hn);
 sum_hidden=da_in*hidden_wei;
 tan_sig=2./(1+exp(-2*sum_hidden))-1; %a = tansig(n) = 2/(1+exp(-2*n))-1
  hidden_output=[ones(da_row,1) tan_sig];
 sum_output=hidden_output*output_wei;
 log_sig=1./(1+exp(-1*sum_output)); %logsig(n) = 1 / (1 + exp(-n))
  err_dis=log_sig-da_ou;
 mean_se=sum(err_dis.^2)/da_row;
 std_err=sqrt((da_row*sum(err_dis.^2)-(sum(err_dis))^2)/(da_row*(da_row-1)));
 tt=(err_dis/std_err).^2;
 z=sum(exp(-0.5*tt))/std_err;
end % logpost
%Function to calculate the MSE
function zz=cal_mse(data_inou,number_hn,matrix_wei) %calculate MSE
  [da_row,da_col]=size(data_inou);
 da_in=[ones(da_row,1) data_inou(:,1:da_col-1)];
 da_ou=data_inou(:,da_col);
 matrix_wei=matrix_wei'; %transform to one row format
 [mawei_row,mawei_col]=size(matrix_wei);
 output_wei=matrix_wei(number_hn*da_col+1:mawei_col)' ;% extract from last segment&convert in one colume format
 hidden_wei=matrix_wei(1,1:number_hn*da_col);
```

```
   hidden_wei=reshape(hidden_wei,da_col,number_hn);
   sum_hidden=da_in*hidden_wei;
   tan_sig=2./(1+exp(-2*sum_hidden))-1; %a = tansig(n) = 2/(1+exp(-2*n))-1
   hidden_output=[ones(da_row,1) tan_sig];
   sum_output=hidden_output*output_wei;
   log_sig=1./(1+exp(-1*sum_output)); %logsig(n) = 1 / (1 + exp(-n))
   err_dis=log_sig-da_ou;
   mean_se=sum(err_dis.^2)/da_row;
   zz=mean_se;
   end % logpost

%Function to calculate the MSE of NNDM
 function ww=cal_test(data_inou,number_hn,matrix_wei) %calculate MSE
    [da_row,da_col]=size(data_inou);
   da_in=[ones(da_row,1) data_inou(:,1:da_col-1)];
   da_ou=data_inou(:,da_col);
   matrix_wei=matrix_wei'; %transform to one row format
   [mawei_row,mawei_col]=size(matrix_wei);
        output_wei=matrix_wei(number_hn*da_col+1:mawei_col)'  ;%  extract  from  last
        segment&convert in one colume format
   hidden_wei=matrix_wei(1,1:number_hn*da_col);
   hidden_wei=reshape(hidden_wei,da_col,number_hn);
   sum_hidden=da_in*hidden_wei;
   tan_sig=2./(1+exp(-2*sum_hidden))-1; %a = tansig(n) = 2/(1+exp(-2*n))-1
   hidden_output=[ones(da_row,1) tan_sig];
   sum_output=hidden_output*output_wei;
   log_sig=1./(1+exp(-1*sum_output)); %logsig(n) = 1 / (1 + exp(-n))
   ww=log_sig;
 end % cal_test
```

C.3 GA Calibration for NNDM

```
function y = GA_FFNNFM(x) %MATLAB programming codes
%Test Function  for GA
% x=x1, x5, x9 . . . bias weight; x2,3,4: weight from input to neuron 1
 data =[ to be inserted here];
% Calculate the size of data
 [rd,cd] = size(data);
input = data(:,2:cd);
obser = data(:,1);
[ri,ci] = size(input);
[ro,co] = size(obser);
inputbias = [ones(ri,1) input]; % insert special input with value =1
[rib,cib]=size(inputbias);
n = 60; % total number of hidden neurons in NNM
no = 1; % total number of output in NNM
nw1 = cib*n;% number of weight at hidden layer
nw2 = n + no ;% number of weight at ouput layer
 tw = nw1+nw2; % total number of weight (x(i)
tx = ones(1,tw);
for i=1:tw
   tx(1,i) = x(i);
end
m=1
for k=1:n
   hiddenweight(k,:)=tx(1,m:m+cib-1);    % hidden neurons n  x weight m
   m=m+cib;
end %for k
outputweight=tx(1,nw1+1:tw);
% x1, x5, x9 . . . bias weight; x2,3,4: weight from input to neuron 1
hiddensum = inputbias*hiddenweight'; % compute weight sum to each hidden neuron
hiddenoutput=2./(1+exp(-2*hiddensum))-1;
```

```
 %n_logsig = 1./(1+exp(-1*n1));
%2./(sqrt(abs(n1)))-1;
%2./(1+exp(-2*n1))-1;
%1./(1+exp(-1*n1)) % compute logsig function)
 hiddentooutput = [ones(rib,1) hiddenoutput]; % add output bias
outputsum=hiddentooutput*outputweight';
outputtarget= 1./(1+exp(-1*outputsum)); ;% compute Purelin function
%Compute the MSE of NNDM
mse60=abs(outputtarget-obser);
y =sum(mse60.^2)/rib;
```

C.4 Illustration of Excel Spreadsheet for Markov model using SOLVER