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SEWER PIPELINE CONDITION PREDICTION USING

NEURAL NETWORK MODELS

presented by

GURUPRAKASH KULANDAIVEL

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of the requirements for the

Master of Science degree in Building Construction Management

Mohammad Najafi
Major Professor's Signature

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SEWER PIPELINE CONDITION PREDICTION USING NEURAL NETWORK MODELS

By

Guruprakash Kulandaivel

A THESIS

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

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2004

ABSTRACT

SEWER PIPELINE CONDITION PREDICTION USING NEURAL NETWORK MODELS

By

Guruprakash Kulandaivel

With an aging underground infrastructure, ever-encroaching population areas and increasing economic pressures, the burden on the municipal agencies to efficiently prioritize and maintain the rapidly deteriorating underground utilities is increasing. Accurate forecasting of pipeline performance is essential for prioritizing and risk management of the underground infrastructure. The essential function of a pipeline asset management system is to consider the pipeline maintenance and improvement needs and to arrive at the program of optimal rehabilitation, replacement, and maintenance. Hence, the development of a pipeline condition prediction model will be indispensable to the concerned authorities in prioritizing the care and rehabilitation of pipelines, and in pipeline asset planning and management. This research developed an Artificial Neural Network (ANN) model for predicting the condition of sewer pipes based on the historic condition assessment data. The neural network model was trained and tested with acquired field data. The developed model is intended to aid in identifying the distressed segments of the overall sewer pipeline network using a set of known input values. These can then be directed toward assessing and prioritizing the maintenance measures needed to prevent accelerated future distress and eventual failure of sewer pipes.

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I would like to thank the City of Detroit and City of Jackson, MI, for their interest and willingness to participate in this research. I hope this thesis will be a guideline for these municipalities to develop models with their own data in the future.

Many thanks go to Ms. Cathy Morrison, Ms. Vickie Lovejoy and Amanda Simpson of the Michigan State University's Construction Management Program for their support and assistance throughout my graduate program.

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CHAPTER 1

INTRODUCTION

1.1 BACKGROUND AND OVERVIEW

The underground infrastructure systems span thousands of miles and form a significant part of the total US infrastructure. Sewer systems form one of the most capital intensive infrastructure systems in the US and they are aging, overused, mismanaged and neglected. Many of these systems are deteriorating and becoming more vulnerable to catastrophic failures often resulting in costly and disruptive replacements. In spite of recent increases in public infrastructure investments, municipal infrastructure is deteriorating faster than it is being renewed. Study after study from the U.S. Environmental Protection Agency to the American Society of Civil Engineers to the American Water Works Association and the Water Infrastructure Network are estimating from $150 billion to $2 trillion is needed during the next 20 years. The American Society of Civil Engineers' 2003 *Report Card for America's Infrastructure* gave wastewater infrastructure a "D," estimating an annual $12 billion shortfall in funding needs nationally. According to the American Water Works Association (AWWA), by the year 2020 the average utility will spend three times as much on infrastructure replacement as it does today. The sewer infrastructure of the US must be assessed and upgraded to meet the requirements of the EPA Sanitary Sewer Overflow Policy and the guidelines of the Government Accounting Standards Board Statement 34 (GASB 34).

Factors such as population growth, tighter health and environmental requirements, poor quality control leading to inferior installations, inadequate inspection and maintenance, and lack of consistency and uniformity in design, construction and operation practices have impacted adversely on municipal infrastructure. North America's water and wastewater pipelines (some of which are more than a century old) are under daily assault from corrosion damage, moving soils, changing temperatures, rainfall/snowfall, in-service stress and the continuous process of structural deterioration. At the same time, an increased burden on infrastructure due to significant growth in some sectors tends to quicken the ageing process while increasing the social and monetary cost of service disruptions due to pipeline failures. These environmental and operating stresses inevitably lead to a number of pipeline failures throughout the year. Increasing concerns over health, safety and the environment have contributed significantly to raising the visibility of pipeline risk management. The rapidly deteriorating old pipes and the expansion of present network due to increasing demands require the municipalities to prioritize the renewal, replacement and new installations of pipelines. However, predicting and monitoring the condition of pipelines generally remains a difficult task.

Maintaining and even enhancing wastewater collection systems is crucial in order to have dependable transfer of wastewater to treatment facilities. When sewer systems deteriorate, water from excessive infiltration and inflow (I/I) enters the system, resulting in a decreased capacity of the sewer system as well as treatment facilities, increased hydraulic loading at collection and treatment facilities, and consequently increased capital and operation/maintenance costs. Therefore, it is necessary to maintain the sewer system in a healthy condition.

Traditionally, municipalities have addressed the maintenance and operation of sewer systems with a crisis-based approach. This practice results in the inefficient use of limited funds, causing more frequent sewer failures which end in difficult and costly rehabilitation or renewal (WEF-ASCE 1994). The cost of sewer failure, i.e., replacement costs, disruptions, adverse publicity, and health and safety problems, could be significantly higher than the cost of rehabilitation and hydraulic upgrading. The major reason for reactive approaches to sewer management is the sewer systems are most often overlooked because they are underground infrastructure facilities whose existing conditions are not readily visible to users. Thus, the actual problems caused by deterioration are not evident until major failures occur. Another issue in sewer management is the fact that the condition of these underground assets is generally not fully documented. While condition assessment is very important in developing a systematic procedure in effective sewer management, most cities do not have complete documentation of sewer condition data in their management information systems. The lack of data on the past and current condition of sewers hinders the system-wide assessment of existing sewers, the development of prediction models, and the evaluation of the effects of rehabilitation on sewer condition.

For underground sewer systems, without a predictive approach to rehabilitation/renewal needs, condition assessment activities will be unfocussed and may overlook high-risk assets. Some utilities try to avoid this by electing to conduct frequent system-wide inspections at an unnecessarily high cost.

There have been efforts in the recent past years to develop a coordinated asset management system to collect, analyze, and store massive quantities of pipeline related data. Development of these new asset management systems open the door for many advanced technologies and resources to be applied for state-of-the-art information storage, retrieval, and management processes. The municipalities are looking beyond the traditional reactive strategies to proactive maintenance of pipeline infrastructure, to deliver the primary goals of a utility provider, which are reliable delivery of clean safe water and wastewater services. Central to meeting these goals is the need for a robust asset management plan that prioritizes the care, maintenance and improvement of pipeline infrastructure, whilst taking into account the social and financial risk consequences of poor pipeline performance and failures. Rather than relying on a reactive approach to pipeline repair and rehabilitation, it is important that municipalities develop procedures that anticipate the need for repair. A systematic approach for the determination of deterioration and obsolescence of sewer systems is necessary to fully gauge the status of these underground systems. This involves routine and systematic sewer structural and hydraulic condition assessments, establishment of a standard condition rating system, and developing and updating prediction models for sewer condition. Predictive modeling permits effective budgeting of inspection and rehabilitation costs. Figure 1.1 depicts a typical asset management structure.

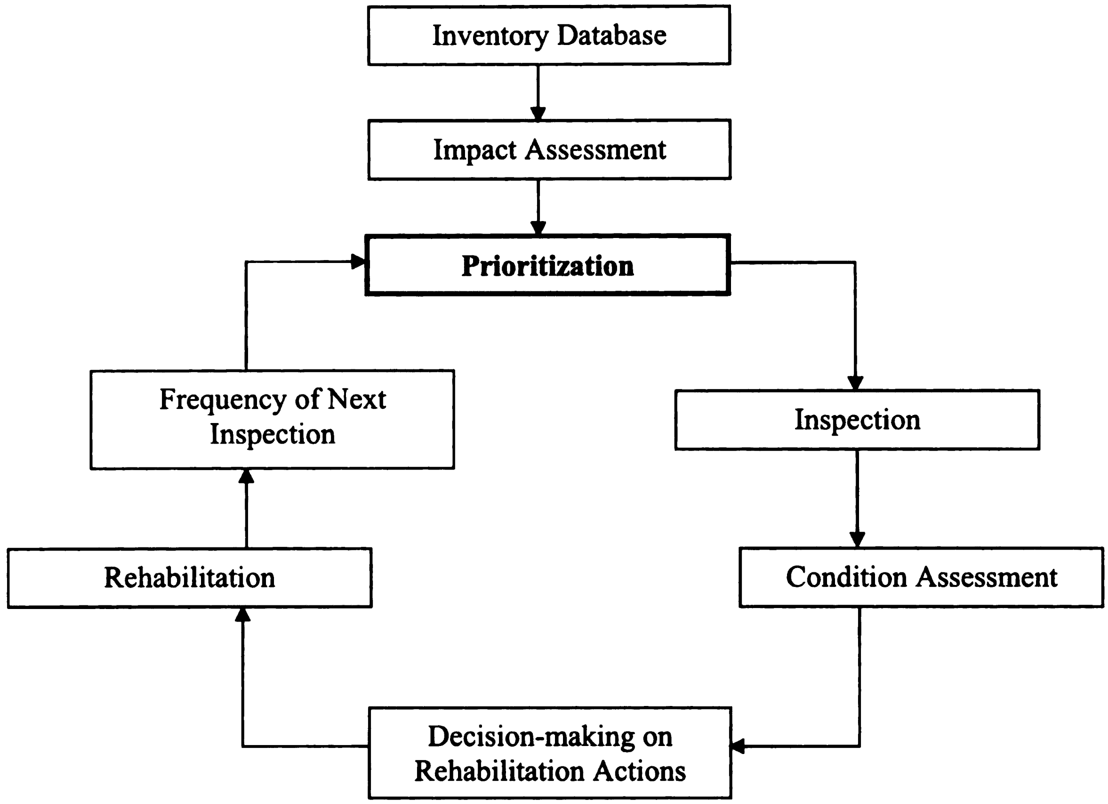


Figure 1.1 - Pipeline Asset Management Structure (McDonald et al. 2001)

In order to identify future improvement needs and perform technical-economic analysis for each alternative, application of deterioration and/or condition prediction models are required. Traditionally, age and material have been the only factors used in prioritizing inspections. Infrastructure is widely distributed throughout a large geographical area making it difficult to track and maintain, and resulting in significant risks to the public and the environment in the event of failure. This traditional approach is not sufficient and does not take into account a deeper understanding of the variables leading to failure, or of the impact of failures on the community and the environment. To be fully effective, the pipeline asset management system must have performance models that combine the rate of deterioration and change in the actual pipeline condition influenced by local factors such as in-service loading, pipe-soil interactions, corrosion damage, pipe strength and resistance to stresses, depth of cover, soil corrosivity, temperature, etc. Two aspects of information on pipeline performance are used in asset management decision-making process: information on current condition, which is obtained through field inspection, and information on future performance, which is obtained using deterioration models and forecasting tools. There are various types of condition assessment tools available to evaluate the present state of pipelines. The development of a model that can predict the condition of pipelines at any given time could be beneficially used to identify the distressed sections of the network. This indeed can help in prioritizing the pipeline sections for further scrutiny and to implement performance improvement measures. Up to now, physical deterioration models and statistical models have been used to identify probabilistic condition and performance of pipelines.

1.2 PROBLEM STATEMENT

1.2.1 STATE OF THE SANITARY SEWER

A sewer is an underground conduit or duct formed of pipes or other structures used for the conveyance of wastewater. Sanitary sewer collection systems are an extensive and vital part of the national infrastructure. In the United States, the average age of sewers was reported to be 47 years, and the maximum age of greater than 100 years (Malik et al. 1997). Although major part of the deterioration is attributed to aging, there are other factors like structural defects, hydraulic overloading, corrosion, etc. that accelerate the rate of deterioration of pipes. Current sewer-condition information available to the asset manager is often subjective, resulting in handicapped financial justification of rehabilitation work, except for gross defects (Campbell et al. 1995). The knowledge of how long a sewer pipe from an intact condition would degrade to cracking with infiltration, and then to a more severe distress condition such as collapse, will allow utility managers to make optimum decisions (Kathula 2001).

A major problem in assessing the condition of sewers is the lack of detailed knowledge about pipeline degradation process. Being covered with soil, the condition of buried pipelines cannot be directly and easily monitored. Moreover, their overall condition changes so slowly that it appears as if they do not change at all. Conditions assessment is the principle objective of any pipeline system inspection program. Optical assessment of the physical attribute of the pipe must be made to establish the best strategy for maintaining and rehabilitating the underground infrastructure. These physical attributes include (1) inventory data defining quantities, types, location of system components, and (2) condition data describing the physical state of a facility or component, e.g., cracking, deterioration, leakage, loss of strength, etc. (Iseley et al. 1997). Sewer system evaluation surveys (SSES) are the standard for gathering information about the condition of sewers. These surveys include activities such as closed circuit television (CCTV) filming, flow monitoring, and manhole inspections. Performing an SSES for the entire sewer network is an expensive and time-consuming process. The budget constraints of most utilities allow only a portion of their sewer systems to be investigated. Therefore it is important to prioritize these inspections to those sewers that are likely to be the candidates for rehabilitation or repair so that the system is efficiently managed as illustrated in Figure 1.2.

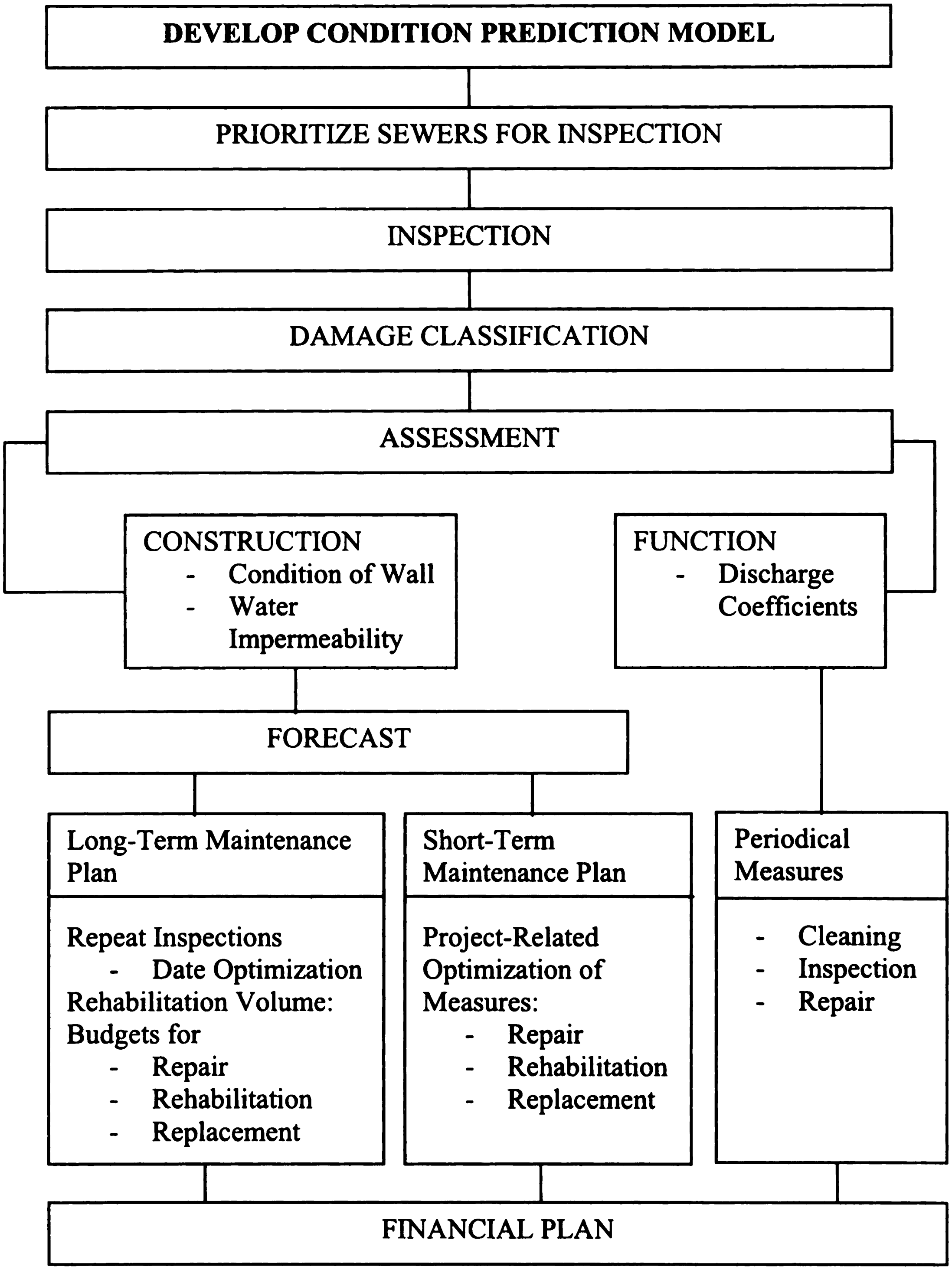


Figure 1.2 - Conceptual Sewer Management Plan

It has been estimated that only 30-40% of local authorities have reasonably satisfactory records, and 15-30% of all public sewers are not recorded at all (Read and Vickridge 1997). According to a survey conducted by Malik et al. 1997, only 45% of the cities use some kind of subjective criteria for repairing sewers in poor condition, 21% of the cities base their decisions for the future upon the historical data, and with only 24% of the cities making an attempt to predict the future condition of the different sections of the system for the repair and maintenance of their sewer systems. So the municipal agencies tend to wait until there is a failure to take care of the network, after the damage is done. Moreover, the distressed segments of the pipelines exert hydraulic stress on other parts of the system, resulting in an expanding web of failures. This is not an ideal situation and results in various ill effects and damages to society and the environment. Therefore, there exists a tremendous need for developing prediction models that can give optimized solutions for the decision-makers in order to provide uninterrupted service and to extend sewer life.

In order to predict when the sections of the pipeline network need to be inspected and maintained, it is necessary to predict the rate of those measurers for which criteria have been established. A pipeline condition prediction model will provide base inputs for pipeline inspection, maintenance and rehabilitation planning. Knowledge of pipeline condition and performance characteristics will serve helpful in the following:

- To inspect and rehabilitate the right pipe at the right time,
- Determination of the action year in which a pipe section deteriorates to the minimum acceptable level,

- Forecasting of the future funding requirement to maintain the pipeline network at an acceptable level,
- Preventing major failures and risks associated with it,
- Prioritizing the segments of the network and better allocation of budget and rehabilitation project phasing strategies.

Traditionally, statistical and physical models have been used to assess pipeline condition, but they have been limited in their application. The use of neural network based models to complement current models can be beneficial to predict dynamically the condition of sewers using historic data that is already available to the municipal agencies. This type of information will enable the municipal authorities to make long-term strategic decisions regarding pipeline maintenance, asset planning and operational management using locally available data.

1.3 OBJECTIVES AND METHODOLOGY

Although there have been tremendous advancements in infrastructure management in the past few years the impact of pipe degradation and failures on the financial and service level requirements of utilities remains significant. To pre-empt these failures and reduce their associated costs, planning models need to be developed to prioritize maintenance and rehabilitation in pipeline networks (Burn et al. 2001).

The main objective of this research is to develop a pipeline condition prediction model based on neural network algorithm, which can identify pipelines at risk of degradation so that inspections can be prioritized. This model may aid the municipal agencies in averting the inherent risks involved with pipeline failures by prioritizing the parts of the network that needs immediate action and optimize their limited inspection and maintenance budget by applying resources where they are most effective. The research is focused on developing a prediction model that will learn on historical information to identify deterioration trends and predict future performance. The developed model will provide adequate knowledge of condition of the assets to answer the following questions that the municipal agencies often seek for:

- What will be the probable condition of a specific pipe – and the entire network?
- Which are the most vulnerable pipes in the network?
- How should the inspection projects be ranked?
- What is the future investments need?
- What is the optimal management of the underground sewer infrastructure asset?

An effective condition prediction model will allow the utility manager to optimize the capital and maintenance budgets by identifying the parts of the network that are critical and initiating further assessment of those segments that are potential candidates for repair or renewal.

The expected cost of failure tends to increase with time due to the increase in the probability of failure. On the other hand, the expected cost of intervention as well as inspection and condition assessment tends to decrease over time due to discounting (Kleiner 2001). The total cost thus typically forms a convex curve over time with t* being the optimal rehabilitation time as illustrated in Figure 1.3.

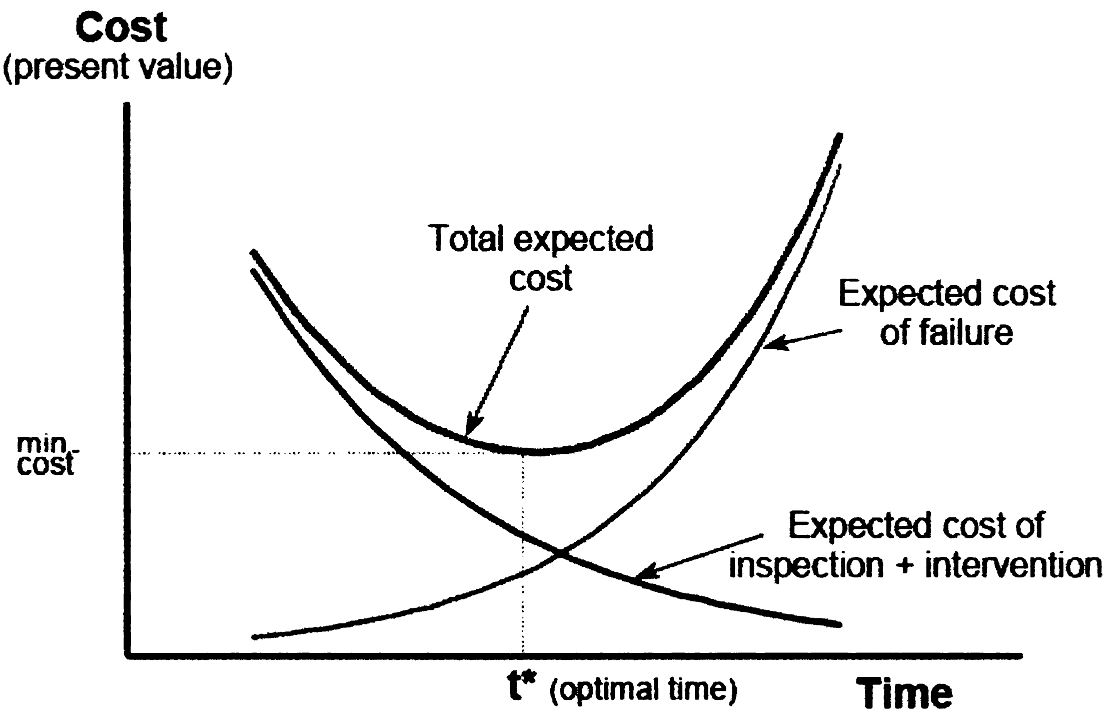


Figure 1.3 - Optimal Renewal of Sewer Pipe with Low Cost of Failure
(Makar et al. 2000)

For the purpose of this thesis, Sewer System Evaluation Survey (SSES) data from the city of Atlanta is considered for model development. The City of Atlanta is faced with the typical problem of rapidly deteriorating sewer systems like most other cities in the US. The city has developed a comprehensive plan to inspect, repair and where necessary, replace its sanitary sewers. The city is currently able to inspect about 304 miles of a possible 2,200 miles of local sewers for cracks, collapses and blockages as a part of their SSET efforts. After extensive investigation and documentation of defects is completed, a rehabilitation plan will be developed, identifying necessary sewer repairs and replacement.

The specific objectives of this research are:

- to review the existing models used to predict pipeline performance and failure characteristics,
- to review the City of Atlanta's sewer pipeline condition assessment database to identify useful pipeline performance data sources for deterioration model development,
- to develop a neural network model for condition prediction based on the historical information, and
- to evaluate the performance of the neural network model with test data.

The research methodology for this thesis is represented in Figure 1.4.

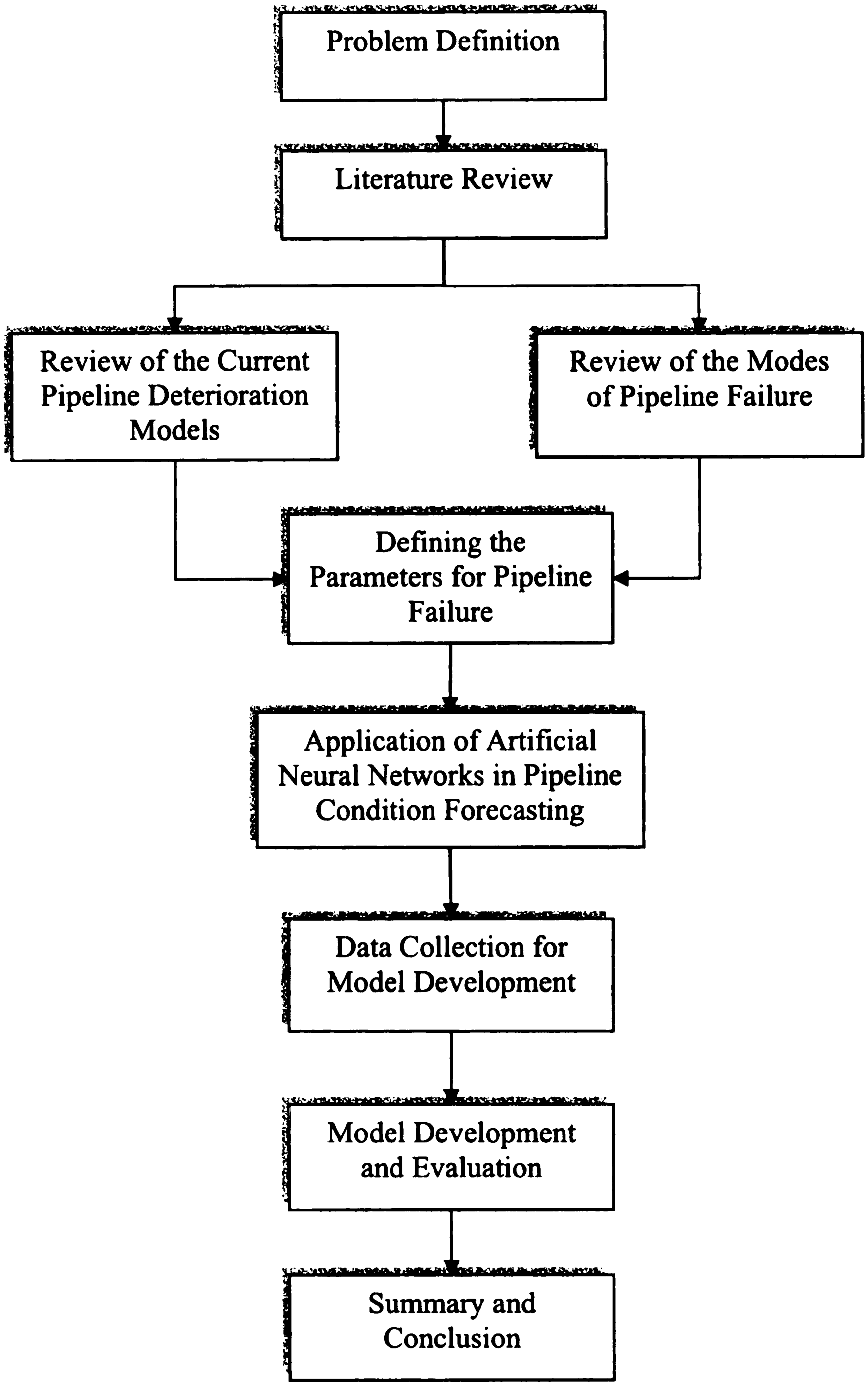


Figure 1.4 – Thesis Methodology

1.4 SCOPE OF THE THESIS

The scope of this thesis is limited to the use of data from the City of Atlanta to develop prediction models for their sewer systems using artificial neural networks. The development of this model and its accuracy will rely heavily on the quality and quantity of their historical and recorded data, condition assessment records and the extent of detailed records of their underground sewer assets.

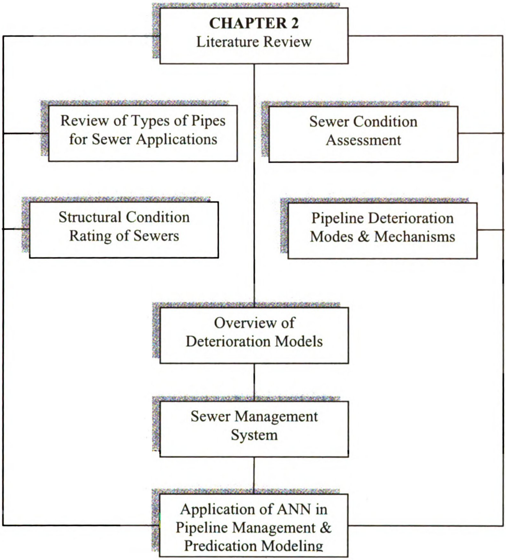
1.5 ORGANIZATION OF THE THESIS

Chapter 1 presents the background, nature of the problem and the objectives of this thesis. Chapters 2 and 3 present an elaborate review of the current prediction models, pipe failure modes and failure mechanisms, pipeline condition assessment techniques and condition ratings, overview of artificial neural networks and their application in pipeline condition prediction and the proposed methodology of the thesis. Chapter 4 presents the data collection, assimilation and the modeling methodology. Chapter 5 presents the neural network model development and summary of results. Chapter 6 presents the thesis summary, conclusions and recommendations for future work. The bibliography chapter contains all the references and other related resources.

CHAPTER 2

LITERATURE REVIEW

This chapter presents the background of sewer systems and builds upon it to describe the motivation for this thesis. A detailed literature review is presented in this chapter that covers pipeline management trends, review of the modes of pipeline failure, deterioration models for pipes and a comprehensive analysis of the parameters that affect the performance of pipelines. The mode and frequency of failure is dependent on the type of pipe and the effect of environmental conditions. Each of these variables is discussed in detail. The following flow chart gives an outline for this chapter.



2.1 TYPES OF PIPES FOR SEWER APPLICATIONS

There are several different pipe materials available for sewer systems, each with a unique characteristic used in different conditions. Until 1850, sewers were generally constructed using brickwork. Over time, because of aging, these sewers have suffered extensive structural damage. Although some sewer systems still contain brick sewers, very few are left. In the middle of the nineteenth century, more and more clay pipes were used to build the sewer systems. Concrete pipes were introduced during the early part of the twentieth century. Modern sewers include polyvinyl chloride, fiberglass, high-density polyethylene, ductile iron, steel and reinforced concrete. In general, pipe materials are grouped into three categories:

- Metallics
- Cement-based
- Clay
- Plastics

The four different pipe materials that are most commonly used for sewer applications are ductile iron, concrete, plastic, and vitrified clay. Pipe material selection considerations include trench conditions (geologic conditions), corrosion, temperature, safety requirements, and cost. Key pipe characteristics are corrosion resistance (interior and exterior), the scouring factor, leak tightness, and the hydraulic characteristics.

The stability of deteriorated sewers depends on the materials used for the construction of the sewer pipe. Rigid pipe materials are usually designed to resist vertical loading on their own, while brick sewers and flexible pipe materials require side support from the surrounding soil. Older sewers were typically constructed of vitrified clay, brick, or concrete. Presently, new materials are used such as plastic, ductile iron, steel, reinforced concrete, and reinforced fiberglass. As shown in the figures below, different pipe materials will fail by different mechanisms.

2.1.1 METALLIC PIPES

The most common types of metallic pipes are cast iron, ductile iron and steel pipes. The first official record of Cast Iron pipe installation was in 1455 in Siegerland, Germany.

Cast Iron pipe was introduced to the United States as early as 1817, when it was installed in the Philadelphia water system. Today, more than 565 utilities (in the United States and Canada) have had Cast Iron mains in continuous service for more than 100 years. Additionally, at least 16 utilities have had Cast Iron mains in continuous service for more than 150 years.

Ductile iron pipe (DIP) is an outgrowth of the cast iron pipe industry. Improvements in the metallurgy of cast iron in the 1940's increased the strength of cast iron pipe and added ductility, an ability to slightly deform without cracking. Ductile Iron not only retains all of Cast Iron's attractive qualities, such as machinability and corrosion resistance, but also provides additional strength, toughness, and ductility. Although its chemical properties are similar to those of Cast Iron, Ductile Iron incorporates significant casting refinements, additional metallurgical processes, and superior quality control (DIPRA 2004). Corrosion control is achieved by using polyethylene encasement.

Steel pipes are versatile and has economic advantages since it is stronger and thus lighter for a given strength. In circumstances in which they are commonly used, they may be susceptible to failure due to high external pressure, since their relatively thin walls buckle easily. Steel pipes may also be more likely to be structurally damaged by corrosion than iron due to their relatively thin walls. Under favorable conditions, the life of steel pipes may exceed 50 years (McGhee 1991).

The main cause of deterioration in buried metallic pipelines is galvanic corrosion. Soils of varying physical and chemical composition create galvanic potential differences between different areas of the pipe. Under suitable soil electrolytic conditions, anodic and cathodic areas are created, which leads to galvanic corrosion. Buried iron pipes are vulnerable to anaerobic corrosion by sulfur-reducing bacteria under specific ground conditions, whilst grey cast iron pipes are susceptible to a unique form of galvanic corrosion, in which selective leaching of iron leaves a relatively weak graphitic network in the pipe wall. This process is commonly referred to as graphitisation.

For example, in metallic pipes, failure can occur solely by corrosion (Figure 2.1), or by corrosion combined with excessive loading (Figure 2.2).

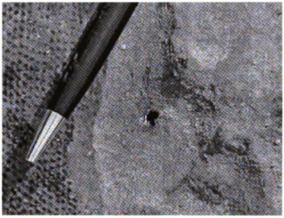


Figure 2.1 - Single Corrosion Pit at the Outer Surface of Grey Cast Iron Pipe

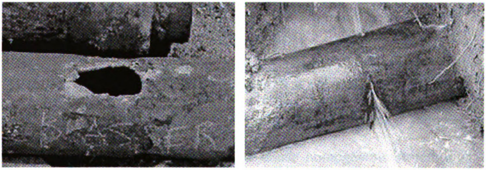


Figure 2.2 - Combined Corrosion/Structural Failure of Grey Cast Iron Pipe: (left) Blown Section; (right) Circumferential Fracture (http://www.cmit.csiro.au/research)

2.1.2 CEMENT-BASED PIPES

Concrete pipes are manufactured in the form of reinforced concrete pipe (RCP), pre-stressed concrete cylinder pipe (PCCP) or asbestos cement pipe (ACP). Generally, they are manufactured by wrapping reinforced wire (high-tensile-strength wire in the case of prestressed concrete) about a steel cylinder which has been lined with centrifugally placed cement mortar. For prestressed concrete pipes, the wire is wound tightly (prestressed) to prestress the core and is covered with an outer layer of concrete. In the case of non-prestressed concrete, a similar pipe is manufactured without prestressing the wire. In rare cases, where leakage is not important, plain concrete pipe may be used. A reasonable estimate of concrete pipe service life is 75 years (McGhee 1991).

Amongst the advantages of concrete pipes, the following may be included: low cost of maintenance, less corrosion if buried in ordinary soil or transporting non-reactive wastes, expansion joints not normally required, and no specially skilled labor force is required for its installation. However, it exhibits a certain tendency to leak due to porosity and shrinkage cracks, has a low corrosion resistance in the presence of acids or alkalis, and is generally difficult to repair (Babbitt et al. 1962).

Asbestos cement pipe is a related product. It is composed of a mixture of Portland cement and asbestos fiber which is built up on a rotating steel mandrel and then compacted with steel pressure rollers into a dense homogenous structure in which a strong bond is effected between the cement and the asbestos fibers (Babbit et al. 1962, McGhee 1991). Amongst its advantages may be mentioned the good corrosion resistance, its light weight, and ease for making connections. Some disadvantages are the low flexural resistance of the pipe as a whole, low chemical resistance against petroleum products, and may be easily damaged by excavating machinery.

Similar failure modes occur in cement-based pipes like other pipe types, but the mechanism of degradation clearly differs (Figures 2.3 and 2.4).

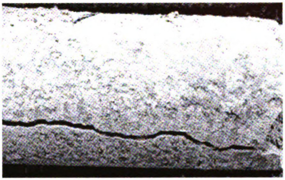


Figure 2.3 - Combined Degradation/Structural Failure of Asbestos Cement Pipe (Longitudinal Fracture)

Asbestos-cement and concrete pipes are subject to deterioration due to various chemical processes that either leach out the cement material or penetrate the concrete to form products that weaken the cement matrix. Presence of inorganic or organic acids, alkalis or sulphates in the soil is directly responsible for concrete corrosion. In reinforced and pre-stressed concrete, low pH values in the soil may lower the pH of the cement mortar to a point where corrosion of the prestressing or reinforcing wire will occur, resulting in substantial weakening of the pipe (Dorn et al. 1996).

Figure 2.4 - Combined Degradation/Structural Failure of Asbestos Cement Pipe (Complex Fracture) (http://www.cmit.csiro.au/research)

2.1.3 CLAY PIPES

Vitrified clay pipes are composed of crushed and blended clay that are formed into pipes, then dried and fired in a succession of temperatures. The final firing gives the pipes a glassy finish. Vitrified clay pipes have been used for hundreds of years and are strong, resistant to chemical corrosion, internal abrasion, and external chemical attack. They are also heat resistant. These pipes have an increased risk of failure when mortar is used in joints because mortar is more susceptible to chemical attack than the clay. Other types of joints are more chemically stable. It has been shown that the thermal expansion of vitrified clay pipes less than many other types (such as DIP and PVC).

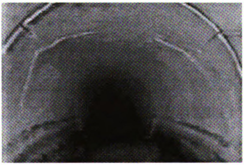


Figure 2.5 - Cracked Vitrified Clay Pipe (NASSCO 1996)

2.1.4 PLASTIC PIPES

Plastics are, in general, synthetic resins of high molecular weight, polymerized from simple compounds by heat, pressure, and catalysis. Plastics used in the manufacture of pipes belong principally to polyvinyl chloride (PVC) and cellulose acetate types.

Plastic pipes are cost effective and also have other advantages such as immunity to corrosion due to chemicals commonly found in the vicinity of buried sewer systems, freedom from damage due to freezing of fluids inside them, ease of bending and joining, adequate strength, resistance to shock, resilience and flexibility. PVC pipes do not deteriorate under attack from bacteria and do not serve as a nutrient to micro-organisms, macro-organisms of fungi. Amongst their disadvantages are a low resistance to heat, inability to conduct electrical current (which can constitute as an advantage too, by making PVC pipes immune to electrolytic corrosion), high coefficient of expansion, and diminishing tensile resistance with an increase of temperature (Uni-Bell 1984).

Plastic pipes function effectively at temperatures between 32° to 90° F. with an extreme temperature drop (below freezing, for example) PVC pipes loose impact strength and become more brittle. Conversely, with an increase in temperature, PVC pipes loose tensile strength and stiffness (Uni-Bell 1984).

Polyethylene (PE) is a thermoplastic material produced from the polymerization of ethylene. PE plastic pipe is manufactured by extrusion in sizes ranging from 2" to 63". PE is available in rolled coils of various lengths or in straight lengths up to 40 feet. Generally small diameters are coiled and large diameters (>6" OD) are in straight lengths.

Whilst plastic pipes (such as PVC, polyethylene, etc.) are relatively 'young', their failure mechanisms must also be understood to forecast future performance. As shown in

Figures 2.6 and 2.7, in the absence of any obvious signs of degradation, fracture failure can still occur in the field. In general, failures in plastic pipes can be split into three categories; plastic collapse, buckling and brittle fracture. Since the design pressures for plastic pipes are based on the yield strength of the pipe material, plastic collapse is rarely seen in practice. Buckling failures, which result in local inversion of the pipe circumference, occur under high external loads when the ratio between pipe wall thickness and diameter is below a critical value. As with plastic collapse, good design practice limits the number of buckling failures observed in service. The majority of failures reported in plastic pipes occur by brittle fracture.

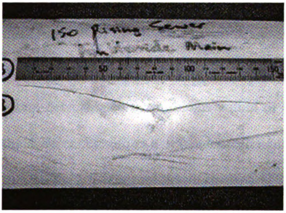


Figure 2.6 - Brittle Fracture of a PVC Pipe

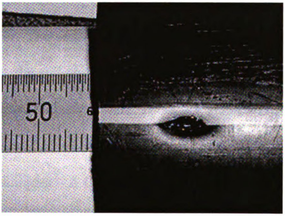


Figure 2.7 - Rupture of a Polyethylene Pipe

To account for these various failure modes, pipeline deterioration models have to be developed to estimate future deterioration rates.

2.2 SEWER CONDITION ASSESSMENT

A reliable condition assessment of a sewer system is essential for its maintenance and for decisions regarding its rehabilitation. The City of Atlanta has currently inspected approximately about 304 miles of the total 2,200 miles of sewer system using various condition assessment techniques. Considering the quantity and length of the sewer pipes, inspection work is often intensive, requiring the collection of voluminous information. It is therefore critical that the inspections are performed on the sections of sewer pipes that are considered to be in the worst potential condition. The model developed in this research will attempt to identify sewer groups in the network that are most vulnerable to deterioration to facilitate prioritization for physical inspections. There are various condition assessment techniques that are used for sewer inspection and can been classified into three different groups (Makar 1999). The first group, including conventional CCTV and advanced SSET™ examinations, are techniques that determine the condition of the inside surface of the sewer. The second group examines the overall condition of the sewer wall and, in some cases, the soil around the pipe. Finally, the third group detects specific problems within or behind the sewer wall. Table 2.1 summarizes the different condition assessment techniques and their utilization.

Table 2.1 - Current Sewer Inspection Techniques – A Comparison (Makar 1999)

Technique	Where to use	What will be found
Inspection of the Inner Surface		
Conventional CCTV	Empty pipes, partially filled pipes above the water surface	Surface cracks, visible deformation, missing bricks, some erosion, visual indications of exfiltration/infiltration
Stationary CCTV	Pipes with less than 50 m. distance between manholes	As CCTV
Light line CCTV	Pipes where deformation is an issue	Better deformation measurements + CCTV results

Technique	Where to use	What will be found
Computer Assisted CCTV	As CCTV, currently small diameter pipes only	As CCTV, but with quantitative measurements of damage
SSET™	Pipes of diameter ranging from 8 – 24 inches	As CCTV, but with higher sophistication and accuracy. Can measure deformation of pipes
Laser Scanning	Partially filled pipes, empty pipes	Surface cracks, deformations, missing bricks, erosion losses
Ultrasound	Flooded pipes, partially filled pipes, empty pipes	Deformation measurements; erosion losses; brick damage
Inspection of Pipe Structure and Bedding Condition		
Microdeflections	Rigid sewer pipes	Overall mechanical strength
Natural Vibrations	Empty sewer pipes	Combined pipe and soil condition, regions of cracking, regions of Exfiltration
Impact Echo	Larger diameter, rigid sewers	Combined pipe and soil condition, regions of wall cracking, regions of exfiltration
Inspection of Bedding		
Ground Penetrating Radar	Inside empty or partially filled pipes	Voids and objects behind pipe walls, wall delaminations, changes in water content in bedding material

2.3 STRUCTURAL CONDITION RATING OF SEWERS

The condition rating which follows sewer evaluation is used to objectively determine the current condition of sewers. A rating system that minimizes subjective evaluation and is repeatable can be effectively used to predict future condition. It is acknowledged that it does not make sense to develop a sophisticated condition rating system if the deterioration process of a sewer structure is not fully understood, as is the case when new methodologies or materials are involved. However, comprehensive and objective rating systems can be developed for the most common sewer pipe materials and when adequate historical performance records are available.

Most rating systems are based on assessment of structural conditions with little consideration of hydraulics and I/I condition, because hydraulic and I/I conditions cannot be easily evaluated. They require hydraulic modeling and simulations (which include comprehensive input data) and in-depth investigations of I/I, which can be expensive.

In the area of sewer management, there is no standard procedure to develop a condition rating of sewer pipes. While a standard procedure for developing a comprehensive sewer condition rating does not exist, several methods of sewer condition rating (for brick and concrete/clay sewers) found in the literature have been reviewed in order to gauge the status of condition assessment methodologies for sewer systems.

Water Research Center (WRc). The Sewer Rehabilitation Manual (WRc 1983) discusses the development of the structural rating system for concrete and brick sewers in the U.K. The rating system involves three levels of structural condition. Each structural defect found in a concrete pipe is numerically scored based on the severity of the defect and the number of defects recorded in a pipe. These defects include: open joint, displaced joint, cracked, fractured, broken, deformed, and collapsed. For brick sewers, the defects are: mortar loss, displaced bricks, missing bricks, surface damage, fractured, and dropped invert. The inspector is provided with pictorial descriptions to determine the type and severity of each defect.

For example, each "circumferential crack" found in a sewer pipe is assigned a score of 1. "Longitudinal" and "Multiple" cracks are given scores of 2 and 5 (per crack), respectively. A single collapsed pipe is scored 165, etc.

The scores of all defects found in a pipe are then compiled to calculate "the peak score" accumulated in any one-meter (3.18-ft) length. Additionally, "the total score" and "the mean score" for the entire length of sewer from upstream to downstream manholes are calculated. Based on these three scores, sewers are rated as grade 1, 2, or 3, where grade 3 represents the worst structural condition.

By considering the condition of the entire length of a sewer line from upstream to downstream manholes, sewer lines of different total lengths but similar scores are not equally rated. Consequently, shorter lines with more serious defects will not be rated below a longer line with less serious defects.

The pipeline assessment codes were developed in the United States by National Association of Sewer Service Company (NASSCO) with the collaboration of Water Research Center (WRc). Table 2.2 describes the various structural condition distress terms proposed by NASSCO. Few of the types of defects encountered in sewer pipes are shown in Figure 2.8 below.

Table 2.2 - Sewer Pipe Structural Condition Evaluation (NASSCO 1996)

Pipe Condition	**Description**
Collapsed pipe	Complete loss of structural integrity of the pipe due to fracturing and collapse of the pipe walls. Most of cross-section area is lost to flow.
Structural cracking with Deflection	Pipe wall displacement plus cracks described by:

Pipe Condition	**Description**
Longitudinal Circumferential Multiple Slab–out	Defect runs approximately along axis of sewer. Defect runs approximately at right angles to the axis of sewer. Combination of both longitudinal and circumferential defects. A large hole in the sewer wall with pieces missing.
Sag	The pipeline invert drops below the downstream invert.
Structural cracking without deflection	Sewer wall cracked longitudinally, circumferentially, or multiple, but not displaced.
Cracked joints	The spigot and /or bell of a pipe is cracked or broken
Open Joints	Adjacent pipes are longitudinally displaced at the joint
Holes	A piece of a pipe wall or joint is missing.
Root intrusion	Tree or plant roots have entered the sewer through an opening in the pipe wall or joint
Protruding joint material	Joint sealing material or gasket is displaced into the sewer from its original location
Corrosion *Condition 1* *Condition 2* *Condition 3*	When the cementitious pipe material shows evidence of deterioration illustrated by the following stages: The pipe wall surface shows irregular smoothness, i.e. wall aggregate is exposed The reinforcing steel is exposed. The reinforcing steel is gone and /or the pipe wall is no longer intact revealing the surrounding soil.
Pulled joint	Adjacent pipe joints are deflected beyond allowable tolerances so that the joint is open.
Protruding lateral	A service outlet or pipe section that protrudes or extends into the sewer varying in magnitude.
Vertical displacement	The spigot of the pipe has dropped below the normal joint Closure
Depth of cover	The amount of soil covering the top of the pipe.

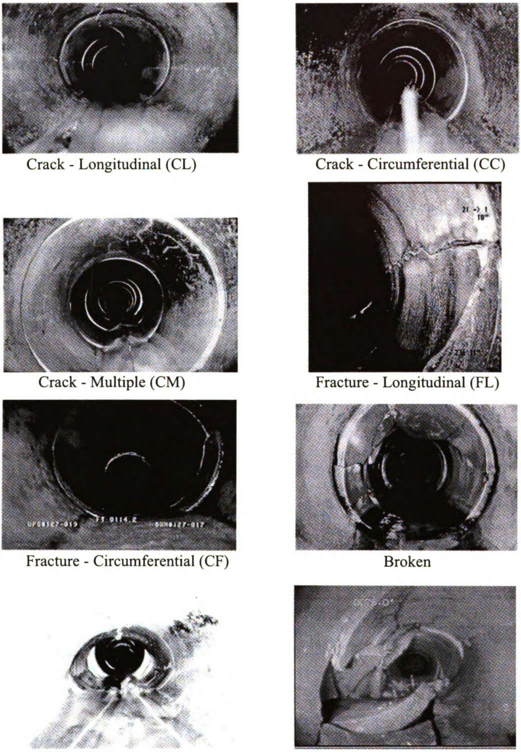

Crack - Longitudinal (CL)
Crack - Circumferential (CC)
Crack - Multiple (CM)
Fracture - Longitudinal (FL)
Fracture - Circumferential (CF)
Broken
Deformation
Collapse

Figure 2.8 – Various Defects during the Life of Sewer Pipe (NASSCO 1996)

Water Environment Federation – American Society of Civil Engineers. WEF-ASCE (1994) suggests assigning an importance factor to each condition evaluation criteria for the structural condition of brick and concrete/clay sewers. The structural condition of brick sewers involves the following aspects: sags, vertical deflection and cracks, missing bricks, lateral deflections, root intrusion, missing mortar, loose bricks, protruding lateral, soft mortar, and depth of cover. Concrete and clay sewer structural condition evaluation criteria include: collapsed pipe, structural cracking with deflection (longitudinal, circumferential, or both), slab-out sag, structural cracking without deflection, cracked joints, open joints, holes, root intrusion, protruding joint material, corrosion, pulled joint, protruding lateral, vertical displacement, and depth of cover.

The sewer degradation is broadly classified into five degradation sequences. All of the sequences started with an intact pipe and progressively degraded starting with the distinct sequences of (1) cracks, (2) open joints, (3) displaced joints, (4) corrosion, and (5) deformation, and ended in collapse. In each degradation sequence, there are various severity levels of each distress before it reaches the collapse from the initial intact condition. Table 2.3 contains a brief description of the degradation sequences.

Table 2.3 - Structural Distress Conditions Included in the Evaluation of Sewer Segments (WEF 1994)

Structural Condition	Description
Intact	Best possible sewer condition
Crack	Separation of pipe materials that runs longitudinally or circumferentially along of the sewer pipe
Open Joint	Adjacent pipes are longitudinally displaced at the joints
Displaced Joint	The pipe is not concentric with the adjacent pipe
Corrosion	The cementious pipe material that shows evidence of deterioration from chemical action. The pipe wall

Structural Condition	Description
	surface shows irregular smoothness and aggregate on the cementitious material in the pipe is exposed
Deformation	Original cross-section of the sewer is altered
Collapse	There is complete loss of structural integrity of the pipe. Most of the cross-sectional area is lost.

Depending on the extent of the condition throughout a given sewer reach, a "minor," "moderate," or "severe" multiplier factor, such as 1, 2, or 3, respectively, is used. The overall numerical structural condition is then determined by calculating the total score. Based on how likely it is the sewer will collapse, the internal condition rating factor for overall structural condition can be determined. Sewers in rating 5 are in the most serious condition. This rating can be adjusted based on external factors such as soil types, surcharge, water table and fluctuation, and traffic condition.

Kathula (2000). Kathula (2000) proposed a structural condition rating system which involves twenty levels of structural conditions. The various levels of sewer conditions are based on the degree and the combination of structural defects commonly found in sewer pipes. The structural defects considered in the evaluation include: intact (or no defects), cracked, open joint, displaced joints, corrosion, holes, deformation, and collapse. Each defect is then rated into three severity levels: low, medium, or high. The twenty conditions of defects in rating structural conditions are listed in Table 2.4.

Table 2.4 - Condition for Various Levels of Distress in Sewer Pipes (Kathula 2000)

Condition Number	Distress and Level
1	Intact
2	Tight Crack (TC)
3	Open Crack + Infiltration Light (OC+IL)
4	Open Joint Light + Infiltration Light (OJL+IL)
5	Multiple Open Crack + Infiltration Light (MOC+IL)
6	Open Joint Medium + Infiltration Light (OJM+IL)
7	Corrosion Light (CL)
8	Multiple Open Crack + Small number of Holes (MOC+H1)
9	Open Joint Medium + Infiltration Medium (OJM+IM)
10	Displaced Joint Medium + Infiltration Medium (DJM+IM)
11	Corrosion Medium (CM)
12	Open Joint Severe + Infiltration Medium (OJS+IM)
13	Displaced Joint Large + Infiltration Medium (DJL+IM)
14	Deformation Low (DL)
15	Corrosion Severe (CS)
16	Open Joint Severe + Infiltration Severe (OJS+IS)
17	Displaced Joint Large + Infiltration Severe (DJL+IS)
18	Corrosion Severe + Large number of Holes (CS+H2)
19	Deformation Severe (DS)
20	Collapse (X)

Each distress type has one, two, or three levels of severity, based upon the impact that the defect has on the continued service of the sewer pipe. The three levels of severity are:

1. *Low severity level:* Functionality is slightly impaired. The defect produces little or no effect on the surrounding environment. Preemptive work in these sewers would not be cost effective unless numerous failures occur in a short pipe length.

2. *Medium severity level:* Functionality is significantly impaired. Repair of these failures has a significant but not critically high cost.

3. *High severity level:* Functionality is seriously impaired. The cost of failure under this condition would be high and affect the surrounding environment to a great extent.

The following Table 2.5 shows the five degradation sequences and their severity levels used by Kathula 2001 based on the degree and the combination of structural defects found commonly in sewer pipe segments.

Table 2.5 - Five Degradation Sequences and their Severity Levels with Abbreviations (Kathula 2001)

Degradation Sequence	Severity Levels with their abbreviations
Cracks	Tight Crack (TC)
	Open Crack (OC)
	Multiple Open Crack (MOC)
	Multiple Open Crack + Small no. of Holes (MOC+H1)
Open Joints	Small Open Joints (SOJ)
	Medium Open Joints (MOJ)
	Large Open Joints (LOJ)
Displaced Joints	Small Displaced Joints (SDJ)
	Medium Displaced Joints (MDJ)
	Large Displaced Joints (LDJ)
Corrosion	Light Corrosion (LC)
	Medium Corrosion (MC)
	Severe Corrosion (SC)

Degradation Sequence	Severity Levels with their abbreviations
	Severe Corrosion + Large no. of Holes (SC+H2)
Deformation	Light Deformation (LD)
	Medium Deformation (MD)

The defects can then be classified, for example as:

1 – Excellent condition, no defects present

2 – Good condition, only low risk defects present.

3 – Fair condition, pipe contains medium severity defects.

4 – Poor condition, pipe contains high severity defects and collapse is imminent.

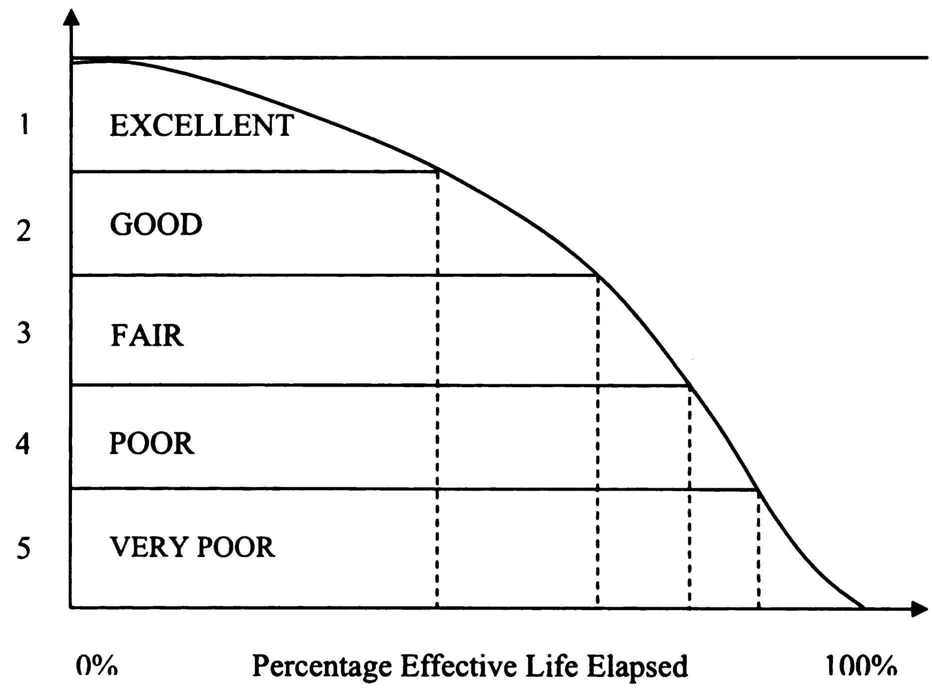


Figure 2.9 – Typical Condition Deterioration Curve

Mehle et al. (2001) proposed a modified Vani Kathula condition coding system incorporated with a condition rating system that is represented in Table 2.6.

Table 2.6 - Condition Coding System Incorporating with a Condition Rating System (Mehle et al. 2001)

Defects	Excellent	Good	Fair	Poor	Failure
Cracks	Intact	TC, OC	MOC	MOC+H1	Collapse
Open Joints	Intact	SOJ	MOJ	LOJ	Collapse
Displace Joints	Intact	SDJ	MDJ	LDJ	Collapse
Corrosion	Intact	--------------	LC, MC	SC, SC+H2	Collapse
Deformation	Intact	--------------	--------------	LD, MD	Collapse
Rating	1	2	3	4	5

City of Atlanta Defect Coding System. The city of Atlanta has developed their own defect coding and condition ranking system based on NASSCO and WRc standards. A detailed list of the defect coding is given in Appendix A.

Once the condition rating has been assigned to a particular pipeline, the worst defect present is used as an indication of the overall sewer condition rating. Although the pipeline may not be in poor condition throughout its length, the worst condition along the length dictates its risk of collapse.

2.4 PIPELINE DETERIORATION

Pipeline systems require constant maintenance and can become impaired for a number of reasons. A comprehensive study performed by WRc (Serpente 1993) concludes that the concept of measuring the "rate of deterioration" of sewers is unrealistic, but deterioration is more influenced by random events in a sewer life span (a storm or an excavation nearby) and severe defects do not always lead immediately to collapse. Sewer pipes are prone to certain types of failures based on the type of material, physical design, age, functionality and external and internal environment. Distress and collapse of a sewer are the result of the complex interactions of various mechanisms that occur within and around the pipeline (Kathula 2000). The impact of the deterioration of the sewer system depends upon its size, complexity, topography and service. While it is almost impossible to predict when a sewer will collapse, it is feasible to estimate whether a sewer has deteriorated sufficiently for collapse to be likely. The mechanisms of pipeline deterioration are:

- Structural – cracks, fractures, breaks, etc.
- Hydraulic – insufficient capacity, flooding, debris, encrustation and grease
- Operational problems – roots, blockages debris, maintenance procedures, etc.

Pipelines can have defects classified as built-in or long term (Najafi 1995). Built-in defects are generated during pipeline construction and represent conditions that affect the performance of pipes after installation. Long-term defects are caused as a result of the deterioration process. Construction-related or built-in defects can be offsets in alignment, joints loosely fitted or loosened by vibrations, flattened or ovaled pipes, sags due to settlement, stresses caused by dynamic loadings of backfill, removal of trench sheathing and pilings, overburden compaction, etc. Joints can experience the construction defects, such as pinching of rubber gaskets, misalignment of gaskets, and squeezing due to "overshoving" of one pipe into another. A structural failure can be a crack, break, split, cavitation of the pipe opening, or separation at a joint (Najafi 1995).

Examples of causes of long-term pipeline deterioration are sulfate corrosion due to sewer gases, excessive hydraulic flows, structural failures, leaks and infiltrations, and erosions. Bacteria in the wastewater stream convert the sulfates to hydrogen sulfides which, when released into the sewer air space, become oxidized into sulfuric acid. The sulphuric acid is reactive to some pipe materials making it to corrode. Severe corrosion can jeopardize the structural integrity of a pipe or manhole and lead to collapse. Any condition of pipeline deterioration which occurs over an extended time period and is not a result of construction practice is considered a long-term deterioration. Proper maintenance of pipelines is essential to keep the pipeline in good health.

The state of the surrounding soil is of fundamental importance in assessing the structural condition of a sewer. The main factors that affect the rate of ground loss include sewer defect size, hydraulic conditions (water table, and frequency and magnitude of surcharge), and soil properties (cohesive or non-cohesive soil). Severe defects (larger than 4 inches), high water table (above sewer level), frequent and high magnitude of hydraulic surcharge, and soil types (silts, silty fine sands, and fine sands) can have serious effects on ground loss. Loss of side support will allow the side of the pipe to move outward when loaded vertically, and collapse will likely once the pipe deformation exceeds 10%. Uneven loading of pipes due to joint displacement also accelerates the pipe deterioration process.

2.4.1 MODES OF PIPELINE DETERIORATION

Pipeline deterioration is a complex process; many factors are responsible for their deterioration and failure – structural, hydraulic, environmental, functional, age of the sewer, quality of initial construction, etc. The intensity of structural failures depends on the size of the defect, soil type, interior hydraulic regime, ground-water level and fluctuation, corrosion, method of construction, and loading on the sewer. Hydraulic failures are caused by infiltration and inflow (I/I) problems. These I/I problems reduce the planned hydraulic capacity of sewers, increasing the potential for collapse. Figure 2.10 illustrates various kinds of internal and external forces acting on a pipe. The modes of failure depend on the type of environment and pipeline material.

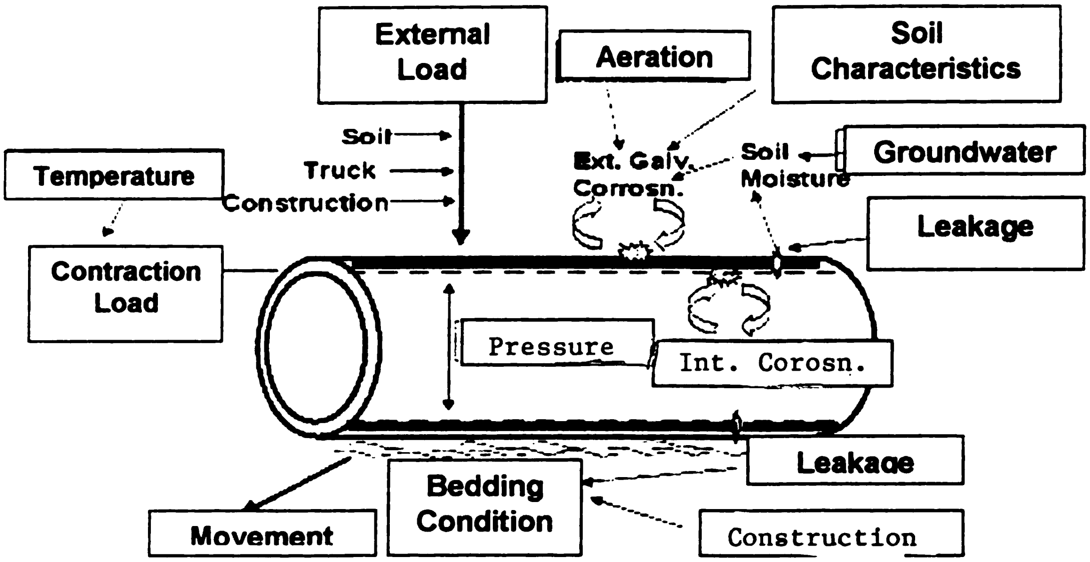


Figure 2.10 - Pipeline Interactions Leading to Failure (O'Day et al. 1986)

Pipe breakage is likely to occur when the environmental and operational stresses act upon pipes whose structural integrity has been compromised by corrosion, degradation, inadequate installation or manufacturing defects. Pipe breakage types were classified by O'Day et al. (1986) into three categories: (1) circumferential breaks, caused by longitudinal stresses; (2) longitudinal breaks, caused by transverse stresses (hoop stresses); and (3) split bell, caused by transverse stresses on the pipe joint. This classification may be complemented by an additional breakage type i.e., holes due to corrosion. Circumferential breaks due to longitudinal stress are typically the result of one or more of the following occurrences: (1) thermal contraction (due to low temperature of the sewage in the pipe and the pipe surroundings) acting on a restrained pipe, (2) bending stress (beam failure) due to soil differential movement (especially clayey soils) or large voids in the bedding near the pipe (resulting from leaks, I/I, etc.), (3) inadequate trench and bedding practices, and (4) third party interference (e.g., accidental breaks, etc.). Table 2.7 lists the most typical type of defects found in sewers.

Table 2.7 - Typical Defects in Sewers Pipes (Davies et al. 2001)

Defect	Description
Longitudinal cracks and fractures	May occur at springing level as well as at the crown and invert. A result of excessive 'crushing' or 'ring' stress.
Tension cracks	Cracks are diagonal and spread from the point of overload which is often a hard spot beneath the pipe.
Circumferential cracks and Fractures	Relative vertical movement of successive lengths of pipe causing cracks and/or fractures due to excessive shear or bending stresses. Most likely to occur near joints.
Broken pipes	Occurs when pieces of a cracked or fractures pipe visibly move from their original position. Normally represents a further stage in deterioration of a cracked or fractured pipe and is a very serious defect.
Socket bursting	Excessive pressure inside the joint due to the expansion of the jointing material may cause a bursting failure of the socket.
Deformed pipes	Occurs when a longitudinally cracked or fractured pipe loses the support of the surrounding ground.

2.4.1.1 STRUCTURAL DEFECTS

Structural defects failure mechanisms include cracks and fractures in the pipeline material that are caused by a change in the forces around a pipeline or a change in the ability of the pipe material to resist existing forces (ASCE 1994, Serpente 1993). The infiltration of groundwater through existing structural defects creates or increases the size of voids as the infiltrating water carries particles from the soil into the pipeline (Delleur 1989). The weakening of this soil makes the land above the pipe vulnerable to surface collapse. The effects of infiltration on void formation are made worse by the process of exfiltration. Exfiltration occurs when water leaves the sewer line through structural defects during periods of hydraulic surcharge. Surcharge wastewater can scour or loosen more fines at the perimeter of the voids (Delleur 1989, Stein et al. 1995).

Dynamic forces that cause structural defects are large one-time events or smaller cyclic events that occur at a variety of frequencies (daily, seasonally, etc.). Large one-time events include periods of heavy surface construction, in-ground utility construction, or non-construction events such as earthquakes or landslides. These events are especially significant when coupled with a weakened material or voids in the soil. Many surface collapse failures are associated with degraded but functioning sewers that fail due to a large one-time event (Delleur 1989, WRc 1986). Smaller cyclical dynamic loads include load transfer from above ground activities, such as routine truck, machinery, and bus or train traffic or in ground movements, such as those caused by expansive soils or frost heave.

2.4.1.2 OPERATIONAL DEFECTS

Operational Defects failure mechanism originates from an increase in demand and a decrease in capacity. Infiltration and inflow, often referred to as I/I, are the two types of demand on a sewer system. Infiltration increases the demand as the number of structural defects grows. Inflow is the demand on the system from service connections and storm waters (ASCE 1994, EPA 1991). A decrease in capacity is the result of a decrease in the effective diameter of the pipeline and an increase in the roughness coefficient. The effective diameter is reduced by structural defects such as open joints, broken pipe sections, root masses or collected debris.

2.5 PIPELINE DETERIORATION MECHANISMS

This section deals in detail about various mechanisms that would affect pipeline deterioration. There are several theories that explain the deterioration mechanisms of buried pipelines. Various pipe deterioration modes have been identified for different types of pipelines, and the mechanisms thought to cause such defects have been studied. Many sewer system deteriorations are attributable to the following predominant mechanisms:

- Deterioration due to natural aging process - lack of maintenance exacerbates age-related deterioration.
- Deterioration of pipes and joints due to soil-pipe interaction, operating conditions and exposure to corrosive substances.
- Freeze/thaw cycles, groundwater flow, and subsurface seismic activity that can result in pipe movement, warping, brittleness, misalignment, and breakage.

2.5.1 AGE OF SEWER

Aging is a part of life. From the minute the sewer pipe is installed, it begins to age. A classical survival function relating the age of the pipeline to the failure rate is denoted by a bath tub curve as shown in Figure 2.11. The early part of the curve shows "infantile failure" which for pipes is representative of failure due to human factors in the actual laying of the pipe (manufacturing faults, tend to appear during that part). A period of time follows in which failure rate is generally low. When failure does occur it may depend on many factors, such as excessive loads not designed for, or settlement. As the pipes tend towards the end of their useful life the failure rate increases exponentially. This classic survival profile is known as the "Bath Tub" curve. The "Bath Tub" curve can be applied to an individual pipe, a group of pipes with similar characteristics or the whole population of a pipe network.

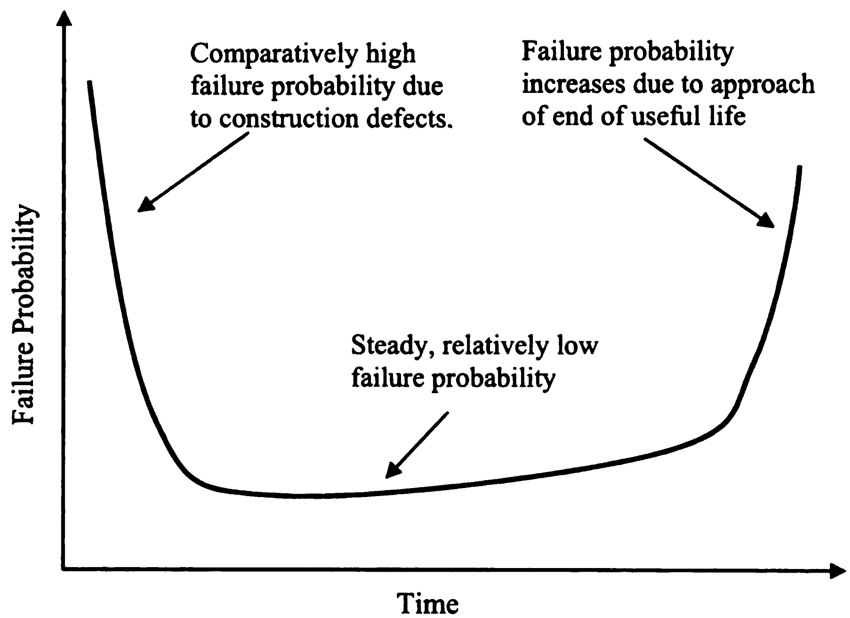


Figure 2.11 - Bath Tub Curve of Sewer Pipe Performance with Age (http://www.pir.gov.on.ca/userfiles/HTML/nts_2_25528_1.html)

The factors that accelerate the aging process of the sewers are discussed in detail in the following sections.

2.5.2 SEWER SIZE

A number of authors have investigated the relationship between sewer size and structural stability. Studies indicate that there is a decreasing trend in pipe failure rate with increasing diameter and is directly attributed to the increasing wall thickness and joint reliability with increase in pipe diameter. Larger wall thickness gives the pipe better structural integrity and improved resistance to corrosion failures (Kettler and Goulter 1985). Many other studies have also shown that a larger proportion of failures have occurred on the smaller diameter pipes (Rajani et al. 1996).

Pipe size also affects the mode of failure (O'Day, 1982). Smaller diameter mains (6 – 8 inches) often experience beam (flexural) failure because of poor bedding conditions, however crushing failures (often longitudinal) are likely to occur due to the relative length-to-diameter ratio. Conversely, larger mains (10-inch or greater) are likely to experience crushing failure, but are not likely to experience beam failure (O'Day 1982).

2.5.3 SEWER SECTION LENGTH

Generally, longer sewer runs are less likely to deteriorate at a faster rate than the shorter ones, which may be due to the fact that longer runs means less bends in the pipe to accumulate debris, creating blockages or damage to the pipe from standing sewage. Another possible reasoning is that the longer runs may be more of conveyance systems rather than collection systems, thus having fewer laterals connected to the pipes which can weaken a pipe system.

Other potential problem area is the length to diameter ratio. Although longitudinal bending stresses increase with increasing pipe diameter, they do so at a slower rate than the increase in the pipe's section modulus, hence pipes which have high length to diameter ratios may be more likely to suffer from excessive bending stresses (Young &

O'Reilly 1983). Despite the fact that this issue is well documented within the literature, there is little evidence of any numerical or statistical investigation of the effect of high pipe length to diameter ratios having taken place.

2.5.4 SEWER GRADIENT

The slope of the pipe is found to have an impact of the condition of the pipe. For all condition states, the steeper the slope is, the higher the possibility that pipe segments deteriorate. This may be due to the fact that steeper pipe segments induce faster flow rates, resulting in greater possibility for damage to the inside walls or joints of pipe segments.

2.5.5 SEWER JOINT TYPE

The main functions of a sewer joint are a follows (ASCE 1982):

- To be water tight;
- To be durable;
- To be resistant to root intrusion

Joint failures are leak failures where pipe joints become separated. Joint type is an issue since the type of joint will influence the susceptibility of the pipe to specific failures. A large part of this may be owing to the amount of flexibility and lateral constraint the joint provides, as well as the pipe joint's actual strength and its ability to resist corrosion.

2.5.6 SEWER DEPTH

In investigating the effect of depth on sewer structural condition, O'Reilly et al. (1989) found a steady decreasing defect rate to a depth of 18 feet below which, the defect rate began increasing with depth. It was suggested that the first occurrence probably reflected the decreasing influence of surface factors such as road traffic and utility/surface maintenance activity. The second occurrence or pattern was explained by the increasing effect of overburden pressure. Jones (1984) suggested that, in shallow sewers, the effect of seasonal moisture variations in the soil surround may be significant. In an analysis of over 4400 sewer failures, Anderson and Cullen (1982) reported that 65% of all incidents occurred at a depth of 6.5 feet or less and 25% from 6.5 to 13 feet deep, although no indication is given of overall sewer depth distribution. Changes in cover depth may also be important in determining a sewer's structural stability.

2.5.7 SURFACE LOADING AND SURFACE TYPE

The location of a sewer will obviously affect the magnitude of surface loading to which it is subject; for sewers beneath roads the main component of such loading is likely to be that from traffic. Pocock et al. (1980) monitored the bending strain developed in a shallow buried pipeline due to static and rolling wheel loads. The measured bending strains were found to increase linearly with axle load, the strains for any given load tending to decrease with increasing vehicle speed. Maximum strains were always associated with pipes that had been deliberately poorly bedded.

2.5.8 FROST HEAVE

Frost heave is defined as the vertical expansion of soils caused by freezing of the soil and ice lens formation. All underground structures require the consideration of frost heave effects as they are capable of displacing portions or the entire underground structure.

Differential heave causes sections of pipe to experience non-uniform displacements, and this results in forceful flexural stresses. Uniform heaving may also prove to be a problem under certain circumstances where pipe joints are not subject to movement. Under this scenario, the pipe experiences stresses similar to a simple beam loading, in which case the pipe will experience bending stresses. Failure of pipe joints may be the result of the frost heave process. This may be a function of the type of connection, and the type of fill material used between joints.

The conditions for frost heave require the following:

1. The presence of a frost susceptible soil;
2. The presence of a sufficient water source, whether it is capillary or a ground water source (for lens formation) and;
3. A ground temperature below freezing point.

With all of the above factors present, there is the potential for damage due to frost heave. The propensity for heave of a soil under freezing conditions is affected by properties such as grain size, rate of freezing, the availability of water, and by applied loads.

2.5.9 FROST LOAD

The failure of sewer pipes during winter could be attributed to increased earth loads on the buried pipes, i.e., frost loads. In a trench, the frost load develops primarily as a consequence of different frost susceptibilities of the backfill and the sidewalls of the trench and the interaction at the trench backfill-sidewall interface. Trench width, differences in frost susceptibilities of backfill and trench sidewall materials, stiffness of the medium below the freezing front and shear stiffness at backfill-sidewall interface play important roles in the generation of frost loads. Thus, it is preferable to use a backfill material that has a matching or lower frost susceptibility than that of the sidewall in order to mitigate against the development of excessive frost loads.

2.5.10 SEWAGE CHARACTERISTICS

Whilst domestic sewage is generally not aggressive to the fabric of sewer system, the quality of the sewage varies from place to place and is dependent on several factors. It can vary from relatively weak domestic sewage, perhaps diluted with large quantities of stormwater or infiltration, to strong and potentially aggressive sewage with a high proportion of trade effluent.

2.5.11 SOIL-PIPE INTERACTION

Soil-pipe interactions are also a possible cause of pipe deterioration. The resistance of the soil-to-pipe union is important because the shear strength of the interaction can affect the degree of mobility of the pipeline and hence its ability to displace. In cold temperatures, the bond between the soil and pipe indicates the amount of restraint the pipe is allowed to shrink axially. A high soil-pipeline interaction will not allow the pipe to contact, and consequently the axial stress in the pipe will increase. It is also possible that a strong bond between the iron pipe and soil will cause excessive soil-pipe interface shear that may cause abrasion of the pipe coating. This abrasion may lead to premature corrosion of the pipe exterior (Yen et al. 1981).

2.5.12 PIPE-WALL TEMPERATURE GRADIENTS

For longitudinal failures, a suspected failure mechanism is the high temperature gradient occurring across the pipe wall. If the temperature difference of the transported effluent and surrounding soil is significant, this temperature gradient can lead to unusually high hoop stresses, subsequently leading to failure (Habibian 1994). Longitudinal failures may also occur in combination with the weakening of the pipe wall due to corrosion, at the weakest portion of the main wall. Another possible cause of longitudinal failure is due to a crushing load. This usually occurs in the large diameter pipes (O'Day 1982).

2.5.13 CORROSION

Corrosion in metallic pipes essentially occurs by an electrochemical reaction between the outer surface of an exposed pipe and its surrounding soil environment. For corrosion to occur, there must be a potential difference between two points that are electrically connected in the presence of an electrolyte, in this case, the surrounding soil. With these conditions satisfied, a current will flow from an anodic area, through the soil to a cathodic area, and then back through the pipe wall to complete the circuit. The anodic area becomes corroded by the loss of metal ions to the electrolyte (Romanoff 1964).

Upon initiation, the corrosion process is self-sustaining (Rossum 1969), resulting in the formation of "pits" at the outer surface of the pipe, with a range of depths and widths. Different pipe materials have different characteristics in their reaction to corrosion. Factors like soil acidity, resistivity, pH content, oxidation-reduction, sulphides, moisture and aeration level have all been reported to influence corrosion rate (Romanoff 1964) and correlations have been proposed between corrosion rates and soil electrochemical properties (Rossum 1969).

The risk of ***Interior Corrosion*** of a pipe interior depends upon the susceptibility of the pipe material to corrosion and the amount of corrosive chemicals in the wastewater. Interior pipe corrosion typically occurs from the formation and release of hydrogen sulfide. Hydrogen sulfide is formed in anaerobic conditions, such as those found in force mains, continually surcharged gravity pipes, debris piles, or pools caused by sagging lines. It is assumed that anaerobic conditions exists in open channel flow at the wetted perimeter and therefore a small amount of hydrogen sulfide is generated and some corrosion can occur if the conditions allow for release (ASCE 1994). Hydrogen sulfide gas is released in turbulent conditions. Such conditions occur at siphon outlets, drop structures greater than 2 feet, discharge of force mains, interceptor intersections, a change in slope and during high wastewater velocities (Hahn et al. 2000).

Exterior Corrosion depends upon the susceptibility of the pipe material to acidic ground substances and galvanic corrosion (Delleur 1989). Acidic soils or groundwater attack unprotected cementious or metal pipe materials, whereas stray currents in the ground cause a galvanic corrosion with metal or metal reinforced pipes.

2.5.14 DIFFERENTIAL PIPE TEMPERATURE

Some literature speculates that a high differential temperature between the internal and external pipe wall can produce high temperature gradients. Under such conditions the inner and outer fibers will be subject to different temperature drops, resulting in differential strains and circumferential stresses.

2.5.15 SOIL TYPE

The significance of the type of soil cannot be overlooked, as it is one of the most important factors, having effects on almost all of the above mechanisms. Its effects on frost heave, strength of soil-pipeline interaction, and external corrosion can be important for many failure mechanisms.

Frost susceptibility is defined as the rate at which frost penetrates the ground. It is generally regarded as one of the most important factors in characterizing frost heave action. Frost susceptibility is ranked greatest to least for soil types in the following order: silt, clay, sand, and then gravel. However, methods of further quantifying and thoroughly characterizing soils in terms of frost susceptibility are not consistent. Use of frost heave rate (inch/day), total frost heave (inch), frost heave ratio (ratio of frost heave rate to total frost heave) and segregation potential (to depict frost susceptibility) have been suggested (Kujala 1993). However, these types of measures are often difficult to find, or do not translate accurately from laboratory to field values (Konrad and Nixon 1994). Therefore characterization of frost susceptibility, and hence frost heaving is difficult using field measurements.

The type of soil the pipe is located in is also important for the aspect of differential heaving and thaw settlement. If a pipe is located at the interface of two different soil types, it has been shown that each soil will experience an uneven amount of frost heaving, and therefore have an influence on the amount of strain experienced by the pipe (Nixon 1994). In the same manner, thaw settlement will lead to differential stress distributions on the pipeline.

Soil corrosivity is a soil characteristic that must be considered for external corrosion predictions. Physical characteristic (particle size, friability, uniformity, organic content, color, etc.) have reflected corrosivity, based on observations and testing. Color has also been linked to corrosivity. Soil uniformity is important because of the possible development of localized corrosion cells. Corrosion cells may be caused by a difference in potential between unlike soil types, with both soils being in contact with the pipe (Smith 1968). If it can be assumed that for a particular soil classification the approximate uniformity coefficient can be estimated, then the possibility of corrosion can be estimated.

2.5.16 SOIL pH

In order to characterize external corrosion, it is necessary to find parameters which indicate the corrosivity of the soil. Soil pH is a good indicator of external corrosion since certain pH ranges allow for different corrosion mechanisms to occur. It has also been found that resistivity is a function of pH [(Morris Jr. 1967); (Jarvis and Hedges 1994)]. For that reason, only one of the two may be required for characterization.

2.5.17 GROUNDWATER LEVEL

Use of the soil water content parameter is important from several aspects. As mentioned earlier, the rate of frost heave is controlled by the availability of free water (McGaw 1972). It is also important for external corrosion.

From the perspective of frost heave, it has been stated that the availability of a water source is one of the necessary elements required for ice lens growth. In the absence of a nearby ground water table, focus then shifts to the availability of water present in the soil itself, i.e., soil water content. In reality, the water content may be a possible surrogate measure for water table depth, as water may enter the soil above by capillary suction.

From the perspective of external corrosion, soil corrosion aggressiveness has been related to moisture content. Soils with moisture content above 20 percent (wet basis) are thought to be particularly corrosive (Jarvis and Hedges 1994). Studies substantiate that moisture content is a factor contributing to soil aggressiveness (Booth et al. 1967).

2.5.18 OVERBURDEN PRESSURE

Overburden pressure is thought to be important due to its ability to help characterize frost heaving and soil-pipeline resistance. It can be characterized by the depth of cover and soil density. Literature indicates that the overburden pressure is important for the rate of heaving [(Anderson et al. 1984); (Roy et al. 1992)].

Bury depth is an important factor. From the perspective of soil-pipeline interaction, it has been demonstrated that the frictional soil resistance is affected by pipe diameter and bury depth (Rajani et al. 1995). Also, from the perspective of mode of failure, larger pipes are more susceptible than smaller pipes to crushing failure. This is due to bury depth, or the external loadings the pipe is subjected to (i.e. roadways, large structures, etc.) (O'Day 1982).

2.5.19 TEMPERATURE

The effects of temperature on pipe breakage rates have been observed and reported by many. Walski and Pelliccia (1982) suggested that pipe breakage rates might be correlated to the maximum frost penetration in a given year. To account for the lack of frost penetration data, they correlated annual breakage rates with air temperature of the coldest month, using a multiple regression analysis with age and air temperature as the covariates

$$N(t, \mathrm{T}) = N(t_0)e^{At}\, e^{BT}$$

Where t = pipe age; $N(t_0)$ = breaks per mile at t_0; T = average air temperature in the coldest month; A, B = constants.

Newport (1981) analyzed circumferential pipe breakage data and found that increased breakage rates coincided with cumulative degrees-frost (usually referred to as freezing index in North America and expressed as degree-days) in the winter as well as with very dry weather in the summer. He attributed the increase in winter breakage rates to the increase in earth loads due to frost penetration, i.e., frost loads, and the summer breakage rates to the increase in shear stress exerted on the pipe by soil shrinkage in a dry summer. He also observed that when two consecutive cold periods occurred, the breakage rates (in terms of breaks per degree-frost) in the first one exceeded those of the second one. He rationalized that the early frost "purged" the system of its weakest pipes, causing the later frost to encounter a more robust system.

2.5.20 PRECIPITATION (SNOW/RAIN)

Snow is indicative of the insulating effect on ground temperature, as the snow will allow for the entrapment of heat into the ground. Rain precipitation coupled with the soil type may be indicative of moisture content or hydraulic conductivity if these parameters are not measured regularly. Some literature indicates that corrosion resistance is enhanced during dry periods of the year (Smith 1968). Therefore, inclusion of this parameter may be necessary to help characterize climatic changes as well as to infer adjustments to soil parameters.

2.6 PIPELINE DETERIORATION MODELS

Incorporating historical condition data to develop deterioration patterns for a city's sewer system is pivotal in obtaining a realistic assessment of the city's infrastructure. Deterioration models are necessary because the determination of cost-effective maintenance actions requires information on the current condition as well as the anticipated future condition. While current conditions are assessed based on sewer inspections, future conditions may only be estimated from the deterioration models.

Although pipelines are designed for a particular lifespan under standard operating conditions, their deterioration never follows a set pattern. The process of deterioration of pipelines is rather complex simply because there are many factors which interactively contribute to such deterioration. Environmental interactions (soil corrosivity, ground movement, etc.) plus exposure to transported waste quality variations and operating abnormalities ensure that pipeline deterioration is never uniform. Eventually, through a combination of internal and external stresses, the pipe fails. Sometimes this process is accelerated when defense measures such as protective coatings are damaged or not repaired properly. The challenge for a condition prediction model is to analyze information on the pipe and its environment to predict, as accurately as possible, its time to failure or probability of reaching a certain condition state. Some of the factors that contribute to deterioration are:

- Construction features
  - Load transfer
  - Standard of workmanship
  - Sewer size
  - Sewer depth
  - Sewer bedding
  - Sewer material
  - Sewer joint type and material
  - Sewer section length (Manhole to Manhole)
  - Sewer connections (Laterals)
- Local external factors
  - Surface use
  - Surface loading and surface type
  - Ground disturbance
  - Groundwater level
  - Ground conditions
  - Soil/backfill type
  - Root interference

Other factors

Age of sewer

Sewer characteristics

Maintenance methods/Frequency

The basic idea of life assessment models is to try to estimate a function for each individual pipe that will provide the probability for that pipe surviving beyond a future time period. Life assessment models assume that pipe lifetimes can be treated as independently and identically distributed random variables. The objective of these models is to estimate the probability of failure of a pipe within a time horizon.

There are two main categories of such predictive models: *Statistical and Physical.* The statistical model can further be classified into: Aggregate Type models, Multiple Regression Type models, Probabilistic Predictive models, Counting Process models, Non-Homogeneous Poison Process models and Events Dependent Renewal Process models. Among the non-purely-statistical ones, physical models of corrosion are the most applicable (Melina and Kalles 2000).

A statistical approach based on historical maintenance data and pipelines inventory is a technique that requires an undertaking of vast amounts of pipe sampling or condition assessments and measurement of long lengths of pipes. The physical approach is based on the knowledge of underlying process, using engineering-based equations in developing simulation models that can be applied in making maintenance decisions.

2.7 AN OVERVIEW OF EXISTING DETERIORATION MODELS

2.7.1 STATISTICAL MODELS

Aggregate Type models group together pipes that have the same intrinsic properties and then use linear regression to establish a relationship between the age of the pipe and the number of failures. They describe the global evolution of failures on all the pipes in the system (Walski 1986). Shamir and Howard (1979) proposed an exponential increase with time of the form:

$$\lambda(t) = \lambda(t_0)e^{A(t-t_0)} \qquad \text{---------- (2.1)}$$

where $\lambda(t)$ is the number of failures/yr/1000 ft at time t, t_0 is the base year for analysis, and A is the growth rate coefficient.

The advantage of these models lies in their ease of implementation. Their drawback is that pipe characteristics, previous break history and environmental variables are not taken into account.

Counting Process models are slightly different from Aggregate Type models because they establish the cumulated number of failures of each group of "identical" pipes as a function of time (Andreou and Marks 1986). In counting process models the pipe failures are assumed to occur along the time, and no assumption is made regarding the status of the pipe after the repair is completed. With counting process models one can see the deteriorating (or improving) trend in time of a group of "identical" pipes and the rate of occurrence of failure of a group of pipes.

Multiple Regression Type models give a regression equation between the number of years from installation to the first break (or the number of failures) and a set of explanatory variables such as material, internal pressure, etc. to forecast the future number of breaks. The advantage of this approach is that it enables explicit identification of the categories of mains. This modeling seems better suited to the school of thought that favors the short-time selection of individual components for maintenance operations.

According to Lawless (1982) and Kalbfleisch & Prentice (1980), two classes of regression models may be distinguished, namely, proportional hazards models (PHM) and accelerated lifetime models.

The Weibull distribution is a very flexible model for lifetime data. It has a hazard rate, which either is monotone increasing, decreasing, or constant. It is the only parametric regression model, which has both a proportional hazards representation and an accelerated failure time representation.

Proportional Hazards Model (PHM) was originally developed for modeling components, which can only fail once. In order to model a repairable system like pipeline network, the lifetime is defined as the inter-arrival time (i.e. time between failures).

A Non-Homogenous Poisson Process models the recurrence of events, assuming the number of them occurring in a given time interval to be Poisson distributed. For an ordinary Poisson process, the mean of the Poisson distribution is the product of the interval length by the intensity function, which remains constant in time.

The Events Dependent Renewal Process is a generalization of the ordinary Renewal Process, allowing the successive inter-arrival times to have different distribution functions, which depend on the rank of the events. An ordinary renewal process models the sequence of current events, occurring in a repairable system by assuming the delays between events to be independent and identically distributed.

Probabilistic Predictive models estimate the probability that a break will occur at some future time and/or the probability of a pipe to enter a particular state (e.g., severe deterioration with multiple failures, Andreou 1986). This can then be used to calculate the economic life of a pipe and therefore when it should be replaced. Andreou et al. (1987) proposed the use of a Cox proportional hazard model (Cox 1972) to relate the hazard function to a set of explanatory variables. The basic form of this model is represented in equation (2.2) below:

$$h(t:z) = h_0(t)e^{zb} \quad \text{----------} \ (2.2)$$

where, $h(t : z)$ is the failure rate (termed hazard function), $h_0(t)$ is some unspecified baseline hazard function, z is a vector of explanatory variables (diameter, soil, etc.), and b is a vector of regression coefficients.

Whilst various mathematical distributions can be used, the Weibull and Herz distributions appear to be most suited to pipe failure statistics (Herz 1998). Provided it is available, pipe replacement data can be used directly to obtain fitting parameters to these distribution functions. For example, Herz, (1998) equated the fraction of pipes that were replaced in a given year to the 'hazard' (or failure rate) associated with pipes of that age. The variation in hazard with pipe age was then used to obtain the lifetime probability density function (Crowder et al. 1991). It should be noted that lifetime distributions determined by this technique are not based on recorded failure data, and merely reflect the replacement strategy used by the utility agency at the time of analysis. Alternatively, in the absence of pipe replacement data, breakage rates can be extrapolated from recorded failure data and used to determine the mean value of a lifetime probability density function. For example, time-exponential equations can be used to forecast future breakage rates, allowing the discounted costs for future pipe replacement to be determined. The mean economic life of a homogenous group of pipes (i.e. the average time for replacement) is assumed to end when the total repair costs attain a minimum (Kleiner et al. 1998). Further research using a proportional hazard approach includes Gat and Eisenbeis (2000) and Lei and Saegrov (1998). Both these authors used a Weibull hazard model to model the useful life of a pipe.

Among various techniques for deriving probabilistic predictive models, the survival analysis has been widely used. The objective of survival analysis is to develop lifetime models based on survival data (or failure data, or lifetime data).

The main shortcomings of the survival analysis approach is that it groups similar pipes and relies heavily on estimating the lifetime of the groups, which may itself be highly variable and dependent on the individual pipe characteristics.

Probability-Based Markovian Models provide a reliable mechanism for developing prediction models. Markov chains can be employed to model stochastic processes, which have the distinct property that probabilities involving how the process will evolve in the future depend only on the present state of the process and so are independent of events in the past (Hillier and Liberman 1995).

The Markov process imposes a rational structure on the deterioration model because it explains the rate of deterioration as uncertain, and it also ensures that the projections beyond the limits of data will continue to have a worsening condition pattern with time. This model has been successfully used in other types of infrastructure deterioration modeling like bridges, pavements, etc.

To model the manner in which a sewer deteriorates with time, it is necessary to establish a Markov probability transition matrix. The transition matrix **P** is a square matrix, m x m, where m is the number of possible states. Thus, if there are five categories in sewer conditions, then five possible states will be involved in the matrix of size 5 x 5. The components of **P**, namely p_{ij}, are the probabilities of being in state i at time 0 and transitioning to state j over a given period Δt. Kathula (2000) in her dissertation assumed a time increment, Δt, of 5 yrs because sewer inspections should generally be conducted every 5 years. If the assumption is accepted that the sewer condition will not drop by more than one state in any 5-yr period, then the condition will either stay in its current state or move to the next lower state in 5 years. Therefore, the one-step transition matrix can be represented as follows (Kathula 2000):

$$P = \begin{bmatrix} p_{11} & p_{12} & 0 & 0 & 0 \\ 0 & p_{22} & p_{23} & 0 & 0 \\ 0 & 0 & p_{33} & p_{34} & 0 \\ 0 & 0 & 0 & p_{44} & p_{45} \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \qquad \text{----------} (2.3)$$

For each row of the transition matrix, $\sum_j p_{ij} = 1$. The value of 1 in the last row indicates an "absorbing" state corresponding to the fact that the sewer condition cannot move from this state (the worst possible state) unless rehabilitation is performed. In this particular transition matrix, the values of four unknown quantities (i.e., p_{11}, p_{22}, p_{33}, and p_{44}) have to be determined. The application of the Markov process (Butt et al. 1994) proposes a nonlinear programming approach to determine the probability values by minimizing the sum of the absolute difference between actual data points and the predicted condition for the corresponding time generated by the Markov chain.

The probability that the sewer is in state *i* at time t = *t* and will be in state *j* after *n* periods is desired. Chapman-Kolmogorov equations provide a method for computing the *n*-step transition probabilities, and the *n*-step transition probability matrix can be obtained by computing the *n*th power of the one-step transition matrix (Hillier and Lieberman 1995). Thus, if the one-step transition matrix **P** corresponds to a 5-yr time period, then the two-step (10-yr time period) transition matrix $P^{(2)}$ is represented by

$$P^{(2)} = P^2 = P \times P \qquad \text{----------} (2.4)$$

Besides the transition matrix **P**, the state matrix X representing the probability distribution of being in *m* different states at time 0 (which is the fraction of sewer network currently in each of the *m* possible states) is also required. X is a single-row matrix (or state vector) where $\sum X_i = 1$ for $i = 1,\ldots, m$. The state vector for any time cycle *t* is obtained by multiplying the initial state vector by the transition matrix P raised to the power of *t*. Thus, the prediction of sewer condition 10 yr from now is then represented by $X^{(2)}$.

$$[X^{(2)}] = [X] \times [P^{(2)}] \qquad \text{----------} (2.5)$$

The use of the Markov chain prediction model is sufficient to formulate the problem as a dynamic programming problem because the knowledge of the current state of the system conveys all the information about its previous behavior necessary for determining the optimal policy henceforth. This property is required in dynamic programming formulation (Hillier and Lieberman 1995). The application of the Markov chain prediction model in conjunction with dynamic programming has several advantages. It uses objective condition measures and has computational efficiency in handling a large number of rehabilitation strategies for each sewer classification/state combination. However, the model development requires sufficient statistical data for establishing sound transition probability matrices.

Table 2.8 - Summary of Statistical Prediction Models for Water and Wastewater Pipelines (Kleiner and Rajani 2001)

Reference	Model	Notation	Data Requirements
Deterministic Time-Exponential Models			
Samir and Howard (1979)	$N(t) = N(t_0).e^{A(t+g)}$	t = time elapsed (from present) in years $N(t)$ = No. breaks per unit length per year (/mile/year) $N(t_0) = N(t)$ at the year of installation of the pipe g = age of the pipe at the present time A = coefficient of breakage rate growth (/year)	Pipe length, installation data and breakage history; formation of homogenous groups essential according to criteria like pipe type, diameter, soil type, overburden characteristics, etc.
Walski and Pelliccia (1982)	$N(t) = C_1.C_2.N(t_0).e^{A(t+g)}$	C_1 = ratio between {break frequency for (pit/sandspun) cast iron with (no/one or more) previous breaks} and {overall break frequency for (pit/sandspun) cast iron} $C2$ = ratio between {break frequency for pit cast pipes 20-inch diameter} and {overall break frequency for pit cast pipes}	Same data as for Shamir and Howard (1979) plus information on the method of pipe casting and pipe diameter
Clark et al. (1982)	$NY = x_1 + x_2D + x_3P + x_4I + x_5RES + x_6LH + x_7T$ $REP = y_1.e^{y2t}.e^{y3T}.e^{y4PRD}.e^{y5DEV}.SL^{y6}.SH^{y7}$	x_i, y_i = regression parameters, NY = number of years from installation to first repair, D = diameter of pipe, P = absolute pressure within a pipe, I = % of pipe overlain by industrial development, RES = % of pipe overlain by residential	Time of installation, breakage history, type and diameter of the pipe, as well as information about operating pressures, soil corrosivity and zoning composition of area overlay pipe. Additional types of data such as the type of breaks and pipe vintage required to enhance model.

		development, LH = Length of pipe in highly corrosive soil, T = Pipe type (1 = metallic, 0 = reinforced concrete), REP = number of repairs, PRD = pressure differential, t = age of pipe from first break, DEV = % of pipe length in low and moderately corrosive soil, SL = surface area of pipe in low corrosivity soil, SH = surface area of pipe in highly corrosive soil	
Deterministic Time-Linear Models			
Kettler and Goulter (1985)	$N = k_0 Age$	N = number of breaks per year k_0 = regression parameter	Same data as for Shamir and Howard (1979)
McMullen (1982)	$Age = 65.78+0.028SR-6.338pH-0.049r_d$	Age = age of pipe at first break (years) SR = saturated soil resistivity (ohm-inch) pH = soil pH r_d = redox potential	Data required typically not available; sporadic data collection not expensive, however, continuous and extensive data collection program is costly; continuous monitoring of soil properties is important where ground water conditions have not reached steady state ot are seasonally dependent.
Jacobs and Karney (1994)	$P = a_0 + a_1$ Length + a_2 Age	P = reciprocal of the probability of a day with no breaks a_0, a_1, a_2,= regression coefficients	Pipe length, age and breakage history; more data enables formation of homogenous groups.

Probabilistic Multi-Variate Models – Proportional Hazards and Accelerated Life			
Proportional Hazards	$h(t, Z) = h_0(t)e^{(b^T)Z}$	T = time to next break $h(t, Z)$ = hazard function $h_0(t)$ = baseline hazard function Z = vector of covariates b = vector of coefficients to be estimated by maximum likelihood	▪ natural log of pipe length ▪ operating pressure ▪ percentage of low land development ▪ pipe "vintage" (or period of installation) ▪ pipe age at second (or higher) break rate ▪ number of previous breaks in pipe ▪ soil corrosivity
Marks et al. (1985)	$h_0(t) = 2x10^{-4} - 10^{-5}t + 2x10^{-7}t^2$		
Andreou et al. (1987a, 1987b) Marks et al. (1987)	Early stage: same as Marks et al. (1985) described above Late stage: $h = \lambda = e^{(b^T)Z}$	h = hazard (constant at the late stage)	Same as above
Brémond (1997)	$h_0(t) = \lambda\beta(\lambda t)^{\beta-1}$	t = time to (next) failure h(t) = hazard function λ, β = scale and shape parameters (respectively) of the Weibull distribution	▪ number of previous breaks ▪ pipe diameter ▪ ground conditions ▪ traffic loading
Time Dependent Poisson Model Constantine and Darroch (1993), Miller	$H(t) = (t/\theta)^{\beta}$ $\theta = \theta_0 e^{\alpha z}$	t = pipe age $h(t)$ = mean number of failures per unit length at age t θ, β = scale and shape parameters, respectively θ_0 = baseline value α = vector of coefficients to be estimated by regression Z = a vector of covariates affecting	▪ mean static pressure ▪ overhead traffic conditions ▪ pipe diameter ▪ soil type

(1993); Constantine et al. (1996)		breakage rate	
Accelerated Life Lei (1997) Accelerated Life Eisenbeis et al. (1999)	$\ln(T) = \mu + x^T \beta + \sigma Z$ $T = f(\mu, \sigma, Z)\, e^{(x^T)\beta}$ Same as Lei (1997) above	T = time to (next) failure x = vector of explanatory variables Z = random variable distributed as Weibull σ = parameter to be estimated by maximum likelihood β = vector of parameters established by max likelihood Z = random variable distributed as Gumbel (extreme distribution for minima)	▪ pipe age group ▪ pipe size ▪ pipe length ▪ pipe material was taken as stratification criterion ▪ log of pipe length ▪ pipe diameter ▪ pipe material ▪ traffic loading ▪ soil acidity ▪ soil humidity ▪ number of previous breaks was taken both as a covariate and as a stratification variate
Probabilistic Single-Variate Group Models			
Cohort Survival Model Herz (1996); Deb et al. (1998)	$f(t) = \frac{(a+1)be^{b(t-c)}}{\left[a+e^{b(t-c)}\right]^2}$ $S(t) = \frac{(a+1)}{a+e^{b(t-c)}}$ $h(t) = \frac{be^{b(t-c)}}{a+e^{b(t-c)}}$	$f(t)$ = probability density function $h(t)$ = hazard function $S(t)$ = survival function t = useful lifetime of pipe a = ageing factor (/year) b = failure factor (/year) c = resistance time (years), i.e., pipe will not be replaced at age < c years	▪ pipe installation dates ▪ pipe "time of death" ▪ valid grouping criteria will enhance accuracy ▪ alternative to "time of death": end of economic life (optimal time for replacement) requires break history
Bayesian Diagnostic Model	Prob.[failure| specifiedcharacteristics] =	P_f = system-wide probability of failure $P_{c/f}$ = probability of observing specified characteristics on a segment that failed	Grouping criteria ("sets of characteristics") such pipe diameter length, age and type, soil

Kulkarni et al. (1986)	$\frac{P_{c/f}.P_f}{P_{c/f}.P_f + P_{c/nf}(1-P_f)}$	$P_{c/nf}$= probability of observing the same characteristics on a segment that has not failed	characteristics, operating conditions such as pressure, etc.
Semi-Markov Chain Gustafson and Clancy (1999)	▪ generalized gamma distribution for t_1 ▪ exponential distribution – identical for all t_i (i>1)	t_i = time between the *(i-1)*th and the ith breaking pipe	▪ pipe breakage history ▪ pipe type ▪ other grouping criteria to enhance accuracy
Break Clustering Goulter and Kazemi (1988); Goulter et al. (1993)	$P(x) = \frac{m^x e^{-m}}{x!}$ $m = m(s, t)$	m = mean number of subsequent failures occurring in the cluster domain x = number of subsequent failures occurring in the cluster domain s = distance from the 1st break in a cluster t = time elapsed from the 1st break in a cluster	Pipe breakage history with the exact time and location of each break
Data Filtering Mavin (1996)	4 rules to filter pipe breakage data, based on calculating the probability of two consecutive breaks (Constantine and Darroch 1993), and discarding the second break if probability is low.		▪ pipe diameter ▪ pipe material ▪ traffic level ▪ soil type

2.1.1 PHYSICAL MODELS

Physical models of the degradation process employ engineering-based equations to derive structurally based estimates of pipe conditions. The physical mechanisms of pipe failure involve three principal aspects: (a) pipe structural properties, material type, pipe-soil interaction, and quality of installation, (b) internal loads due to operational pressure and external loads due to soil overburden, traffic loads, frost loads and third party interference, and (c) material deterioration due largely to the external and internal chemical, bio-chemical and electro-chemical environment. The existing physical models can broadly be classified into deterministic and probabilistic, and most cannot simultaneously address all three principal aspects listed above. Based on actual failure mechanisms, physical failure models can also be used to estimate changes in pipe condition and future failure rate. To develop these models for the full range of pipe materials in use, expertise is needed to quantify corrosion rates in metallic pipes, rates of degradation in cement-based pipes and the fracture mechanics of plastic pipes. Additional expertise is required to understand the interactions between the electrochemical properties of surrounding soils and degradation rates. Physical models rely on input from accurate condition assessment techniques, and can provide performance indicators. It appears that the physical mechanisms that lead to pipe breakage are often very complex and not completely understood, and little data are available to validate models based on these mechanisms.

2.2 SEWER MANAGEMENT SYSTEM

For proper monitoring and maintenance of underground infrastructure, a thorough asset management strategy is required to perform many functions including inventory, condition assessment, condition forecasting, inspection, scheduling, budget forecasting, localized maintenance programs, and annual and long-range maintenance and rehabilitation planning. More municipalities are beginning to realize of the obvious fact that it is much more economical to repair or renew the sewers before they are fully deteriorated. If maintenance and rehabilitation is performed during the early stages of deterioration, substantial repair costs can be avoided in addition to avoiding service disruption and other social costs. In today's economic environment, as the sewer infrastructure has aged, a more systematic approach to determine maintenance and rehabilitation needs and priorities is necessary (Kathula 2001).

2.3 APPLICATION OF NEURAL NETWORKS IN PIPELINE MANAGEMENT AND PREDICTION MODELING

In recent years, artificial neural networks have been advocated as an alternative to traditional statistical models. Neural networks are application of an algorithm inspired by research into human brain which can "learn" directly from the data. It can be defined as "highly simplified models of human nervous system, exhibiting abilities such as learning, generalization, and abstraction." One of the advantages of a neural network model is that a well-defined mathematical process is not required for algorithmically converting an input into an output. A collection of representative examples of desired translation will suffice. Once trained, a neural network can perform classification, clustering and forecasting tasks. Thus, the pipeline industry can harness this technology to model dynamic deterioration of pipes using the historically available data. Once the pipeline deterioration pattern is modeled, it is then possible to predict future condition and deficiencies of the pipelines. Feasible strategies can then be synthesized to further examine the actual condition of those pipelines.

Past Research in ANN Application for Pipeline Application. Sacluti (1999) in his Master's thesis applied an artificial neural network (ANN) to predict the pipe breaks in the water distribution system of a sub-division in Edmonton, Canada. The ANN model was applied to the entire network as a single entity (rather than to individual pipes) and was trained with data that included temperature (water and ambient), rainfall, operating pressure and historical data on break numbers. Since the model considered an entire network as a single entity, variants such as pipe age, type and diameter could not be considered, as well as geographical varieties such as soil properties. The network consisted of spun-cast 6-inch water mains. His work focused on the frequency modeling of water distribution pipe failure mechanisms in cold weather climates.

The ANN model was applied to a relatively small network with water mains that were relatively homogeneous with respect to type of pipe and operational and environmental conditions. A more heterogeneous set of water mains would likely require more data. The model predicted the number of water main breaks based on a 7-day weather forecast. This requirement limited its ability to short term response than its use for long term planning purposes. In its present form, the model can only be applied to homogenous groups of water mains, for short-term planning of the maintenance work force required during an anticipated cold spell.

2.4 SUMMARY AND CONCLUSIONS

The literature review in this chapter indicates that research in pipeline deterioration and forecasting model development has been in focus lately. Various modes and mechanisms of pipeline deterioration were reviewed and the possibility of the application of neural network in pipeline management and forecasting was discussed. Also, sewer condition assessment techniques and structural condition rating of sewers were documented to develop a broad-based understanding of the technology that are available in the market for condition assessment and classification of distressed sewer pipes. The literature review indicates that there is a good possibility to develop a successful neural network based model if the critical parameters that contribute to the deterioration of pipelines are obtained. A neural network model for predicting pipeline performance trends based on historical condition assessment data will be developed in this effort.

CHAPTER 3

NEURAL NETWORK METHODOLOGY AND APPLICATION

The previous chapter dealt with the literature review that gave the necessary background for pursuing this thesis. This chapter presents the methodology used in this thesis for the development of a sewer pipeline condition prediction model. The prediction model is based on neural network modeling technique. A detailed description of neural networks is presented in this chapter, along with the pragmatic method appropriate for modeling sewer condition prediction.

3.1 ARTIFICIAL INTELLIGENCE AND NEURAL NETWORKS

The term artificial intelligence has be traditionally used to refer to the field of computer science dedicated to producing programs that attempt to be as smart as humans. Expert systems and neural networks are two forms of artificial intelligence, each with distinct strengths and weaknesses. Most implementations of artificial intelligence are programs that simulate either the deductive or inductive intelligence of human being. Deduction reasons in steps to a conclusion based on given premises. Deductive systems, which can be simulated by expert systems, require rules or instructions executed one at a time to arrive at the answer. By contrast, induction takes in a large amount of information all at once and then draws a conclusion. Neural networks can be used to simulate the inductive behavior of humans. Once trained, the neural network is able to look at input data and produce an appreciate answer. In a comparison to expert systems, Garrett (1992) presents the following advantages to the use of neural networks:

- Neural networks have the ability to present a model for a situation where only examples are presented.
- Expert systems require "certain factors" or "levels of belief" as means of accounting for uncertainty, whereas neural networks are trained to deal with uncertainty since training data is obtained from situations very close to the situations in which the network will operate.
- Expert systems are very brittle in that all data must be complete and correct in order for a system to be analyzed. On the other hand, neural networks have the ability to allow for minor errors or omissions in the input data and also for slight deviations from existing training cases.

Neural Networks can be used to:

- recognize patterns and images
- construct a decision tree to solve a problem
- classify data
- predict outcomes
- study thematic evolution of a process and construct cost effective models

A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the human brain in two aspects:

- knowledge is acquired by the network through a learning process, and

- connection strengths between neurons, which are known as synaptic weights, are used to store the knowledge

In computing terms, neural networks have a unique set of characteristics derived through its massively parallel-distributed structure and its ability to learn and generalize. These two information-processing capabilities make it possible for neural networks to solve complex problems in the real world. The key characteristics of neural networks can be summarized as follows (Lou et al 1999):

Learning from experience: Neural networks are particularly suited to solve problems whose solution is complex and difficult to specify, but which provide an abundance of observed data.

Generalizing from examples: An important attribute of neural networks is the ability to learn from previous experiences and then give the correct response to the data that it has not encountered.

Nonlinearity: Neural networks can be trained to generate nonlinear mappings, which often give them an advantage for dealing with complex, real-world problems. Nonlinearity is a particularly important property if the underlying physical mechanism is inherently nonlinear.

Computational efficiency: Although the training of a neural network is computationally intensive, the computational requirements of a fully trained neural network applied on test data are modest. For large problems, speed can be gained through parallel processing, as neural networks are intrinsically parallel structures.

Adaptivity: Neural networks have a built-in capability to adapt their synaptic weights to changes in the surrounding environment. In particular, a neural network trained to operate in a specific environment can be easily retained to deal with minor changes in the operating environmental conditions.

A neural network is an excellent candidate for any application requiring pattern recognition. Neural networks are able to recognize patterns, which may consist of visual, numeric, or symbolic data, even when the data is noisy, ambiguous, or distorted. In general, neural network tasks may be divided into five types of distinct applications:

Classification: Deciding into which category an input pattern falls into.

Association: Acts as a content addressable memory that recalls an output with reduced dimension. The opposite task, decoding, may also be of interest.

Simulation: The creation of a novel output for an input that acts as stimulus. The network has been exposed to a sample of possible stimuli.

Modeling: The network mapping process involves nonlinear functions that can consequently cover a greater range of problem complexity. Although other nonlinear techniques exist, the neural network is superior in its generality and practical ease in implementation.

3.2 NEURAL NETWORKS AND STATISTICAL MODELING: A COMPARISON

A neural network may be considered as a data processing technique that maps, or relates, some type of input stream of information to an output stream of data. For example, the input may be the pipeline condition data like pipe material, pipe age, diameter, slope, environmental conditions, etc., and the output may produce an estimate of the probable condition of the pipeline. On the other hand, the goal of statistical modeling is to find an equation that captures the general pattern of a relationship, which is usually derived from observed examples. Therefore, the fields of statistical modeling and neural networks are closely related in the context of input-output mapping. The principal difference between these two fields is that traditional statistical models typically need an equation to be specified, which could be difficult in complicated nonlinear cases, while neural networks have been mainly used to deal with nonlinear problems without requiring a pre-specified function form. However, with the appearance of the backpropagation neural network (BPNN), of which the learning paradigm is called supervised learning, these two fields touch most closely in solving mathematical modeling problems. This technique solves one of the central problems in neural networks, and it is a useful modeling tool as well.

Supervised learning involves the modification of the synaptic weights of a neural network by applying a set of training examples. Each example consists of a unique input signal and the corresponding desired response. The network is presented an example picked at random from the set, and the synaptic weights of the network are modified so as to minimize the difference between the desired response and the actual response of the network produced by the input signal in accordance with an appropriate statistical criterion. The training of the network is repeated for many examples in the set until the network reaches a steady state, where there are no further significant changes in the weights. Thus, the network learns from the examples by constructing an input-output mapping for the problem at hand. The key characteristics of a neural network can be summarized as follows:

- a large number of attributes can be considered in parallel
- neural networks learn by example, therefore, knowledge acquisition is not difficult
- quick response can be provided by a neural network model
- classification based on given inputs can be attained and, input classification characteristics can be extracted
- an incomplete data set can be analyzed due to the neural network's ability to generalize
- a fault tolerant property allows for small errors in training data to have only a slight effect on the processing elements
- only a small amount of memory is required as only network weights need to be stored for recall programs

Statistical modeling techniques are used to derive relationships between variables from examples as well. In the case of pipeline condition prediction, the examples are the performance history in the last few years. To derive the equation from the examples, the values of the independent and dependent variables for each example need to be known. In this case, the independent variables involve the performance history data and the other pipeline descriptive information, and the dependent variable is the present condition of the pipeline. During the running mode, a running file needs to be prepared, which contains the independent variables of each new example for which an estimate of the dependent variable is desired.

The prototypical example of a statistical modeling technique is linear regression. The equation produced by a modeling method can be thought of as a mapping, because it permits us to map any point in the space of the independent variables onto a point in the space of dependent variables. The error of the mapping comes from two sources. The first source of error is noise, which includes inaccuracies in the data introduced by measuring instruments, and inaccuracies due to the fact that the independent variables do not contain all the information needed to determine the dependent variables. The second source of error is the fact that the mapping function may not have the same form as the target function. The so-called target function could be an idealized and unknowable function that expresses the "true" relationship between the independent and dependent variables.

The fact that linear regression imposes a linear form on the mapping function can severely limit its accuracy. In cases where the problem domain is not a linear space, it is usually necessary to transform the variables so as to make the relationship linear. A better approach is to automate the process of deciding what shape the mapping function should have. What is needed, then, is a modeling technique based on a mapping function that is complex enough to be flexible. Although some simple curves, such as polynomial regression and exponential equation, have been used to simulate the real world condition, the optimum solution is a technique that can take on any form the data requires. One of these advanced modeling techniques is the backpropagation neural network (BPNN).

NeuralWare (1993) compares the abilities of neural networks to other means of artificial intelligence. Table 3.1 presents a comparison of neural networks to other means of modeling problems.

Table 3.1 – NeuralWare Modeling Comparison

Technique	**Limitation**	**Advantage of Neural Network**
Traditional Programming	The number of variations is limited as each variation is required to be programmed into the model.	Neural networks are trained and, therefore, can handle unlimited numbers of variations without additional work.
Expert Systems	System requires that an expert knowledgeable in the topic set rule basis for processing.	Knowledge and explicit setting of rules is not necessary for neural networks since historical data is used for training (knowledgeable checks and input, however, are still advisable).
Regression Analysis	Level of analysis is limited to a certain number of parameters.	There are fewer limitations, such as the need for a sufficient training data, to the number of inputs that can be analyzed by neural network.

3.3 THE NEURAL NETWORK ALGORITHM

There are many types of neural networks, but all have three things in common. A neural network can be described in terms of its individual neurons, the connections between them (topology), and its learning rule. Both biological and artificial neural networks contain neurons, real or simulated. These neurons have many connections to each other which transfer information. The knowledge of a network is distributed across the interconnections between the neurons. A typical neuron receives input, either excitation or inhibition, from many other neurons. A neuron calculates its own output by finding the weighted sum of its inputs, generating an activation level and passing that through an output on transfer function. The point where two neurons communicate is called a connection. The strength of the connection between two neurons is called a weight. The collection of weights arranged in rows and columns is called the weight matrix. A neural network learns by changing its response as the inputs change. Because the weights in the network can change, the relationship of the network's output to its inputs can be altered as well. In this sense, the learning rule is the very heart of a neural network, which determines the behavior of the network and how that behavior can change over time.

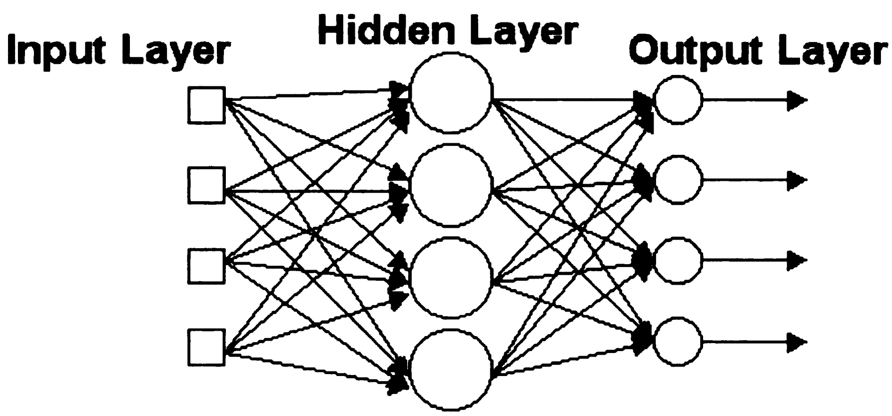


Figure 3.1 - Anatomy of a Neural Network

3.3.1 SINGLE NEURON

Artificial neurons as information processing devices were first proposed more than fifty years ago. As shown in Figure 3.2, a neuron computes a weighted summation of its *n* inputs, the result of which is then thresholded to give a binary output y which is either +1 or -1. The bias weight, θ, is introduced whose input is fixed at +1. This bias weight is adaptive like the others and its use allows greater flexibility of the learning process.

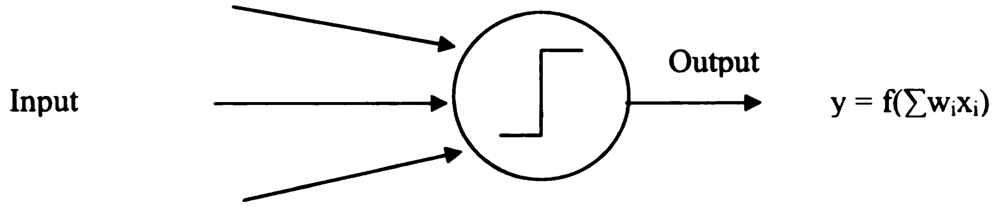


Figure 3.2 - Schematic Diagram of an Artificial Neuron

For a classification problem, the neuron assigns input patterns, represented by the vector of numbers $x = (x_1, x_2, \ldots, x_n)$, either to class A (for which y would be +1) or class B (for which y would be -1). Thus:

$$y = f\left(\sum_{i=1}^{n} w_i x_i\right) = \begin{cases} 1 \text{ when } \sum_{i=1}^{n} w_i x_i > 0 \\ \\ -1 \text{ when } \sum_{i=1}^{n} w_i x_i \geq 0 \end{cases} \qquad \text{-------------} (3.1)$$

In the above equation (3.1), y is the neuron output and f is a hard-limiting of threshold function, sometimes known as the neuron's transfer function, which gives an output of +1 whenever $\sum w_i x_i$ is greater than zero (the threshold value) or -1 whenever $\sum w_i x_i$ is less than (or equal to) zero.

The learning process is to adjust all the weights and let the output y approach the desired output so that the neuron performs the classification task correctly. Multi-class problems can also be solved by having a number of neurons operating in parallel.

3.4 BACKPROPAGATION NEURAL NETWORK (BPNN)

By far, the BPNN is the most popular one used for mathematical modeling. Backpropagation is a supervised learning scheme by which a layered neural network with continuously valued neurons is trained to become a pattern-matching machine. It provides a way of using examples of a target function to find the weights that make a certain mapping function hidden in the neural network approximate the target function as closely possible. As shown in Figure 3.3, the neurons of the networks are structured in multiple layers: input, hidden, and output. Each hidden-layer neuron receives input from all neurons in the input layer through weighted connections (w). In addition, each neuron is associated with a bias term, called the threshold, θ. This bias term works as a horizontal shift for the origin of the transfer function to accommodate the magnitude of incoming signals to the neuron. Specific values of both w and θ for a given neural network are determined during the training phase.

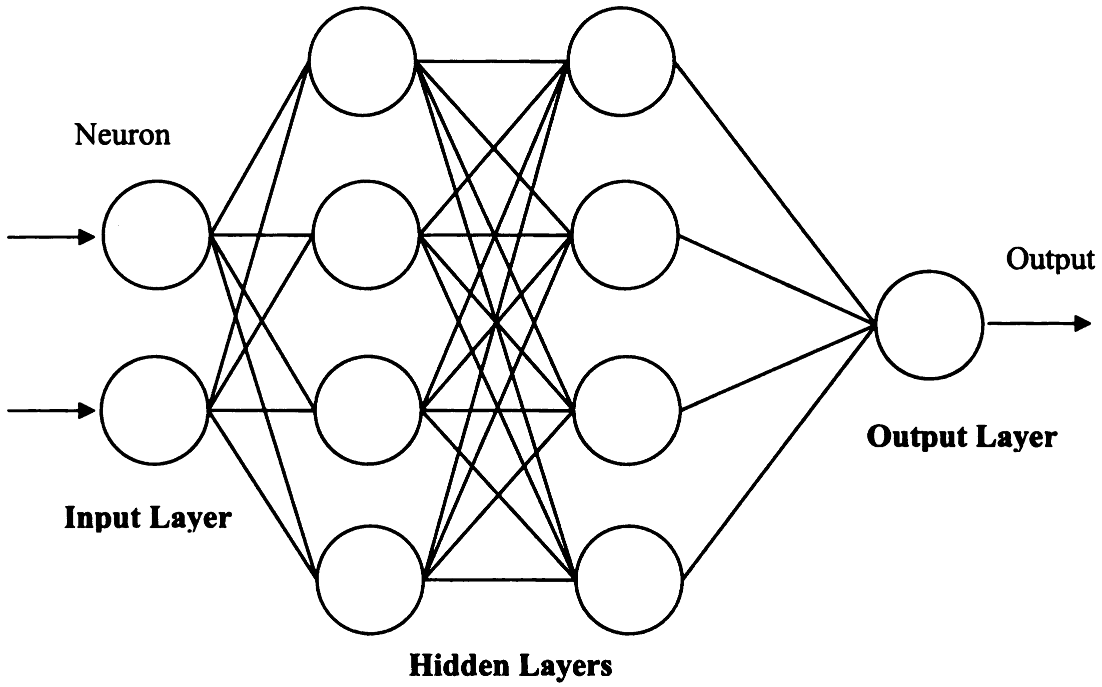


Figure 3.3 - A Three-Layer Backpropagation Neural Network

3.4.1 BPNN MODELING

The BPNN network operates in two modes: mapping and training mode. In mapping mode, information flows forward through the network, from inputs to outputs. In the training mode, the information flow alternates between forward and backward. In the mapping mode, the network processes one example at a time, producing an estimate of values of the dependent variables based on the values of the independent variables for the given example. First, a set of values for the independent variables is loaded onto the input layer of the network. The input-layer neurons do no calculation – each neuron merely sends a copy of its value to all the hidden-layer neurons. Each hidden neuron calculates the weighted sum of the inputs using its unique connection strengths as weights. Next, each hidden neuron computes a transfer function of its input sum and sends the result to all the output-layer neurons. Then, each output-layer neuron performs a similar calculation and outputs the resulting value as an estimate of the dependent variable it represents.

The training mode refers to the process in which the network is exposed to examples with correct output values known. The training algorithm consists of three steps. In the first step, the training patterns obtained from the database are fed into the input layer of the network. These inputs are propagated through the network until reaching the output layer. The output of each neuron is calculated by the following transfer function (Lou et al. 1999):

$$a = \sum_{i=1}^{n} w_i x_i \qquad \text{----------} (3.2)$$

$$O = f(a) = \frac{1}{1+e^{-ga}} \qquad \text{----------} (3.3)$$

where:

O = neuron output,

a = input to the transfer function,

x_i = i^{th} input,

w_i = weight of connection i,

g = gain of sigmoid function, and

n = number of inputs to one neuron.

In the second step, the neural network outputs are subtracted from the desired values to obtain an error signal. This error signal is the basis for the coming backpropagation step. The following equation (3.4) defines the error signal (Lou et al. 1999):

$$E_{RMS} = \sqrt{\frac{\sum_{j=1}^{N_o} \sum_{k=1}^{N_e} (T_{jk} - O_{jk})^2}{N_o N_e}} \qquad \text{----------} \ (3.4)$$

where:

E_{RMS} = root mean square error,

N_o = number of neurons in the output layer,

N_e = total number of patterns in an epoch,

T_{jk} = target (desired) value of the j^{th} neuron, and the k^{th} pattern, and

O_{jk} = output of the j^{th} neuron, and the k^{th} pattern.

In the third step, error is minimized by the backpropagation of the error signal through the neural network. In this process, the respective contribution of each hidden neuron is computed and corresponding weight adjustments needed to minimize the error are derived.

For each output neuron k, compute the δ value, defined as follows:

$$\delta_k = (T_k - O_k)\, f'(x_k) \qquad \text{----------} \ (3.5)$$

where:

δ_k = adjusted error for output neuron k;

T_k = target value of output neuron k;

O_k = output value of output neuron k; and

x_k = input to output neuron k.

Backpropagate the δ value through the network to the preceding hidden layer. For each hidden layer neuron j connected to the output neurons k, compute the new δ value (Lou et al. 1999):

$$\delta_j = f'(x_j) \sum_k \delta_k w_{jk} \qquad \text{----------} \ (3.6)$$

where:

δ_j = adjusted error of hidden neuron j;

x_j = input to the hidden neuron j;

δ_k = adjusted error of output neuron k connected with hidden neuron j; and

w_{kj} = connection weight between neuron j and k.

The weight connecting any two neurons is updated by the following equation:

$\bullet p \rightarrow \bullet q$

$$Vw_{qp} = \alpha \delta_q O_p \qquad \text{----------} \ (3.7)$$

Vw_{qp} = adjustment of weight between preceding layer neuron p and proceeding layer neuron q;

δ_q = adjusted error of proceeding layer neuron q;

O_p = output of preceding layer neuron p; and

α = learning coefficient (a positive constant).

The training process repeats steps 1 through 3 for all patterns in the training set until the overall error is acceptably low based on a given criterion. If the network has not converged then go back to the step 1, otherwise stop training. Once trained, the neural network has the capability of adapting to changing input. If the trained network results in good accuracy on the testing and validation data set, the development process is completed.

Although theoretically complicated, the training process is typically implemented by a computer program, within which the training algorithm has been incorporated. Popular neural network development packages in the market include MATLAB™ Neural Network Toolbox, DataEngine, BrainMaker, NeuroSolutions, etc. These software packages vary in terms of training speed, pre- and post- data processing utility, and convenience of user interaction. Once trained, the BPNN can be incorporated into other programs; the running of this model can be implemented through a user-friendly interface. In this effort, BrainMaker is selected as the development tool, the detailed training and testing process with BrainMaker is described in Chapter 4.

3.5 NEURAL NETWORKS AND ITS APPLICATION IN PIPELINE CONDITION PREDICTION

The inherently nonlinear time series, such as that found in pipeline deterioration process, are more suitable for analysis by the general nonlinear mapping provided by a neural network, than by linear based statistical models. Neural networks are nonlinear models that can be trained to map past and future data of a time-series, thereby uncovering the hidden relationships governing the data.

Primarily, two distinct types of models can be developed for pipeline performance forecasting similar to the pavement condition models proposed by Lou et al. (1999). The first type is a static model and can be conceptually described by the following equation:

$$PC_t = f(S_t, E_t, M_t, t, L, \text{etc.}) \qquad \text{----------} \ (3.8)$$

Where:

PC_t = pipe condition at age t,

S_t = pipe structural condition at age t,

E_t = environmental conditions at age t,

M_t = pipe material characteristics at age t,

L = external and internal load conditions.

The second type, a dynamic model, can be described by the following equation:

$$PC_t = f(PC_{t-x1}, PC_{t-x2} \ldots PC_{t-xN}) \qquad \text{----------} \ (3.9)$$

Pipeline condition at age t, PC_t, is forecast using historical condition data at ages t-x_1, t-x_2,..., t-x_N. This type of model is based on historical performance of pipeline characteristics, which is difficult to obtain because of the lack of continuous monitoring process by the municipal agencies.

The dynamic model requires historical data of continuous monitoring of the asset which is not the common practice by the municipal agencies maintaining sewer pipelines. A static model will be developed in this research effort due to the limited availability of pipeline condition data. The association of different variables that contribute to the deterioration of the sewer system will be analyzed and modeled with actual data from the city of Atlanta.

3.6 MODEL INPUT PARAMETERS

To identify the condition of a sewer pipe, the type of defect needs to be classified and severity level assigned. Each distress condition will be assigned severity levels based on the degree and the combination of structural defects found commonly in sewer pipe segments. Typically this information needs to be documented by the municipal agencies while performing condition assessment. This information will serve as the input parameters for the neural network.

As an outcome of the literature review in Chapter 2, various parameters that affect the condition of sewer pipes during their lifetime were identified. The parameters that are determined to have substantial impact on sewer pipe deterioration are summarized in the Table 3.2 below.

Table 3.2 – Ideal Input Parameters for Model Development

Pipe Data	Pipe Material
	Pipe Age
	Pipe Diameter
	Length of Sections
	Joint Type and Material
	Wall Thickness
Zoning	Residential/Commercial/Industrial
Depth of Cover	Typical depth – 8 to 15 feet
	Shallow – less than 8 feet + high live load
	Deep – more than 15 ft
Gradient	Slope of Pipe
Bedding Conditions	
Backfill Type	Cohesive Soil
	Non-Cohesive (Granular) Soil

Soil Characteristics	Soil Type	
	Corrosivity	
	Resistivity	
	pH Content	
	Sulfide Content	
	Moisture Level	
Groundwater Condition	High Groundwater table (pipe crown is below GWT)	
	Low Groundwater table (pipe crown is above GWT)	
Ground Movement	Due to expansive soils, etc.	
Internal Service Loads	Operating pressures, surcharges, etc.	
External Loads	Soil Load	
	Traffic Loading	
	Other Surface Loads	
	Frost Load Factor	
Wastewater Characteristics		
Maintenance Frequency		
Tree Root Problems		

3.7 MODELING METHODOLOGY

The data once obtained will be analyzed for erroneous processing and reduction, after which the original raw data will be transformed into a new format that is suitable for further analysis.

To determine whether or not the database contains enough samples, two factors will be considered important: (1) the form of the target function: to maintain a given accuracy, sample size needs to increase as the target function becomes more complex, and (2) the noise in the data: to maintain a given accuracy, sample size needs to increase as noise increases. Given a target function of a certain complexity, and a certain amount of noise in the data, there will be an absolute limit to the accuracy the model can achieve. An infinite sample size would be needed to achieve the limit of accuracy. For neural network modeling, since the complexity of the target function is not a limit, noise alone will determine the limit of accuracy. If the sample is large enough, the complexity of the network's mapping function could be increased to match the complexity of the target function. Consequently, as sample size increases, neural network model's accuracy will be limited only by the noise in the data. Usually, neural network can benefit more from large samples than regression can. Because larger samples allow us to use more hidden neurons or to continue training longer, the accuracy can be improved by increasing sample size. On the other hand, neural network model does not require a larger sample than a regression model. As the sample size gets smaller, we can use fewer hidden neurons or halt training sooner to avoid overfitting. The basic rule, therefore, is to use the largest sample available.

The model development in this study will include training, testing and validation. Training a neural network involves repeatedly presenting a set of examples to the network. The network takes in each example, makes a response as the output, checks this response against the correct answer, and makes corrections to the internal connections. Testing the network is the same as training it, except that the network is shown with the examples it has never seen before, and no weight adjustments are made during testing. Validation occurs after the neural network has been developed. Validating a network consists of presenting it with new input data and gathering the network outputs. Unlike testing, there is no known output, only known inputs in the validation.

3.7.1 NEURAL NETWORK DESIGN PROCESS – AN OVERVIEW

To design a neural network, the problem must be defined clearly. The user should decide what tasks the network is to perform. These tasks could be forecasting, recognizing, or classification. One cannot just throw all the spreadsheet data at the network and expect it to figure out what to learn from the data.

The user also needs to choose the information on which the neural network will base its forecasting, recognition or classification. This should consist of whatever information is available that is relevant in determining the desired output. Neural networks learn by making associations between inputs and outputs. A network can associate the inputs "red", "medium", "round", and "fruit" with the output "apple".

The user does not need to figure out procedures, rules, or formulas in the neural network development. The user should think about what kinds of input data the neural network can use to make an association with the desired output. Having a variety of data types increases the chance that various significant correlations can be found within the data. A network would probably not be able to accurately predict stock prices based solely on a collection of daily stock prices. It is better to have one or two extra items of data than not enough. The neural network will learn to pay attention to the items that are important and to ignore the few that don't matter.

Another important part of design process is preparing to train the network by gathering examples for which correct answers are known. For example, to recognize a face, a network would need to have seen a picture of that face before. The training data were organized as facts (patterns) in a spreadsheet format. A fact is a collection of inputs coupled with the correct output(s). Each fact can be thought of as flash card that is used to train the neural network. One side of the card contains the input information, and the other side contains the known answer which the neural network will learn to output during training. The deck of training cards is called the training set.

A random sampling of facts should be set aside from the training set of facts for testing the network. Since the network generalization capability depends on its performance on the testing data set, it is not as important for neural network to learn a training set perfectly as it is for it to be able to provide correct answers for inputs it has never seen before.

Once, trained, the neural network can be called from within some other program, perhaps an integrated system. The network may also be downloaded onto a chip for fast running. A trained neural network is considered intellectual property and may be copyrighted in the United States.

3.8 SUMMARY AND CONCLUSIONS

The discussions in this chapter reinforced the suitability of using neural network methodology for predicting the condition of pipelines. A comprehensive list of parameters that affect the condition of the sewer pipes along with the modeling methodology was presented. It was discussed previously that the availability of data from the municipal agencies regarding the quantitative values for all the parameters is not a reality, as such extensive documentation is not prevalent. The following chapter will discuss the review of the data obtained from the City of Atlanta and preprocessing before it is fed into the neural network software for modeling.

CHAPTER 4

DATABASE REVIEW AND PROCESSING

This chapter describes the detailed efforts of database review and data reduction. The physical attributes of sewer systems owned by the City of Atlanta were extracted from their existing database. The data items in Atlanta's database include Pipe ID, Pipe Material, Age, Diameter, Length, Depth of Cover, etc. that was surveyed during their SSES efforts. It was found that not all the parameters that were identified in the literature as contributing factors to sewer deterioration are readily available in the database. Hence, the model was developed using the available factors. After erroneous data processing and reduction, the original data was transformed into a new format which would be suitable for further analysis and modeling.

4.1 DATA ACQUISITION

The dataset used for the development of the prediction model using artificial neural network for sewer pipes is described in this section. This information includes the background information of Atlanta's SSES surveys, attributes of the data, condition assessment and rating standards and condition summary of sewer group one.

4.1.1 BACKGROUND INFORMATION ON ATLANTA'S SSES EFFORTS

The dataset used in this thesis is acquired from the Department of Watershed Management, City of Atlanta sewer asset database. The City of Atlanta's Department of Watershed Management manages approximately 2,200 miles of sanitary sewer lines. Atlanta's sewer system is comprised of 260 sewersheds, which are prioritized into six separate 'Sewer Groups'. The First Amended Consent Decree (FACD) defines "sewershed" as a subdivision of a sewerbasin that typically consists of 10,000 to 50,000 linear feet of hydraulically linked sewers that are tributary to a point in the sewer system. The formal definition of a Sewer Group is a group of sewersheds within a common level of priority for evaluation, rehabilitation and relief requirement.

The SSES work on sewer group one has been completed at the time of this study and will provide the base data for the model development that may aid in prioritizing the inspection work for other sewer groups. The total length of pipes within the Sewer Group 1 database is 304 miles, whilst the length of the entire sewer network is 2,200 miles – providing a sample size of approximately 13.8%. The Sewer Group 1 study area is illustrated in Figure 4.1 below. Total linear feet of sewer in SG1, i.e., inventory is 1,655,117 LF out of which 1,340,943 LF has been inspected by CCTV. The database that was obtained for this study consisted of condition assessment data from sewersheds SRV10 and PTC19A of Sewer Group 1.

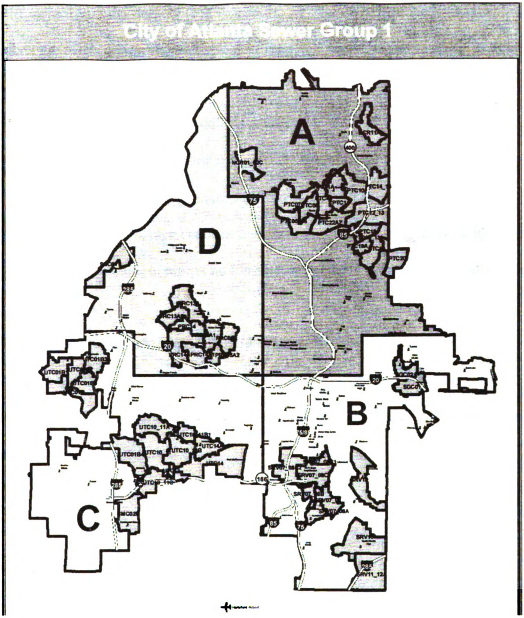


Figure 4.1 – Map Showing the Project Study Area (Sewer Group 1)

4.1.2 CONDITION ASSESSMENT

The condition rating system used for the inspection consists of 119 criteria. The entire rating system is composed of four sub-groups: Structural, Service, Construction, and Miscellaneous. Each sub-group contains rating criteria describing both the characteristics and the severity of the defects (see Appendix A). The prioritization and rehabilitation decisions are taken depending on the defect type and severity. The severity of defects is classified as follows:

1 – Excellent condition, no defects present

2 – Good condition, only low risk defects present

3 – Fair condition, pipe contains medium severity defects

4 – Poor condition, pipe contains high severity defects and collapse is imminent

5 – Failure condition, pipe is no longer functioning and is not structurally intact

4.1.3 CONDITION SUMMARY OF SEWER GROUP 1

The results of the sewer group one inspections are summarized in this section. The predominant sewer structural deficiencies observed from the SSES inspections of Sewer Group 1 include (see Figure 4.2):

- Circumferential cracks
- Circumferential fractures
- Multiple fractures
- Holes
- Displaced joints (medium)
- Defective junctions
- Open joints (medium)

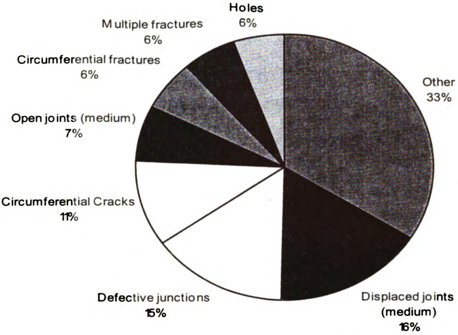


Figure 4.2 - Proportion of Structural Deficiencies Observed from SSES Inspections of SG1

The predominant sewer service condition deficiencies observed from the SSES inspections of SG1 include (see Figure 4.3):

- Debris (general)
- Grease
- Light Encrustation
- Fine roots
- Fine Roots at joints
- Root masses

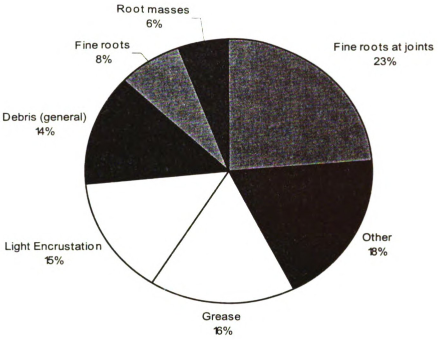


Figure 4.3 - Proportion of Service Condition Deficiencies Observed from SSES Inspections of SG1

This research will focus on modeling the structural condition of the sewers and will not account for the service and other defects. Table 4.1, following, gives the percentage distribution of mainline sewer structural defects encountered during the SSES inspection of SG1. See Appendix A for full list of the city of Atlanta's sewer defects coding system and abbreviations.

Table 4.1 – Mainline Structural Defect Summary (City of Atlanta)

Main Line Defect Summary				
Condition	**Defect**	**Code**	**Number**	**Percentage of Total**
Structural	Pipe Broken	B	2,136	4.9%
Structural	MH Cover Cracked or Broken	BC	2	0.0%
Structural	Crack Circumferential	CC	4,672	10.7%
Structural	Crack Longitudinal	CL	1,848	4.2%

Main Line Defect Summary				
Condition	**Defect**	**Code**	**Number**	**Percentage of Total**
Structural	Cracks Multiple	CM	1,599	3.7%
Structural	Connection Intruding	CNI	234	0.5%
Structural	Connection Defective	CX	1,518	3.5%
Structural	Connection Defective Intruding	CXI	1,278	2.9%
Structural	Deformed	D	122	0.3%
Structural	Brick Displaced	DB	3	0.0%
Structural	Deformation Horizontal	DH	7	0.0%
Structural	Dropped Invert	DI	5	0.0%
Structural	Deformation Vertical	DV	4	0.0%
Structural	Exposed Pipe	EXP	13	0.0%
Structural	Fracture Circumferential	FC	2,658	6.1%
Structural	Fracture Longitudinal	FL	1,363	3.1%
Structural	Fractures Multiple	FM	2,542	5.8%
Structural	Hole	H	2,395	5.5%
Structural	Soil Fissures	HOL	177	0.4%
Structural	Hole in Storm Ditch	HSD	6	0.0%
Structural	Joint Displaced Large	JDL	990	2.3%
Structural	Joint Displaced Medium	JDM	7,239	16.6%
Structural	Junction Defective	JX	6,468	14.8%
Structural	Liner Defect	LN	175	0.4%
Structural	Brick Missing	MB	2	0.0%
Structural	Multiple Soil Fissures	MLK	77	0.2%
Structural	Missing Mortar Surface	MS	8	0.0%
Structural	Open Joint Large	OJL	644	1.5%
Structural	Open Joint Medium	OJM	2,909	6.7%
Structural	Open Joint Slight	OJS	9	0.0%
Structural	Surface Damage Corrosion Large	SGL	23	0.1%
Structural	Surface Damage Corrosion Medium	SGM	278	0.6%
Structural	Storm Manhole	SMH	5	0.0%
Structural	Surface Damage Spalling Large	SSL	66	0.2%
Structural	Surface Damage Spalling Medium	SSM	95	0.2%
Structural	Surface Damage Wear	SW	197	0.5%
Structural	Surface Wear Large	SWL	335	0.8%
Structural	Surface Wear Medium	SWM	871	2.0%

Main Line Defect Summary				
Condition	**Defect**	**Code**	**Number**	**Percentage of Total**
Structural	Surface Wear Slight	SWS	629	1.4%
Structural	Collapsed	X	57	0.1%
Structural	Collapsed Manhole	XM	1	0.0%
Structural Total			**43,660**	**100%**

4.2 DATA COLLECTION AND PREPROCESSING

The effectiveness of an ANN model depends on the availability of reliable input data. Finding data that represents or corresponds to the possible factors reviewed was important for representing the physical cause-effect relationships. The reliability of the data is measured by the amount of "noise" inherent in the data (Sacluti 1999). Noise is data patterns that contain inaccuracies and discrepancies, which does not allow the model to make proper associations between input and output patterns. Use of data with little apparent noise would result in a more accurate and precise model.

Data collection involves evaluating all available data based on accessibility, relative ease of obtaining long-term relevant data, and the prospect of future availability of the same type of data for future models. This data must have characteristics that are significant for model convergence. If all the proposed model input parameters are used for the model, the run times for model training will be exceedingly long, and hence would result in insufficient use of time. Also, if insignificant (or inappropriate) data is not eliminated initially, the redundant input parameters will be treated as "noise" by the ANN model, and as such may decrease the likelihood of the model convergence.

4.2.1 PARAMETER COLLECTION AND ANALYSIS

Because of the nature of pipeline deterioration, literature indicates that to fully predict their condition, it is necessary to have a wide range of representative data parameters. Due to limitations in the collection of input data, it became necessary to restrict the scope of the output being predicted to the overall condition of the pipes rather than the probability of specific type and magnitude of defects. To determine the entire deterioration pattern, it was assumed that no improvement activities were performed over the life of the sewer pipes. Investigations into available data indicated that a large number of the suggested input parameters that met the requirements (reliable and available in reasonable abundance) were difficult to collect. The database after initial screening and preprocessing contains the following variables that are considered to have an impact on pipe condition and for training the model:

Pipe Material

Pipe Age

Sewer Size (diameter)

Section Length (MH to MH)

Sewer Type (Sanitary, Storm, Combined)

Average Depth of Cover

Slope/Gradient

After the initial review of the information, it was observed that data was either lacking or too general for application within the scope of this study; simplifying assumptions had to be made. For example, it was assumed that the study area was a uniform soil type, had similar operating conditions, bedding conditions, loading factors, etc.

Sewer pipeline sections were classified in the study to group sewer sections with similar properties. After carefully sifting and comparing, pipe type (concrete, clay or other) and size were selected as grouping factors. It should be noted that the grouping of the pipes were done only to perform initial statistical analysis. It was found in this study that data preprocessing is necessary for BPNN model development. This preprocessed database was then used to train, test, and validate the BPNN model.

4.3 SOFTWARE SELECTION FOR DATA PREPROCESSING

The original data was stored in Microsoft Access database. Microsoft Excel was selected as a data processing and analysis tool because of its versatility for spreadsheet analysis. The amount of data in this study required an integrated statistics software package which could provide complete control over data access, management, analysis and presentation. The MiniTab statistical software package was selected for data processing because of its power, flexibility, and ease of use.

4.4 DATA ANALYSIS

A total of seven variables were used in modeling process as shown in Table 4.2. However, depending on the availability of data, other variables such as source of sewer (industrial and residential), soils surrounding pipes, ground water level, traffic volume above pipe segments, and frequencies of overflow, etc. identified in the literature review can be included in future analysis. This information, however, was not available for this study.

Table 4.2 - Variables used for Neural Network Modeling

Name of Variable	**Description of Variable**
Length	Length of pipe segments between manholes in feet
Size	Diameter of pipe segments in inch
Type of material	Concrete, Vitrified Clay, PVC, etc.
Age of Sewer	Age of pipe grouped on a five year period
Depth of Cover	The average buried depth of the pipe
Slope	Slope of pipe segments between manholes Slope = (Elevation of upstream invert – Elevation of downstream invert)/Length
Type of Sewer	Sanitary/Stormwater/Combined (The sewer database obtained for this research consisted of only sanitary sewers)

Data analysis involved the examination of all collected data as means of determining preliminary factor influences on the sewer condition. Furthermore, the analysis was used as means of exposing data inconsistencies and errors. Microsoft Excel was used to perform statistical tests on the collected data. Minimum, maximum, mean, mode, standard deviation and correlation values were developed for all factors. The correlation of an input provides an indication of whether an input will properly, or satisfactorily, train with a neural network. For instance, an input with a good correlation (value close to either 1 or -1) will typically be more influential in a neural network than an input with a poor correlation (value close to 0). The correlation, however, can be deceiving as it only accounts for the effect of a single factor. The intent of this research is to develop the combined effect of different factors. To this end, correlations were examined only as means of preliminary input influence determination and not used to eliminate factors deemed unimportant. A histogram and a scatter plot were also developed for each input factor. The purpose of the histogram is to provide a representation of the range and consistency of the collected data. The histograms exposed a number of gaps in the collected data. The scatter plots were primarily used to expose data inconsistencies. Furthermore, the scatter plots provided preliminary input influences. The following Figures 4.4 – 4.13 represent the various statistical analysis performed with the data.

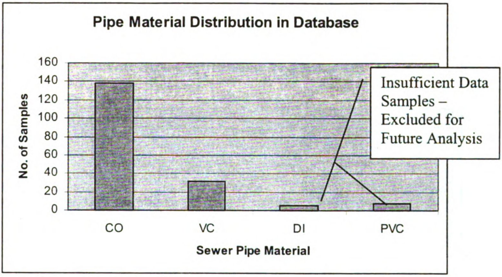


Figure 4.4 – Representation of the Sewer Material Distribution

LEGEND

CO – Concrete Pipe

VC – Vitrified Clay Pipe

DI – Ductile Iron Pipe

PVC – Poly Vinyl Chloride

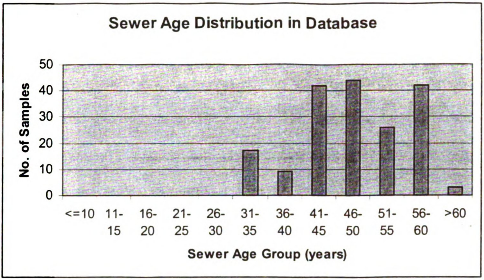


Figure 4.5 – Representation of the Sewer Age Group Distribution

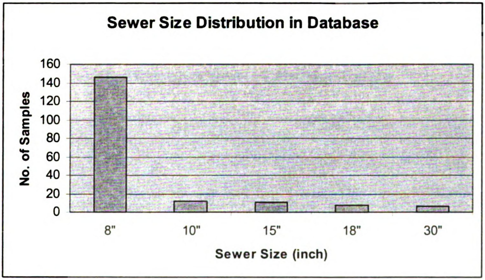


Figure 4.6 – Representation of Sewer Size Distribution

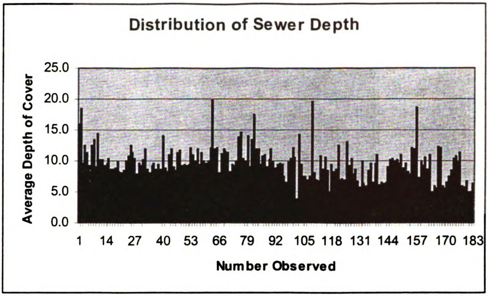


Figure 4.7 – Representation of the Sewer Depth Distribution

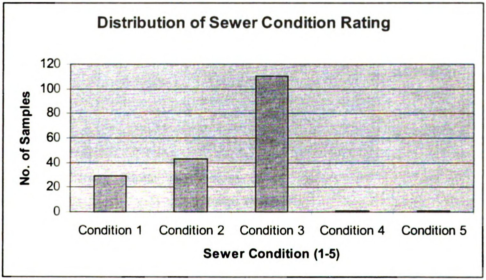


Figure 4.8 – Representation of the Sewer Condition Distribution

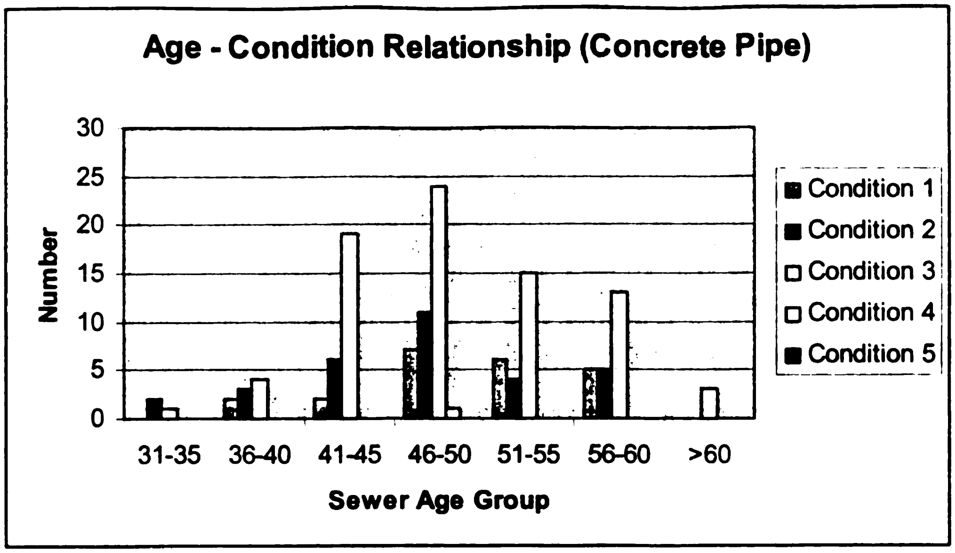


Figure 4.9 (a)

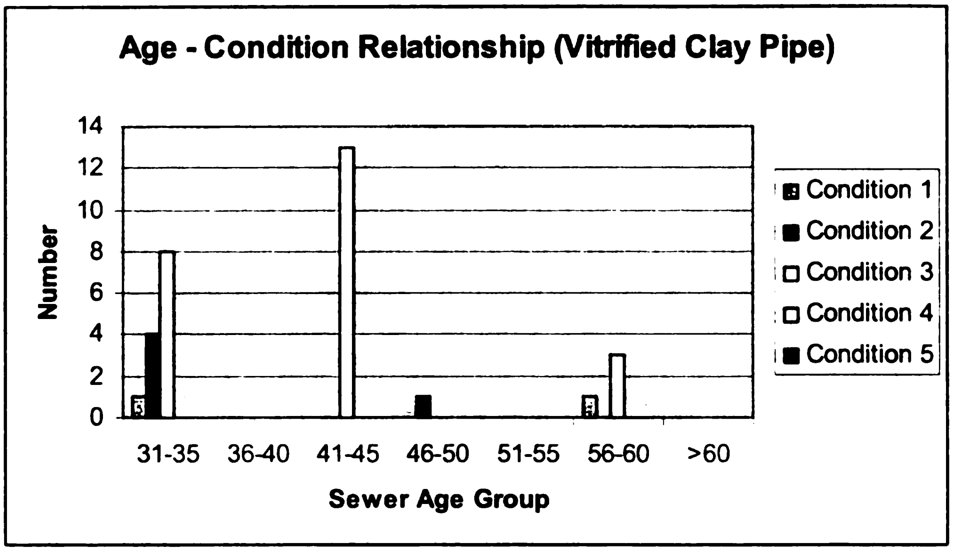


Figure 4.9 (b)

Figure 4.9 (a & b) – Representation of Sewer Age – Condition Relationships for CO and VC Pipes

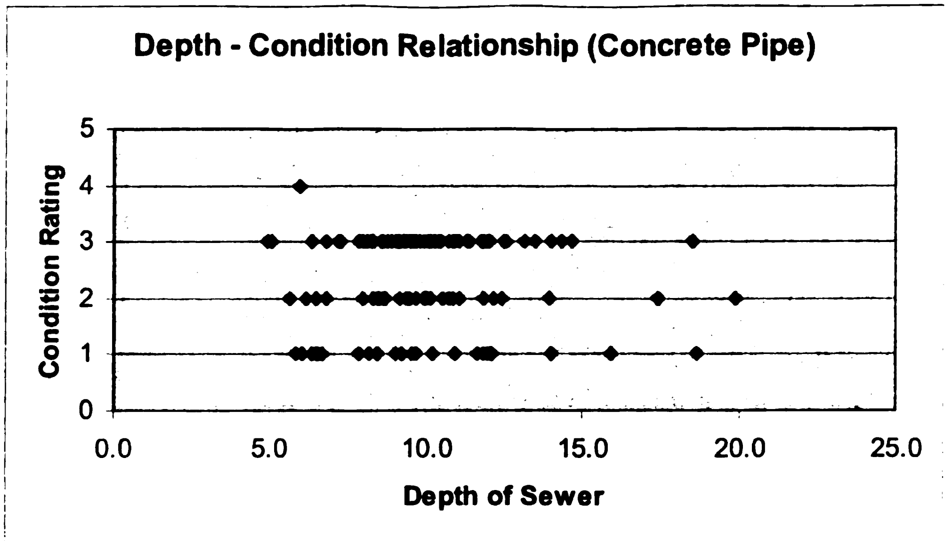


Figure 4.10 (a)

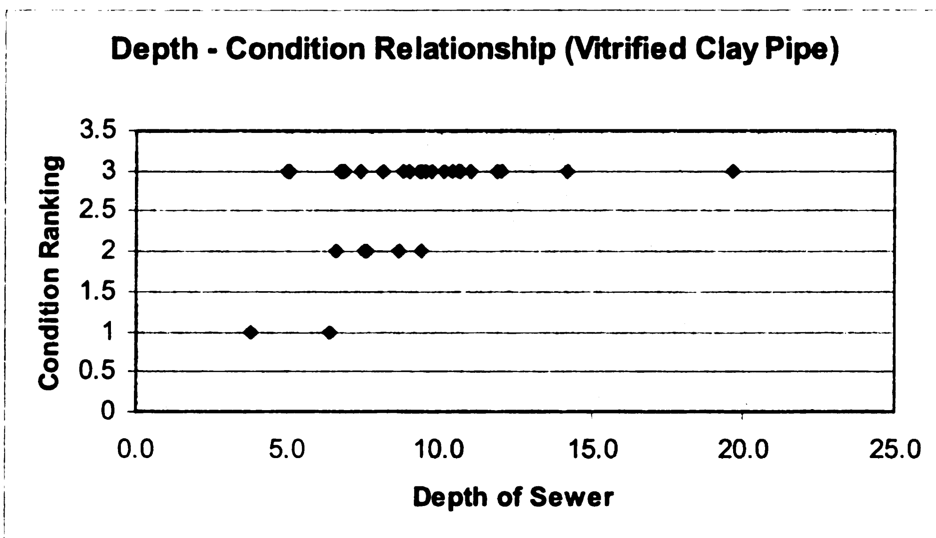


Figure 4.10 (b)

Figure 4.10 (a & b) – Representation of Sewer Depth – Condition Relationships for CO and VC Pipes

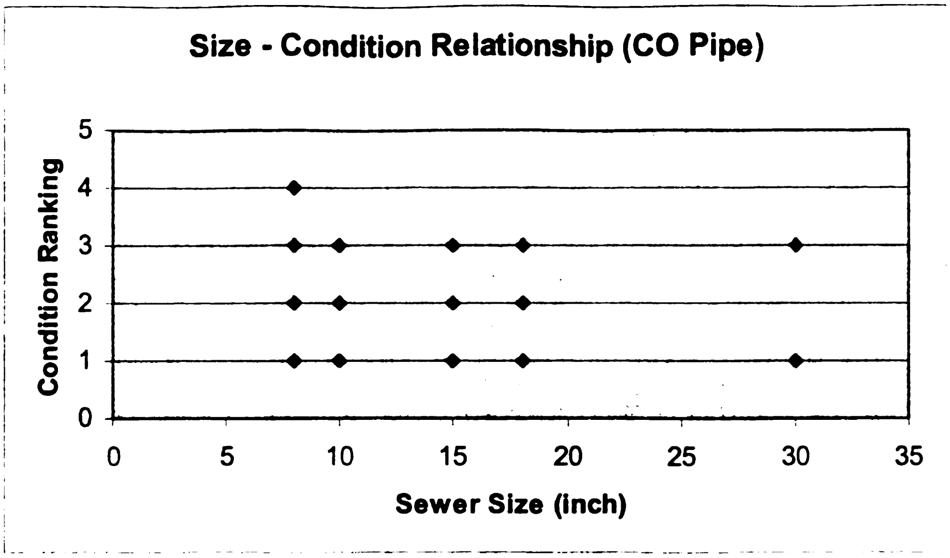


Figure 4.11 (a)

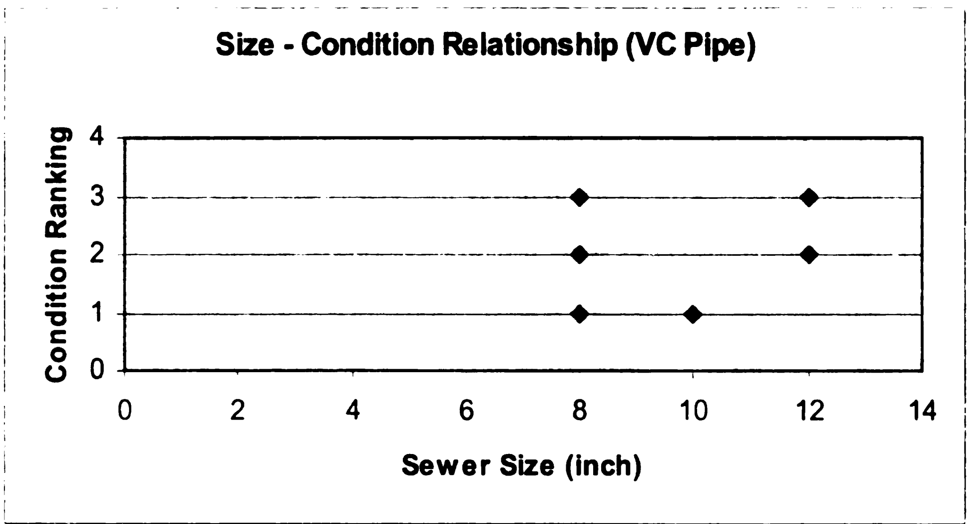


Figure 4.11 (b)

Figure 4.11 (a & b) – Representation of Sewer Size – Condition Relationships for CO and VC Pipes

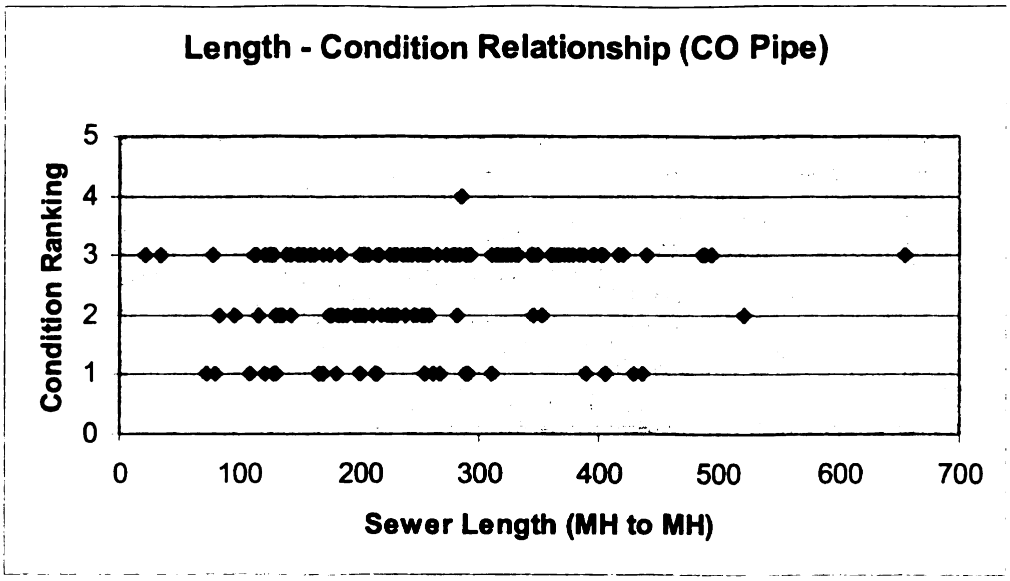


Figure 4.12 (a)

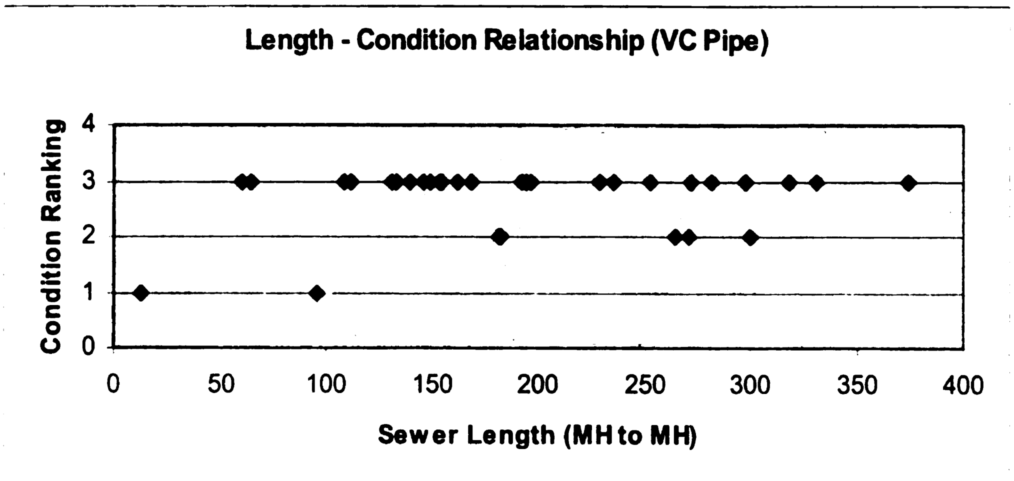


Figure 4.12 (b)

Figure 4.12 (a & b) – Representation of Sewer Length – Condition Relationships for CO and VC Pipes

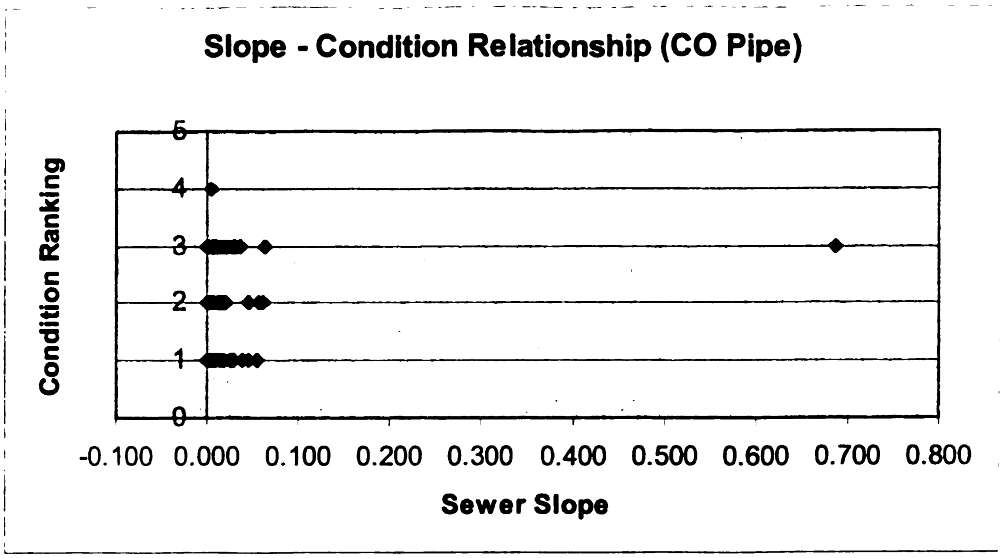


Figure 4.13 (a)

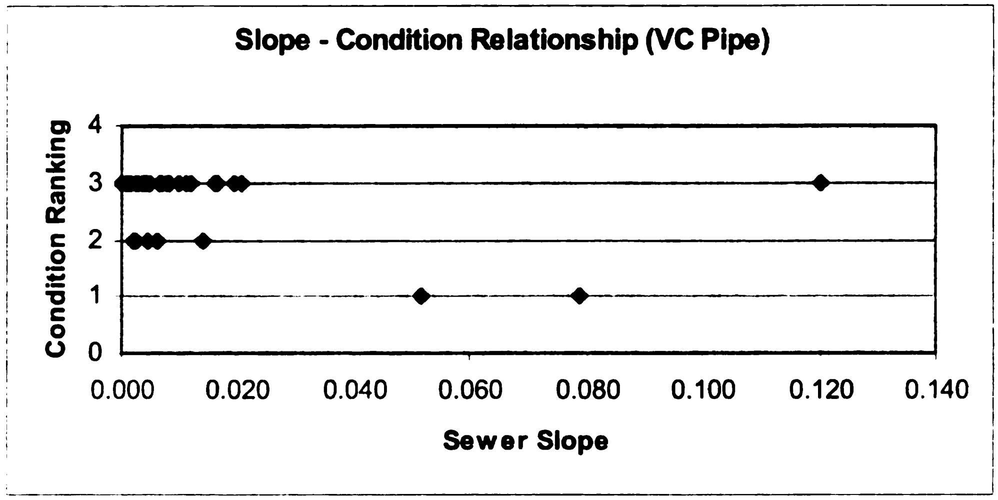


Figure 4.13 (b)

Figure 4.13 (a & b) – Representation of Sewer Gradient – Condition Relationships for CO and VC Pipes

4.4.1 INTERPRETATION OF RESULTS

The signs of the parameter estimates are consistent over the estimation results. Figure 4.4 represents the histogram representing the different classes of materials in the sewershed database in consideration. It can be seen that the majority of the sewers were concrete pipes constituting about 75% of the sample with vitrified clay pipes being the second highest number followed by PVC and ductile iron pipes. The DI and PVC pipes will be excluded from the model due to the insufficient number of samples.

Figure 4.5 represents the distribution of the sewer age groups of the samples in the database. It can be observed that the age of pipes in sewersheds in this study ranges between 31 years and up. This might pose a setback as the model being developed will not have learned the behavior of younger pipes.

Figure 4.6 represents the sewer size distribution obtained from the database. It can be seen that the majority of sewer pipes are in the 8-inch category. Figure 4.7 shows the distribution of the depth of cover within the group and Figure 4.8 shows the condition ranking of sewers indicating that the average condition of sewers in these sewersheds are in condition level 3.

Figures 4.9 to 4.13 show the plots of the present condition of the sewer with age, depth, size, length and gradient of sewers. A few of the observations from the above graphs are summarized in the following paragraph.

The relationship between the age and sewer condition ranking as observed in Figure 4.9 indicates a slight correlation between the two. The condition of the sewers tends to worsen as it ages. The relationship between the sewer depth and condition in Figure 4.10 shows a slight pattern of increase in condition ranking with the depth. This may be attributed to high overburden pressures acting on the pipe conforming to the literature. The relation between size of the sewer and condition does not show any correlation within this sample. The relationship between sewer length and condition ranking is illustrated in Figure 4.12. It can be visually observed that the condition ranking of the sewer has a higher value with the increase in length of the sewer. This scenario may be related to the facts presented in the literature review. As per Figure 4.13, the condition ranking increases as the slope or the gradient of the pipe increases.

Although there is slight relationships observed from the plots, there is no substantial correlation seen with the condition of the sewer and the individual parameters. This gives a strong case for adopting neural network modeling methodology as it is capable of capturing such subtle global relationships with ease.

4.5 DATABASE TRANSFORMATION

After necessary parameters have been identified, the original database was transformed to a new format that can be used for BPNN model development and analysis. Table 4.3 represents the database that will be used for further analysis and modeling. This database will then be fed first to NetMaker, a preprocessing utility provided by Brainmaker in order to assign the input-output parameters and then convert into files that can be utilized by BrainMaker for training, testing and validation.

Table 4.3 - Format of the Transformed Database after the Selection of Relevant Parameters

SType (OUTF /LAT)	Length	Pipe Dia	Pipe Matl	Sewer Age Group											Avg Dpth	Gradient	Condition
				<=10	11-15	16-20	21-30	31-35	36-40	41-45	46-50	51-55	56-60	>60			
OUTF	215	18	CO	0	0	0	0	0	0	0	0	1	0	0	15.9	0.001	1
OUTF	350	18	CO	0	0	0	0	0	0	0	0	1	0	0	18.5	0.013	1
OUTF	273	15	CO	0	0	0	0	0	0	0	0	1	0	0	9.7	0.005	1
OUTF	328	10	CO	0	0	0	0	0	0	1	0	0	0	0	11.3	0.004	3
OUTF	405	18	CO	0	0	0	0	0	0	0	0	1	0	0	12.0	0.009	1
OUTF	331	18	CO	0	0	0	0	0	0	0	0	1	0	0	11.9	0.009	3
OUTF	96	8	CO	0	0	0	0	0	1	0	0	0	0	0	9.3	0.000	2
OUTF	190	18	CO	0	0	0	0	0	0	0	0	1	0	0	10.7	0.002	2
OUTF	169	8	VC	0	0	0	0	0	0	1	0	0	0	0	12.0	0.008	3
OUTF	318	8	VC	0	0	0	0	1	0	0	0	0	0	0	14.2	0.005	3
OUTF	265	12	VC	0	0	0	0	1	0	0	0	0	0	0	9.4	0.014	2

4.1 SUMMARY AND CONCLUSIONS

This chapter presented a detailed discussion about the data acquisition, preprocessing and analysis. The raw database was transformed into a standardized format is ready for neural network model development. The available parameters for the model development were identified and their relevance examined through statistical analysis. Although certain variables have a low amount of correlation to the condition of sewers and deterioration, it is important to include such parameters as neural network is capable of capturing even subtle relationships.

CHAPTER 5

MODEL DEVELOPMENT

The previous chapter described the preprocessing and statistical analysis of the acquired data. This chapter deals with the detailed account of the model development process. The model development in this thesis includes training and testing. Training a neural network involves repeatedly presenting a set of examples to the network. The network takes in each example, makes a response as the output, checks this response against the correct answer, and makes corrections to the internal connections. Testing the network is the same as training it, except that the network is shown with the examples it has never seen before, and no weight adjustments are made during testing. Validation occurs after the neural network has been developed. Validating a network consists of presenting it with new input data and gathering the network outputs. Unlike testing, there is no known output, only known inputs in the validation. Due to time and resource constraints validation was not performed for the model developed in this thesis. The following sections provide a detailed discussion about the model development process. Figure 5.2 represents the neural network design structure used in this thesis.

5.1 DATA SUBDIVISION

In this research, the purpose of preprocessing the data was to establish a database which can be directly used for further model development. The processed data set was further divided into three sub data sets. As shown in Figure 5.1, approximately 85 percent of data were used for network training and 15 percent of data were used to test the generalization ability of the network when facing data unseen in the training period.

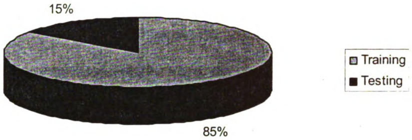


Figure 5.1 - Database Subdivision

5.2 SOFTWARE SELECTION

A developmental platform is usually a requirement to train neural network. Often referred to as neural network simulators, these platforms are commercially available. Some factors worth considering when choosing a suitable neural network simulator are required level of expertise, complexity, and the pre- and post-processing facilities. In this study, BrainMaker, a commercially available neural network simulator distributed by California Scientific Software, was used for the development of the proposed neural network model.

The BrainMaker neural network simulator uses popular backpropagation training algorithm for network training. BrainMaker reads three kinds of neural network files: definition files, fact files, and network files. BrainMaker also creates different types of statistics and output files. They are all human-readable and editable. A definition file describes everything there is to know about the network to BrainMaker, such as the number of neurons in each layer, the type of data, and what is going to be displayed on the screen. BrainMaker uses the definition file to create the neural network. The default extension for the definition file is ".def". A fact file gets the data into BrainMaker. There are fact files for training, testing, and running. The default extension for the training fact file is ".fct", for testing it is ".tst", and for running it is ".in". A network file is created by BrainMaker during training using the data in the training fact file and the instructions in the definition file. The network file contains the actual connection information as well as training parameter information. The default extension for a network file is ".net". The network file plus the testing fact file are used for testing. When the answers are not known, the training network file plus the running fact file are used for running.

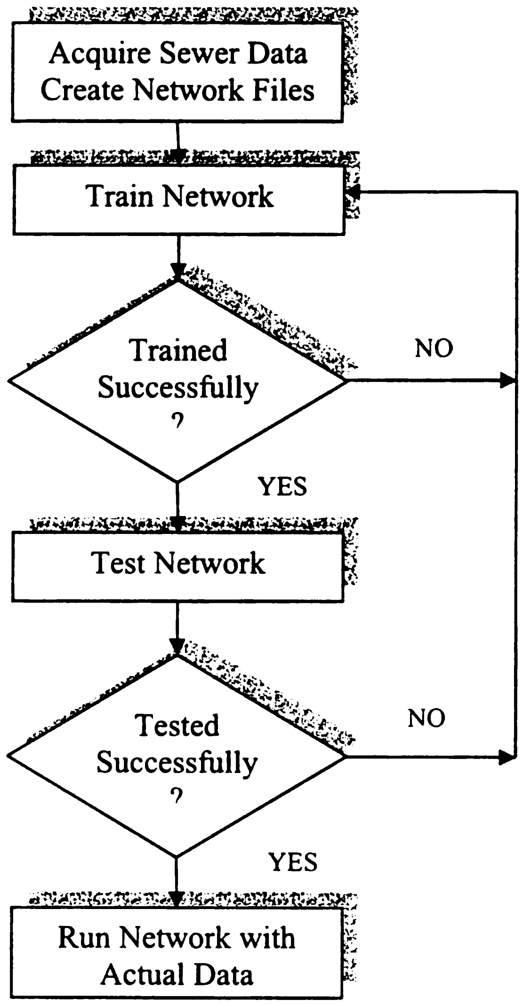


Figure 5.2 – Neural Network Design

5.3 NEURAL NETWORK DESIGN, TRAINING AND TESTING

To develop a neural network model, one must decide precisely what the neural network is expected to forecast, generalize, or recognize. The original database needs some preprocessing before it can be used for training and testing. Then the neural network needs to be trained and tested with some certain rules. Finally, a new data set is used to validate the neural network.

5.3.1 FRAMEWORK FOR NEURAL NETWORK DEVELOPMENT

In this research, the BPNN model was developed through a procedure presented in Figure 5.3. Each developing stage shown in Figure 5.3 is discussed as follows:

- ***Database Review*** – Database investigations was performed to ensure that the database contained sufficient information for neural network development and for pipeline condition prediction.
- ***Data Preprocessing*** – The database was processed and reorganized to form a new database ready for model development. The new database was divided into subsets to create a training data set and testing data set.
- ***Network Design and Training*** – Several different architectures of the neural network were designed and trained in order to obtain the best architecture resulting in the best testing performance.
- ***Network Testing and Error Analysis*** – Each of the architectures were tested independently using the testing data set. Assessments were made for generalization ability and accuracy.

- *Network Implementation* – The best network architecture was then chosen and proposed to be embedded in the working environment.

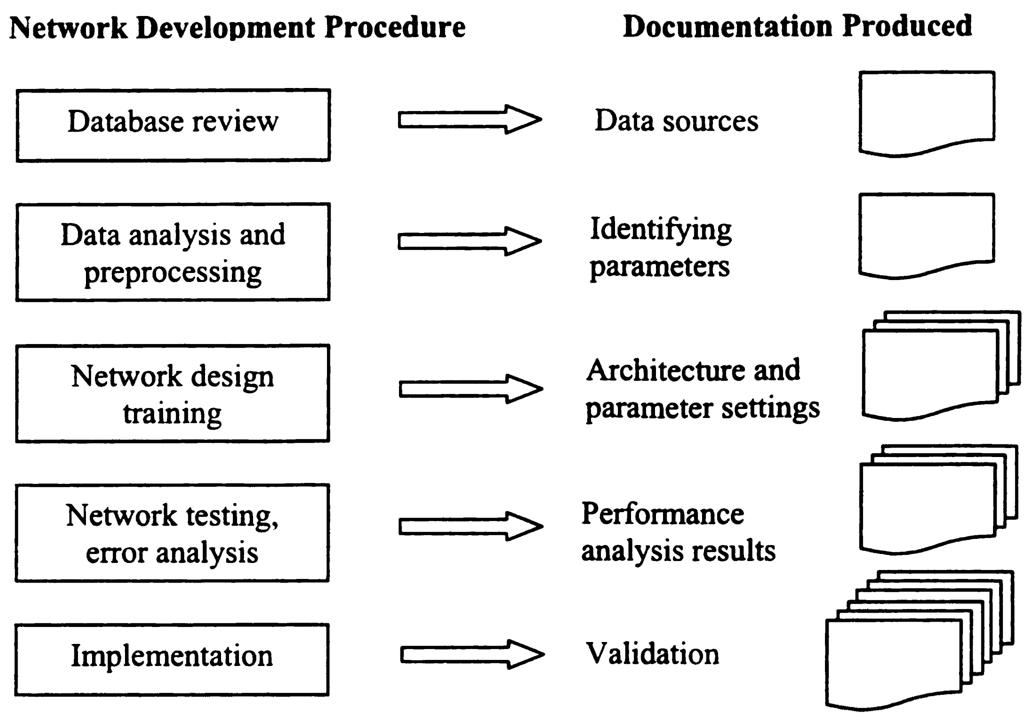


Figure 5.3 - The Procedure for Neural Network Development

It must be kept in mind that the model being developed will be able to predict the probability of sewer pipe being in a certain severity level, but is not meant to predict the probability for individual pipe defects. The main purpose of this model study is to demonstrate the possibility of using ANN modeling for predicting the sewer condition so that physical inspections can be prioritized. As such, further research and model development will likely be necessary.

5.3.2 NEURAL NETWORK TRAINING AND TESTING

The specification of input and output for the BPNN is presented in Table 5.1. The BPNN is designed to predict the condition of sewer pipes given the variables that are identified to affect its deterioration process. Training a neural network involves repeatedly presenting a set of examples (facts) to the network. The network takes each input, makes a guess as to the output, checks this guess against the output (correct answer), and makes corrections to the initial connections (weights) if its guess is incorrect. This process is repeated for each fact in turn until the network learns the facts well enough to be useful.

Table 5.1 - BPNN Architecture

Neuron Type	**Neuron Number**	**Description**	**Range of Variables**
Inputs	1	Pipe Material	CO, VC, PVC, etc.
	2	Pipe Age	Age of Sewer in 5-yr increments
	3	Pipe Diameter	8- inches and up
	4	Section Length	Manhole to Manhole Length in feet
	5	Depth	Average Depth
	6	Slope	Gradient of Pipe
	7	Sewer Type	Outfall/Lateral
Output	1	Condition	1-5

As described in Chapter 4, the above inputs are first fed into NetMaker for labeling the inputs and the outputs. The proportion of training and testing facts are assigned before saving the file as BrainMaker readable and executable files. Now the database is ready to be modeled using the BrainMaker software. Figure 5.4 depicts the typical structure of the neural network with the given set of input parameters.

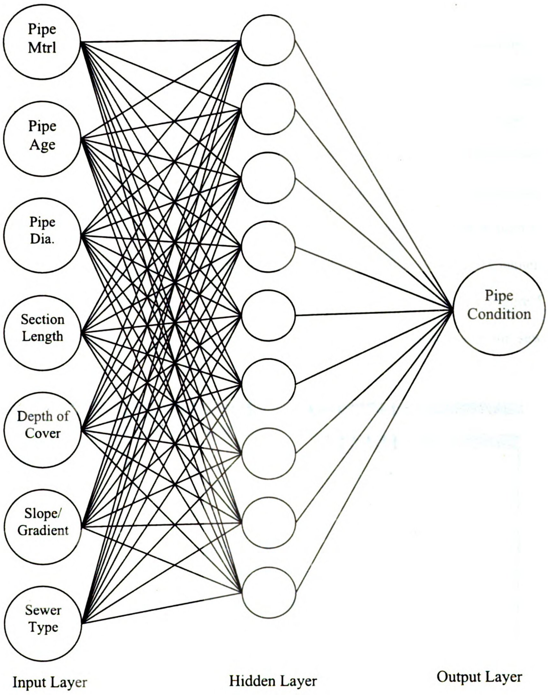


Figure 5.4 – Schematic Architecture of the Neural Network

The training file created using NetMaker is accessed through BrainMaker for modeling analysis. Histograms and the Network Progress Display, two useful tools provided by BrainMaker, can help determine whether the network is making progress in training and still has capacity to learn. Figure 5.5 (a) shows the training histogram of a neural network (19 hidden neurons, 83 epochs) with the horizontal axis representing the values of connection weights. This bell-shaped histogram indicates the network is healthy and still has the capacity to learn. Another tool is the Network Progress Display, as shown in Figure 5.5 (b). The top part of the screen shows a histogram of the errors over a training run. It gives a quick snapshot of the distribution of errors, making it easy to see how close the network is to achieving the pre-specified tolerance level. The bottom part shows the progress of the Root Mean Square (RMS) error, which is defined in Chapter 3, during training. This graph shows how well training is progressing over runs. Figure 5.6 illustrates the step by step process of neural network model development for sewer condition prediction.

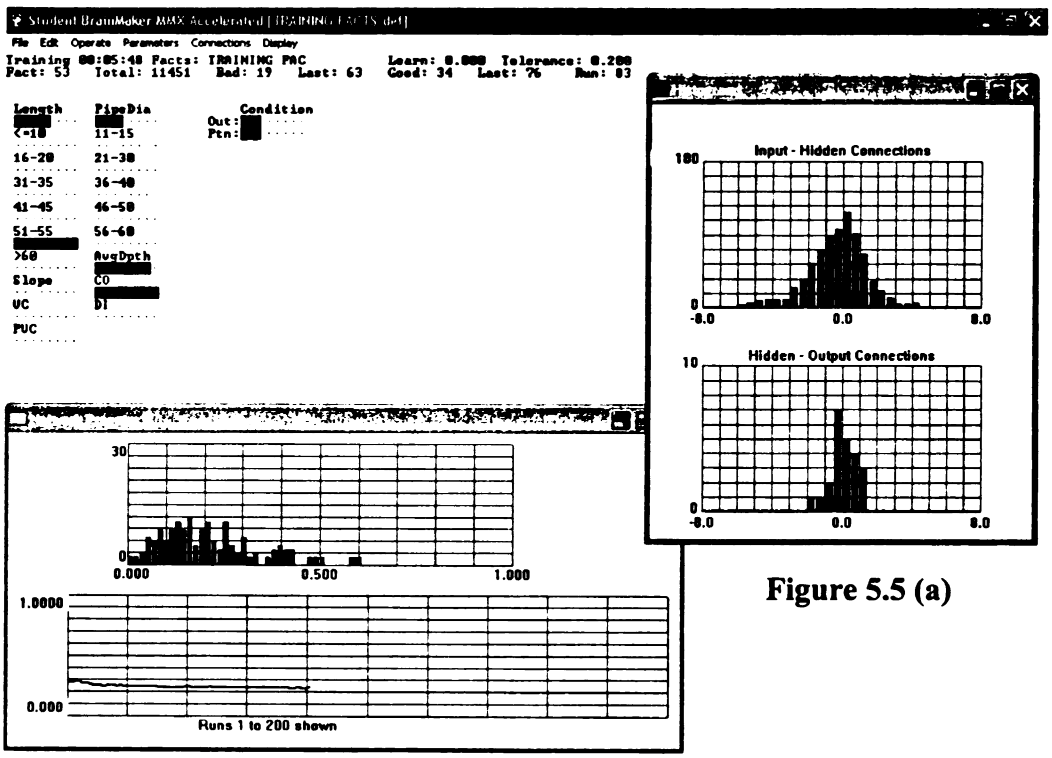


Figure 5.5 (a)

Figure 5.5 (b)

Figure 5.5 (a & b) – Connection Weights Histogram and Network Progress in Training

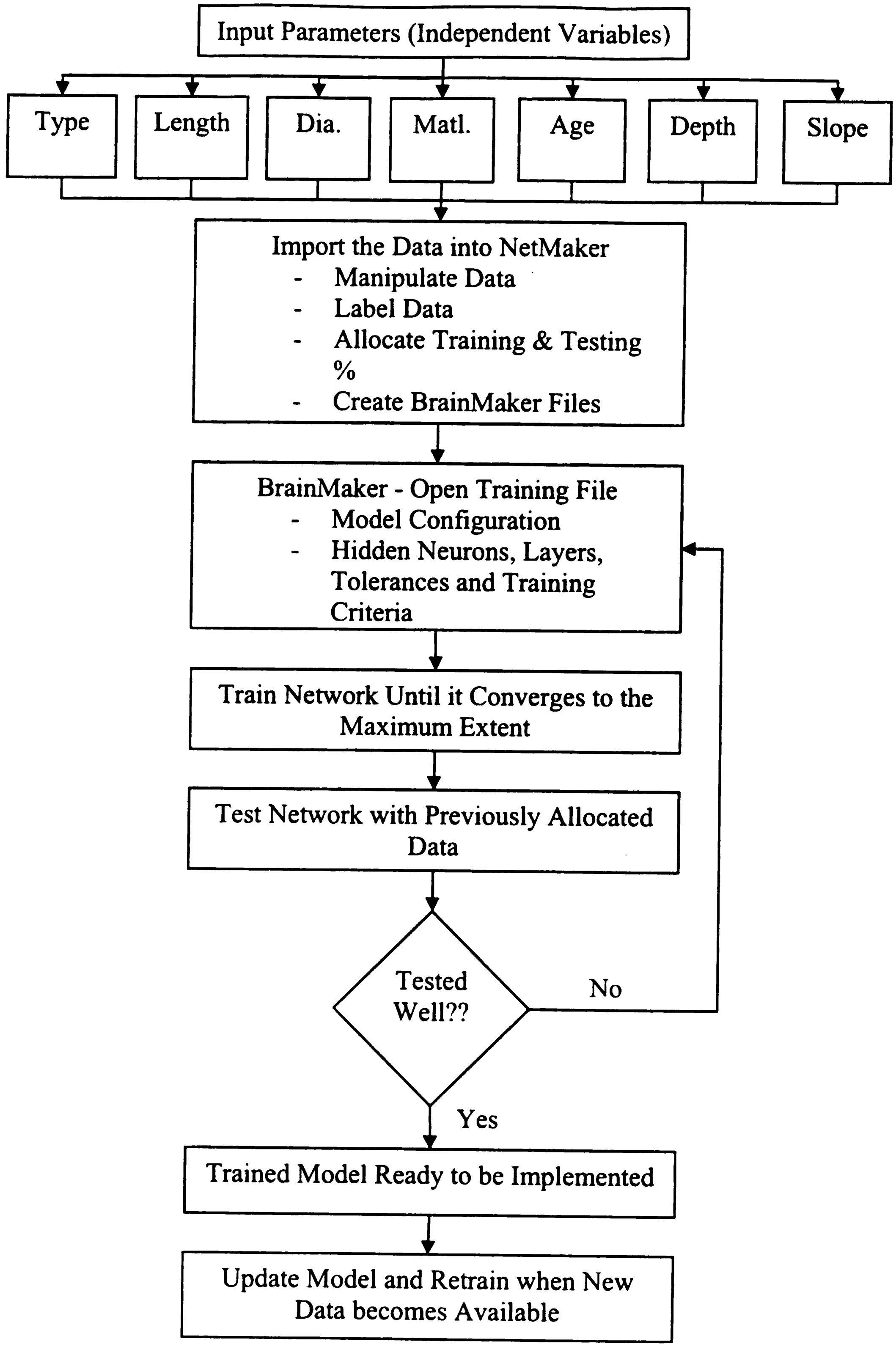


Figure 5.6– Neural Network Modeling Process

5.3.3 DETAILED OVERVIEW OF MODEL DEVELOPMENT

The first step in creating a neural network model using BrainMaker is to preprocess the data using NetMaker tool provided in the software bundle. NetMaker has a number of utilities useful for manipulating the data to present the best possible data structure for model development. It is here that Inputs and Outputs of the model are assigned. The dataset is split randomly into training (85%) and testing (15%) facts using the NetMaker preferences. Figure 5.7 shows the typical NetMaker window.

NetMaker - CompleteData BrainMaker.txt

File Column Row Label Number Symbol Operate

	Input	Input	Input	Input	Input	Input	Input	Input	Input	Input	Input	Input	Input	Input	Input
	Length	PipeDia	CO	VC	<=10	11-15	16-20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60
1	215	18	1	0	0	0	0	0	0	0	0	0	0	1	0
2	350	18	1	0	0	0	0	0	0	0	0	0	0	1	0
3	273	15	1	0	0	0	0	0	0	0	0	0	0	1	0
4	362	30	1	0	0	0	0	0	0	0	0	0	0	1	0
5	416	30	1	0	0	0	0	0	0	0	0	0	0	1	0
6	166	30	1	0	0	0	0	0	0	0	0	0	0	1	0
7	241	15	1	0	0	0	0	0	0	0	0	0	0	1	0
8	494	30	1	0	0	0	0	0	0	0	0	0	0	1	0
9	489	30	1	0	0	0	0	0	0	0	0	0	0	1	0
10	324	15	1	0	0	0	0	0	0	0	0	0	0	1	0
11	259	15	1	0	0	0	0	0	0	0	0	0	0	1	0
12	367	15	1	0	0	0	0	0	0	0	0	0	0	1	0
13	404	15	1	0	0	0	0	0	0	0	0	0	0	1	0
14	238	8	1	0	0	0	0	0	0	0	0	0	1	0	0
15	293	8	1	0	0	0	0	0	0	0	0	0	1	0	0
16	388	8	1	0	0	0	0	0	0	0	0	1	0	0	0
17	208	8	1	0	0	0	0	0	0	0	0	1	0	0	0
18	332	8	1	0	0	0	0	0	0	0	0	1	0	0	0
19	205	8	1	0	0	0	0	0	0	0	0	1	0	0	0
20	245	8	1	0	0	0	0	0	0	0	0	1	0	0	0
21	162	8	1	0	0	0	0	0	0	0	0	1	0	0	0
22	240	8	1	0	0	0	0	0	0	0	0	0	1	0	0
23	254	8	1	0	0	0	0	0	0	0	0	0	1	0	0
24	255	8	1	0	0	0	0	0	0	0	0	1	0	0	0
25	267	8	1	0	0	0	0	0	0	0	0	1	0	0	0
26	360	8	1	0	0	0	0	0	0	0	0	1	0	0	0

Figure 5.7 – View of the NetMaker Data Processing

After the completion of data preprocessing, the file is saved to a BrainMaker file. NetMaker creates three files, namely, definition (.def), training (.fct) and testing (.tst). The data is now ready to be operated with BrainMaker for modeling.

5.3.4 SELECTION OF OPTIMAL NUMBER OF HIDDEN NEURONS

Selection of optimal number of hidden neurons is an important issue in the neural network training process. The goal of training is to obtain a neural network with best generalization capability. Generalization is defined as the ability of a neural network to store in its weights general characteristics which are common to a group of examples. Usually, a neural network with too few hidden neurons will not be able to learn sufficiently from the training data set, whereas a neural network with too many hidden neurons will allow the network to memorize the training set instead of generalizing the acquired knowledge for future unseen examples. Unfortunately, there is no precise formula for determining the ideal number of hidden neurons for a given application. There are several ways to determine a good number of hidden neurons. One solution is to train the neural networks with the number of hidden neurons calculated using the formula:

$$\text{Number of Hidden Neurons} = \frac{\text{of Data sets} - \text{Outputs}}{C\,(\#\,\text{Input} + \#\,\text{Output} + 1)} \qquad \text{----------}\ (5.1)$$

Where, C = 2 – 5.

Therefore the # of Neurons = (167 – 1) / 3 * (15 + 1 + 1) ≈ 4 Neurons

The second equation suggested in BrainMaker manual is:

$$\begin{aligned}\text{Number of Hidden Neurons} &= (\#\,\text{Inputs} + \#\,\text{Outputs})/2 \qquad \text{----------}\ (5.2)\\ &= (15 + 1)/2 \approx 8\ \text{Neurons}\end{aligned}$$

The third solution is to begin with a small number of hidden neurons and add more while training if the network is not learning. In this research, the first method (4 Hidden Neurons) was used to train initially and gradually more neurons are added to train several neural networks with varying number of hidden neurons. The neural network that resulted in the least testing error was selected, resulting in the best generalization capability. The "testing while training" method was used to trace the testing errors (generalization ability) of the neural network during training process. After training, it was convenient to find the best network with the least testing errors.

In order to identify the best BPNN model for pipeline condition prediction, a variety of neural network architectures were experimented in this study. Table 5.2 presents the training and testing errors resulting from typical BPNN architectures that were tested in this effort. Since the generalization capability of the neural network is typically represented by the testing errors, the testing RMS error was selected as the major criterion to evaluate the BPNN performance. It can be seen that Model #7 presented in Table 5.2 with 10 hidden neurons resulted in the best BPNN model with lowest testing error.

Different network architectures were tried with the same facts to examine which architecture best suites the problem in hand. In all the models experimented, 85% of the total facts were used for training and 15% of the facts were set aside for testing. The number of hidden layers used for all the models was one and the training and testing tolerances were set at 0.3 and 0.3 respectively. It is assumed that these tolerances were acceptable based on the fact that values for all the parameters that contributed to the pipeline deterioration were not factored in the model due to the unavailability of data attributed to the lack of monitoring of such data. After the model with optimal number of hidden neurons was selected from this prescreening process, it will undergo further processing in order to enhance the tolerance and accuracy levels.

Table 5.2 – Training and Testing Errors of Different BPNN Architectures

Model	Architecture	$RMS_{TRAINING}$	$RMS_{TESTING}$
1	15-4-1	0.2412	0.1881
2	15-5-1	0.2644	0.2115
3	15-6-1	0.2422	0.1882
4	15-7-1	0.2499	0.1769
5	15-8-1	0.2458	0.1795
6	15-9-1	0.2378	0.1760
7	15-10-1	0.2386	0.1478*
8	15-11-1	0.2411	0.1746
9	15-12-1	0.2713	0.1971

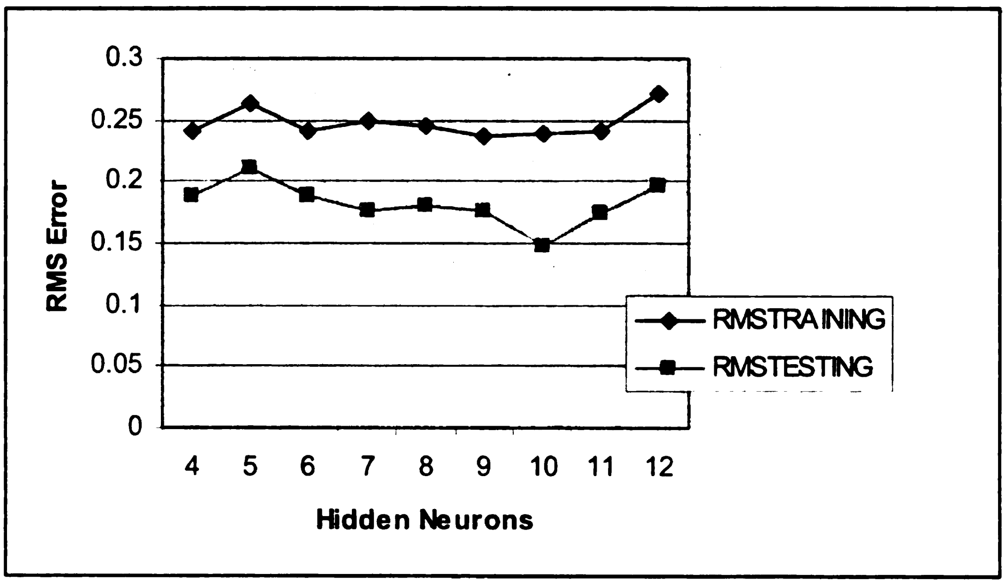


Figure 5.8 – Graphical Representation of Training and Testing Errors for different Architectures

Figure 5.8 presents the RMS error and average error of the neural networks with different number of hidden neurons. It can be seen that the network with 10 neurons in the hidden layer resulted in the least RMS error and average error. Hence, Model #7 is chosen as the best architecture and will be used in further analysis and model development using BrainMaker.

From the BrainMaker interface, the number of hidden neurons is set to 10 and the necessary values for the training and testing tolerances are made before the model is ready for training. The training and testing statistics files were activated to capture the network progress statistics that would be helpful in identifying the best run. Figure 5.9 shows the network during the beginning of the training. Figures 5.10 and 5.11 show the network after training and testing processes with tolerances of 0.3 and 0.3 respectively.

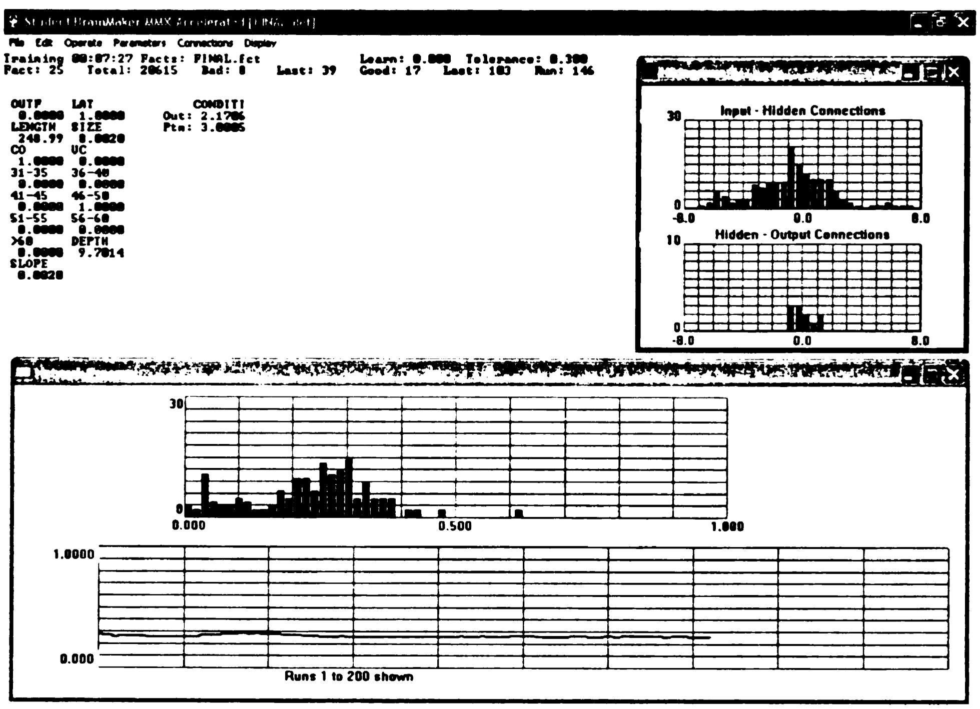


Figure 5.9 – Neural Network Training Progress

Table 5.3 – Network Architecture and Specifications of Model #7

Inputs	**Hidden Neurons**	**Layers**	**No. of Training Facts**	**No. of Testing Facts**	**Training Tolerance**	**Testing Tolerance**
15	10	1	142 (85%)	25 (15%)	0.3	0.3

Figures 5.10 and 5.11 shows the training and testing results of the model #7 configuration (15-10-1).

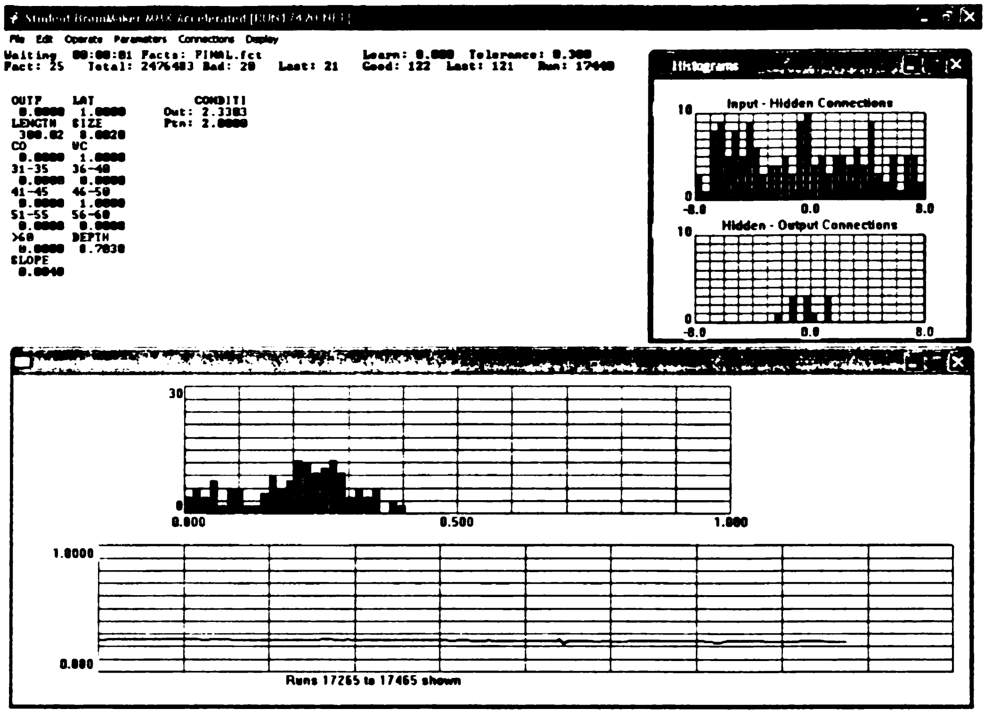


Figure 5.10 – Training Results of Model #7

The training is stopped when the neural network settles at the lowest possible training and testing errors and there is no visible convergence in the training statistics. The summary of training and testing statistics is given in Table 5.4 below.

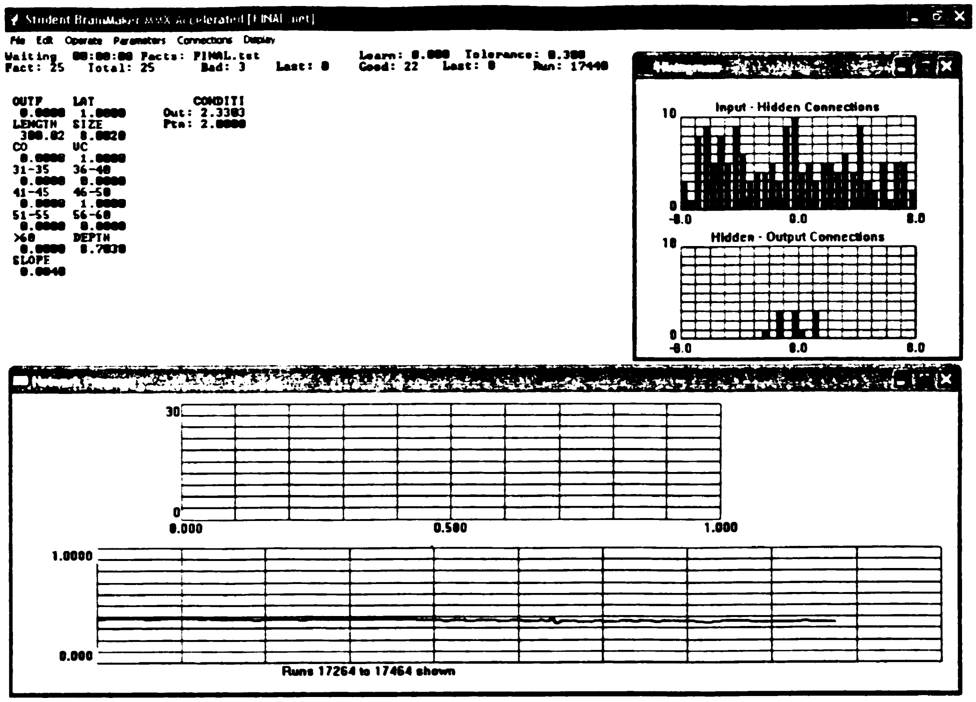


Figure 5.11 – Testing Results of Model #7

Table 5.4 – Summary of Training and Testing Results (Model #7)

Training (156 Facts)		Testing (27 Facts)	
Bad	**Good**	**Bad**	**Good**
20 (14%)	122 (86%)	3 (12%)	22 (88%)

Although the model learned 86% of the facts presented to it and predicted 88% of the testing facts right, the tolerances are on the higher side. Figure 5.12 shows the plot of the predicted condition versus the actual condition. It can be observed that the model almost always under predicted the sewers in condition rating level 3. This indicates that the model will have to be further fine tuned to pick up the condition rating 3 scenario.

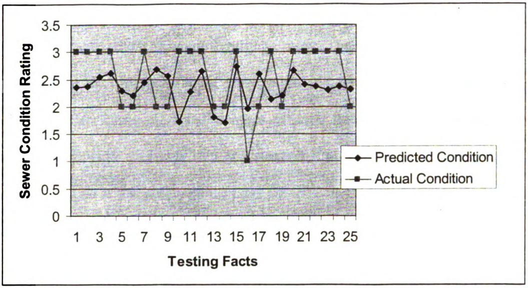


Figure 5.12 – Plot showing the Predicted and the Actual Condition of the Testing Sample (Model #7)

5.4 MODEL PERFORMANCE ENHANCEMENT

There are some tools available in BrainMaker that help in enhancing the performance of the models. The application of these utilities to get better results with a lower tolerance is explained in this section. The main objective of this effort is to converge the neural network training as much as possible with the lowest tolerances so that the network learns most number of facts presented. This model will then be tested with a lower testing tolerance of 0.25 as compared to the tolerance of the initial model which was set at 0.3. The network was set to test and save every 20 runs automatically to enable the best network configuration to be selected after training.

Model #7 had previously learned 86% of the facts presented with a testing tolerance of 0.3 and it had tested successfully 88% of the facts with testing tolerance of 0.3. First, the model 7 is opened in BrainMaker to be retrained and tested with a tolerance of 0.25. One of the techniques available in the software is to randomize the network connections and to add some noise to the network. This helps the network to learn some hard to learn facts which it has difficulty learning. The connections were randomized with a constant of 5 (default) and a noise value of 0.15 is set. The network was then retrained until it learns the most number of facts and also tests successfully. The reconfigured network was able to learn maximum of 92% of the training facts. The training is stopped at this point and the facts are ready to be tested. Figure 5.13 shows the trained model with 131 of the total 142 facts learned by the network.

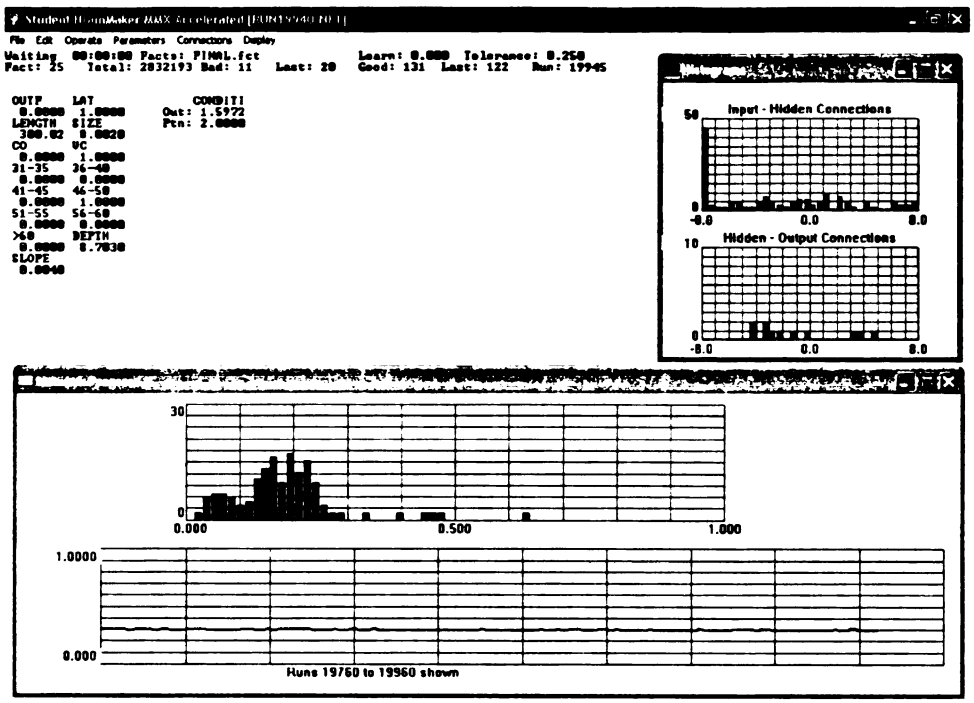


Figure 5.13 –The Model after Training Maximum Facts

The neural network file was initially programmed to test the allocated data automatically for every 5 runs while training progresses. The testing statistics file that tracks the network configuration was pulled to select the best network that has the least testing as well as training RMS errors. Figure 5.14 shows the snapshot of the testing phase. This model tested 21 out of the total 25 facts set aside for testing with a tolerance of 0.25.

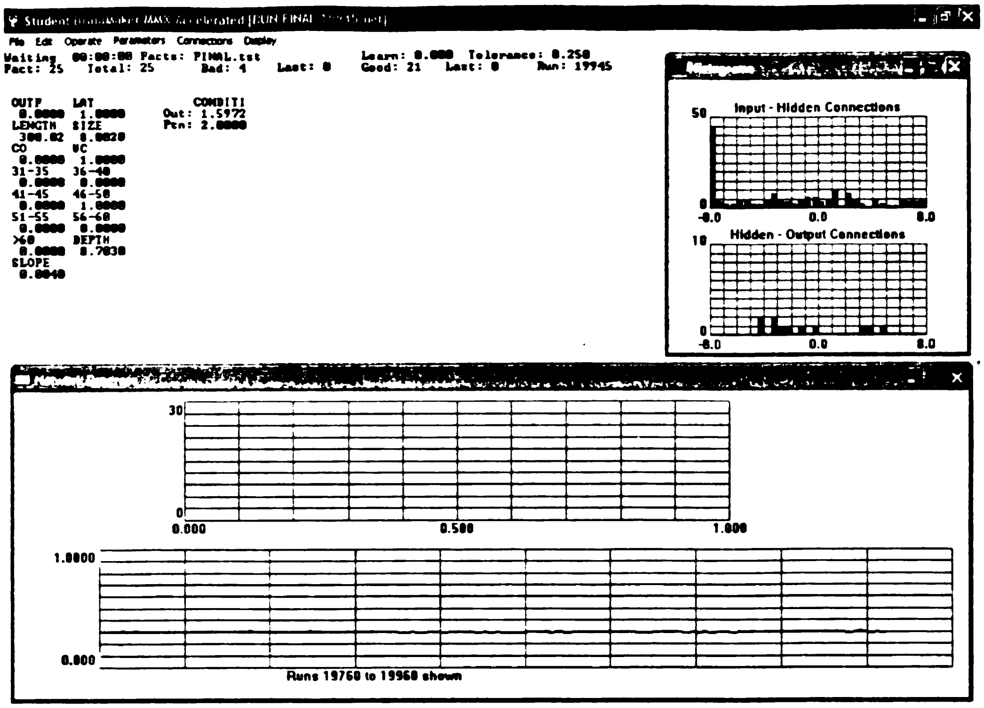


Figure 5.14 –The Trained Model while Testing

The network information for this model can then be accessed from the training statistics file as shown in Figure 5.15. The testing configuration of this network is given in Table 5.5.

Table 5.5 – Testing and Training Network Statistics

No. of Runs	Total Facts	Good	Bad	Training/Testing Tolerance	Average Error	RMS Error
Training Configuration						
19945	142	131	11	0.25	0.1770	0.1966
Testing Configuration						
19945	25	21	4	0.25	0.1649	0.1979

FINAL TRAINING STATS - Notepad

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Run	TotFacts	Good	Bad	BadOutputs	TotalBad	Learn	Tolerance	AvgError	RMSError	hh:mm:ss
19886	2823815	125	17	17	702196	0.0000	0.2500	0.1752	0.1961	00:01:56
19887	2823957	122	20	20	702216	0.0000	0.2500	0.1760	0.1970	00:01:56
19888	2824099	124	18	18	702234	0.0000	0.2500	0.1733	0.1957	00:01:56
19889	2824241	128	14	14	702248	0.0000	0.2500	0.1783	0.1990	00:01:56
19890	2824383	125	17	17	702265	0.0000	0.2500	0.1789	0.1990	00:01:56
19891	2824525	129	13	13	702278	0.0000	0.2500	0.1785	0.1973	00:01:56
19892	2824667	128	14	14	702292	0.0000	0.2500	0.1790	0.1985	00:01:56
19893	2824809	121	21	21	702313	0.0000	0.2500	0.1765	0.1982	00:01:56
19894	2824951	122	20	20	702333	0.0000	0.2500	0.1740	0.1977	00:01:56
19895	2825093	129	13	13	702346	0.0000	0.2500	0.1779	0.1980	00:01:56
19896	2825235	127	15	15	702361	0.0000	0.2500	0.1780	0.1987	00:01:56
19897	2825377	124	18	18	702379	0.0000	0.2500	0.1758	0.1963	00:01:56
19898	2825519	126	16	16	702395	0.0000	0.2500	0.1762	0.1968	00:01:56
19899	2825661	118	24	24	702419	0.0000	0.2500	0.1760	0.1987	00:01:56
19900	2825803	130	12	12	702431	0.0000	0.2500	0.1734	0.1952	00:01:56
19901	2825945	122	20	20	702451	0.0000	0.2500	0.1821	0.2050	00:01:57
19902	2826087	124	18	18	702469	0.0000	0.2500	0.1792	0.2009	00:01:57
19903	2826229	130	12	12	702481	0.0000	0.2500	0.1771	0.1966	00:01:57
19904	2826371	126	16	16	702497	0.0000	0.2500	0.1772	0.1979	00:01:57
19905	2826513	123	19	19	702516	0.0000	0.2500	0.1773	0.1982	00:01:57
19906	2826655	130	12	12	702528	0.0000	0.2500	0.1765	0.1969	00:01:57
19907	2826797	124	18	18	702546	0.0000	0.2500	0.1808	0.2014	00:01:57
19908	2826939	128	14	14	702560	0.0000	0.2500	0.1761	0.1966	00:01:57
19909	2827081	123	19	19	702579	0.0000	0.2500	0.1787	0.1987	00:01:57
19910	2827223	132	10	10	702589	0.0000	0.2500	0.1806	0.1997	00:01:57
19911	2827365	125	17	17	702606	0.0000	0.2500	0.1812	0.2016	00:01:57
19912	2827507	122	20	20	702626	0.0000	0.2500	0.1787	0.2003	00:01:57
19913	2827649	126	16	16	702642	0.0000	0.2500	0.1794	0.2000	00:01:57
19914	2827791	128	14	14	702656	0.0000	0.2500	0.1790	0.1992	00:01:57
19915	2827933	127	15	15	702671	0.0000	0.2500	0.1792	0.1993	00:01:57
19916	2828075	118	24	24	702695	0.0000	0.2500	0.1755	0.1980	00:01:57
19917	2828217	117	25	25	702720	0.0000	0.2500	0.1794	0.2047	00:01:57
19918	2828359	123	19	19	702739	0.0000	0.2500	0.1797	0.2005	00:01:57
19919	2828501	123	19	19	702758	0.0000	0.2500	0.1790	0.1990	00:01:57
19920	2828643	131	11	11	702769	0.0000	0.2500	0.1780	0.1980	00:01:57
19921	2828785	128	14	14	702783	0.0000	0.2500	0.1786	0.1982	00:01:57
19922	2828927	122	20	20	702803	0.0000	0.2500	0.1776	0.1987	00:01:57
19923	2829069	122	20	20	702823	0.0000	0.2500	0.1763	0.1980	00:01:57
19924	2829211	126	16	16	702839	0.0000	0.2500	0.1782	0.1979	00:01:57
19925	2829353	129	13	13	702852	0.0000	0.2500	0.1782	0.1972	00:01:57
19926	2829495	125	17	17	702869	0.0000	0.2500	0.1767	0.1973	00:01:58
19927	2829637	125	17	17	702886	0.0000	0.2500	0.1805	0.1997	00:01:58
19928	2829779	126	16	16	702902	0.0000	0.2500	0.1787	0.1984	00:01:58
19929	2829921	125	17	17	702919	0.0000	0.2500	0.1772	0.1974	00:01:58
19930	2830063	129	13	13	702932	0.0000	0.2500	0.1780	0.1980	00:01:58
19931	2830205	127	15	15	702947	0.0000	0.2500	0.1828	0.2028	00:01:58
19932	2830347	128	14	14	702961	0.0000	0.2500	0.1769	0.1969	00:01:58
19933	2830489	120	22	22	702983	0.0000	0.2500	0.1760	0.1982	00:01:58
19934	2830631	121	21	21	703004	0.0000	0.2500	0.1781	0.2007	00:01:58
19935	2830773	121	21	21	703025	0.0000	0.2500	0.1762	0.1980	00:01:58
19936	2830915	124	18	18	703043	0.0000	0.2500	0.1774	0.1987	00:01:58
19937	2831057	125	17	17	703060	0.0000	0.2500	0.1730	0.1953	00:01:58
19938	2831199	128	14	14	703074	0.0000	0.2500	0.1742	0.1970	00:01:58
19939	2831341	117	25	25	703099	0.0000	0.2500	0.1830	0.2055	00:01:58
19940	2831483	114	28	28	703127	0.0000	0.2500	0.1836	0.2071	00:01:58
19941	2831625	122	20	20	703147	0.0000	0.2500	0.1756	0.1980	00:01:58
19942	2831767	128	14	14	703161	0.0000	0.2500	0.1728	0.1938	00:01:58
19943	2831909	125	17	17	703178	0.0000	0.2500	0.1762	0.1975	00:01:58
19944	2832051	122	20	20	703198	0.0000	0.2500	0.1752	0.1973	00:01:58
19945	2832193	131	11	11	703209	0.0000	0.2500	0.1770	0.1966	00:01:58

Figure 5.15 –Network Training Statistics for Model

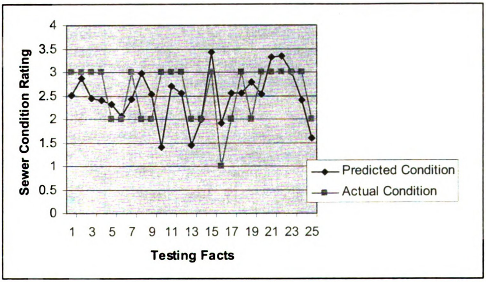


Figure 5.16 – Plot showing the Predicted and the Actual Condition of the Testing Sample after 19945 Runs

The model automatically tests 15% or 25 facts that were set aside initially with a testing tolerance of 0.25. The model tested 21 out of 25 facts as good or 84% successfully within the 0.25 testing tolerance. Figure 5.16 shows a comparative plot of the predicted condition versus the actual condition of sewers. This graph indicates a better trend than the earlier results represented in Figure 5.12.

Finally, the network is again calibrated to a lower testing tolerance level of 0.2 and then trained longer. The network in this mode could test only 15 out of 25 facts, but with higher accuracy level. Figure 5.17 represents the plot of the predicted and the actual condition. This plot has more accurate facts than the previous models because of the stringent tolerance levels. It is assumed that a testing tolerance of 0.2 is acceptable and will be able to give a fair judgment as to what the condition ranking of the pipe will likely be, given the combination of input parameters. The model's accuracy can be increased as more input parameters identified to affect the sewer condition are available for modeling.

Table 5.5 – Testing and Training Network Statistics

No. of Runs	Total Facts	Good	Bad	Training/Testing Tolerance	Average Error	RMS Error
Training Configuration						
40995	142	126	16	0.2	0.1568	0.1868
Testing Configuration						
40995	25	15	10	0.2	0.1367	0.1792

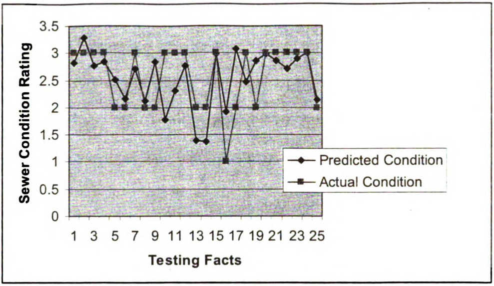
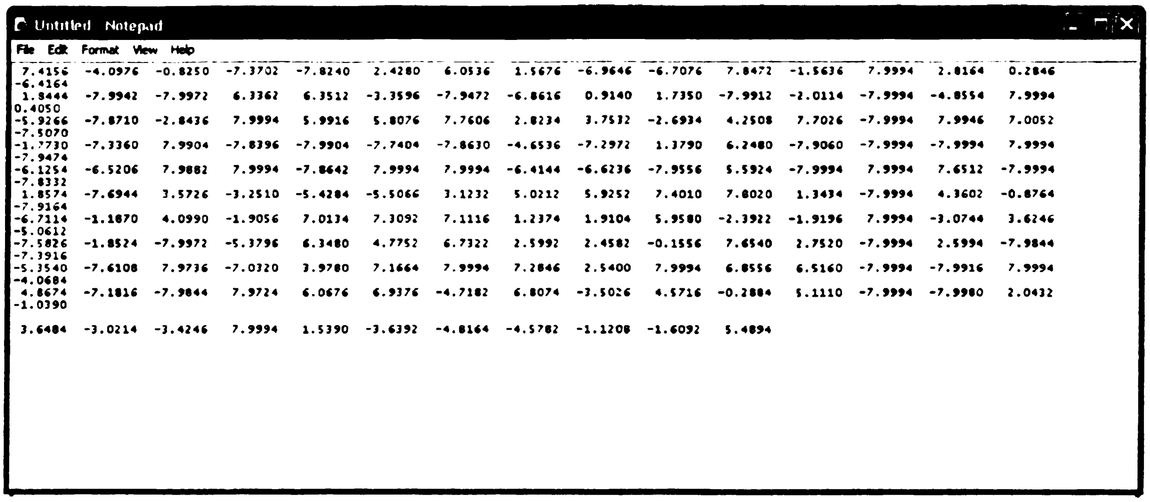


Figure 5.17 – Plot showing the Predicted and the Actual Condition of the Testing Sample (40995 Runs)

The neural network automatically configures the weights of the hidden neurons based on the training. Figure 5.18 represents the weight matrices for the hidden neurons. There are two blocks (input to hidden and hidden to output) in the Figure 5.18. The first block has 16 numbers per row (15 inputs plus the threshold) and there are 10 rows (for the 10 hidden neurons). The second block has 11 numbers per row (10 hidden plus the threshold) and there is only 1 row (for 1 output). Weights from threshold neurons always go at the end of the row.



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File Edit Format View Help
 7.4156 -4.0976 -0.8250 -7.3702 -7.8240  2.4280  6.0536  1.5676 -6.9646 -6.7076  7.8472 -1.5636  7.9994  2.8164  0.2846
-6.4164
 1.8444 -7.9942 -7.9972  6.3362  6.3512 -3.3596 -7.9472 -6.8616  0.9140  1.7350 -7.9912 -2.0114 -7.9994 -4.8554  7.9994
0.4050
-5.9266 -7.8710 -2.8436  7.9994  5.9916  5.8076  7.7606  2.8234  3.7532 -2.6934  4.2508  7.7026 -7.9994  7.9946  7.0052
-7.5070
-1.7730 -7.3360  7.9904 -7.8396 -7.9904 -7.7404 -7.8630 -4.6536 -7.2972  1.3790  6.2480 -7.9060 -7.9994 -7.9994  7.9994
-7.9474
-6.1254 -6.5206  7.9882  7.9994 -7.8642  7.9994  7.9994 -6.4144 -6.6236 -7.9556  5.5924 -7.9994  7.9994  7.6512 -7.9994
-7.8332
 1.8574 -7.6944  3.5726 -3.2510 -5.4284 -5.5066  3.1232  5.0212  5.9252  7.4010  7.8020  1.3434 -7.9994  4.3602 -0.8764
-7.9164
-6.7114 -1.1870  4.0990 -1.9056  7.0134  7.3092  7.1116  1.2374  1.9104  5.9580 -2.3922 -1.9196  7.9994 -3.0744  3.6246
-5.0612
-7.5826 -1.8524 -7.9972 -5.3796  6.3480  4.7752  6.7322  2.5992  2.4582 -0.1556  7.6540  2.7520 -7.9994  2.5994 -7.9844
-7.3916
-5.3540 -7.6108  7.9736 -7.0320  3.9780  7.1664  7.9994  7.2846  2.5400  7.9994  6.8556  6.5160 -7.9994 -7.9916  7.9994
-4.0684
 4.8674 -7.1816 -7.9844  7.9724  6.0676  6.9376 -4.7182  6.8074 -3.5026  4.5716 -0.2884  5.1110 -7.9994 -7.9980  2.0432
-1.0390

 3.6484 -3.0214 -3.4246  7.9994  1.5390 -3.6392 -4.8164 -4.5782 -1.1208 -1.6092  5.4894
```

Figure 5.18 – Network Weight Matrices (40995 Runs)

5.5 WEIGHTAGE OF INDIVIDUAL PARAMETERS

In order to determine the importance of each of the parameters, different models were trained with the targeted parameter excluded during training. The corresponding parameter that is excluded in the model with the highest RMS Error will be the most important parameter followed by the other parameters ranked descending based on the RMS error value. The following table lists the parameters in descending order of their importance based on the Average and RMS errors resulting from the elimination of the particular parameter.

Table 5.6 – Excluded Parameters and the Resulting Errors Generated by the Model

Excluded Parameter	No. of Runs	Training Tolerance	Average Error	RMS Error
Size	19945	0.25	0.2481	0.2733
Type	19945	0.25	0.2311	0.2646
Length	19945	0.25	0.2093	0.2376
Age	19945	0.25	0.1961	0.2188

Depth	19945	0.25	0.1884	0.2045
Material	19945	0.25	0.1706	0.1968
Slope	19945	0.25	0.1612	0.1844

5.6 RESULTS OF THE ANN MODELING EFFORT

Although the data obtained was noisy and inadequate for a thorough statistical analysis, it was demonstrated that the neural network was adept in capturing the subtle relationships that gives an indication of the pipeline condition state. This experiment indicates that the neural network is capable of learning the deterioration trends and relates it to the condition ranking of sewers during training. But the fact that it could learn only 70% with ease indicates that additional parameters identified in the literature review are needed to account for the full deterioration pattern to predict the actual condition of sewer pipes. As access to more detailed information identified in the literature is available, the network can perform at a better rate and the tolerances can be set at a lower value to result in a more accurate model.

This model is essentially designed to be able to predict the condition probability of the sewer pipes. If the pipe attributes are known, such as pipe age, average depth of cover, manhole to manhole length, pipe diameter, pipe material, the deficiency probability can be predicted from the trained neural network model. The output of the model ranges from 1 to 5, 1 being the best and 5 being the worst possible condition. High priority should be placed on the pipe with high deficiency probability. If the resulting condition predicted by the model is higher than a set threshold (usually determined by the municipal agency), the recommended action is to perform a physical inspection to those sewer sections to determine the condition state of that pipe.

The model developed in this thesis effort was intended to generate the deficiency probability that will aid the decision-maker along with other factors like expert judgment, location importance factors, etc. to prioritize "at risk" sewers. Physical inspections can then be scheduled to these prioritized sewers to optimize the inspection resources and to carry out any appropriate performance improvement measures in a proactive manner.

5.7 SUMMARY AND CONCLUSIONS

This chapter presented the detailed overview of the development of the neural network model. Various configurations were experimented and the best architecture among them was chosen for further description and development. It was observed that the model exhibited a good learning tendency towards the facts presented, but there were problems due to noise in the data because of the fewer number of available facts, outliers and the missing parameters that account for rest of the deterioration process. It is concluded that the application of neural network to solve the problem of condition prediction of sewers is feasible and the accuracy of the model depends on acquiring a larger and more inclusive sample size.

CHAPTER 6

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

6.1 SUMMARY

According to the literature review results, many researchers have developed regression models for pipeline deterioration and condition forecasting. Although widely used and easy to understand, these models are less accurate due to the complexity of deterioration mechanism involved in pipeline deterioration models. On the other hand, development of the traditional models needs a function form to be pre-specified. This could be difficult in the presence of a huge pipeline condition data because of the multitude of variables associated with pipeline deterioration. As an alternative, this thesis attempted to develop a sewer pipeline condition prediction model using artificial neural networks, which does not require a pre-specified function form. The outcome of this thesis demonstrates the ability to develop neural network based condition prediction models for sewer pipes using the available condition assessment data. Although complicated in the neural network training algorithm, the development of neural network is usually implemented by commercially available software packages. In this research, the BPNN model was developed with the City of Atlanta's sewer condition assessment database by using BrainMaker, a popular neural network training platform. After the training process is completed, the BPNN model can remember all the necessary information in its weight matrix and can be drawn to validate new datasets.

There are several factors involved in determining the threshold of the pipe condition. If the predicted pipe condition exceeds the threshold, inspection to that pipe section must be performed to prevent worsening of the condition. If the predicted pipe condition is lower than the threshold, low priority is placed in the inspection of that pipe section. Budget availability, historical record and experience will play important role in determining the threshold.

The predicted pipe condition using this model is essential in sewer rehabilitation scheduling as it provides the decision-maker with a priority based inspection ranking system. At project level, the model can help identify the maintenance needs and strategies for sewers. A higher priority should be placed on the higher deficiency prediction of the sewer system. Physical inspections can be scheduled to optimize inspection so that necessary repairs can be performed in a proactive manner prior to sewer collapse or other adverse effects and to rehabilitate the pipe at the most optimal time. At the network level, the decision-makers can propose the annual budget and maintenance plans by using the above information.

6.2 LIMITATIONS OF THE RESEARCH

As indicated previously, this research is undertaken mainly to demonstrate the possibility of using neural network models as a screening tool to prioritize inspections. The availability of fewer numbers of deterioration parameters and limited data availability posed the primary drawback to effective neural network training and caused the main limitation to this thesis.

Environmental parameters affecting the pipe, such as overburden pressure, soil type and properties, soil pH, soil water content and other factors identified in the literature were omitted due to lack of monitoring of the data. Review of literature showed these parameters to be appropriate measures of corrosion and soil-pipe interaction. Hence the largest limiting factor for modeling ease and accuracy was the unavailability of all encompassing and comprehensive data.

6.3 CONCLUSIONS

Due to their low visibility, rehabilitation of underground sewer system is often neglected until a catastrophic failure occurs. This, more often than not, results in costly and difficult rehabilitation due to the urgent nature of ensuring that the sewer system is operational. A majority of sewer repair projects are executed on a "reactionary" basis, rather than adopting a "proactive" approach. There are two main reasons for this: the first is the unavailability of adequate information regarding the condition of the sewer system; and the second is the ineffectiveness of predicting sewer deficiency prior to failure or an adverse condition so that inspection and repairs could be performed prior to failure of the system that might lead to a costly fix and other risks.

The main contribution of this thesis is the development of a neural network model to assess the probable condition of sewers to prioritize inspection requirements. This prediction model is developed to improve the objectivity of proactive management of sewer systems.

The neural network model was developed utilizing the City of Atlanta's condition assessment survey database. Since all the parameters that were identified to affect the sewer deterioration, as identified in the literature were not readily available to be incorporated in this model, it is recommended that the model be expanded to encompass those parameters and retrained. Through this process the neural network will keep learning the updated information and adjust its hidden weights to ensure the forecasting accuracy.

To accurately quantify the effect of certain input parameters for sewer deterioration, it will be useful to develop a neural network model, as demonstrated in this thesis as an initial starting base. However, subsequent models with more descriptive parameters will enhance the understanding of the effects of influencing input parameters on sewer systems.

6.4 RECOMMENDATIONS FOR FUTURE WORK

Since the developed model does not include a number of parameters thought to be important to sewer deterioration, the model developed in this exercise is not complete. While it demonstrates the utility of using Artificial Neural Networks for predicting sewer condition, further work for data collection and model development is required to ensure that the model is more accurate and reliable for future applications.

Having made the above conclusions, it is clear more work is required to facilitate future use of the model. This thesis illustrates the need for the following actions, to facilitate ease, and more comprehensive development of Artificial Neural Network models for sewer condition prediction:

- Inclusion of more descriptive data.

- Collection technique improvements of present data. Advances in embedded sensor technology can be used to get more information on the deterioration trends in the sewer pipes, and information obtained from this can be used to enhance the prediction capabilities of the model.
- Exploration of input parameter importance, and other factors affecting sewer deterioration.

To further the development of neural network models that are accurate and flexible, inclusion of more descriptive data is needed. The model developed in this research required making assumptions that were scope limiting since it required values from some factors that may affect the sewer deterioration process. The availability of detailed soils parameters, physical pipe characteristics, and in-situ pipe conditions would be assets to fully understand and model the deterioration of sewers and accurately predict their condition. A list of possible parameters that can be factored into the model is listed below.

Table 6.1 – Recommended List of Parameters that needs to be incorporated in Future ANN Models

Parameter	Range of Variables
Surface Loads	High (1)/Low (0)
Groundwater Level	High (1)/Low (0)
Frost Heave Factor	High (1)/Low (0)
Bedding Condition	Good (1)/Poor (0)
Backfill Soil Type	Cohesive (1)/Non-Cohesive (0)
Soil Aggressivity	High (1)/Low (0)
Soil Stability Factor	High (1)/Low (0)

Parameter	Range of Variables
Sewerage Characteristics	Corossivity, pH, etc.
Number of Laterals	Number
Tree Root Problem	High (1)/Low (0)
Sewer Location	Residential/Commercial/Industrial
Construction Quality	Expert Factor (0-1)
Ground Movement	High (1)/Low (0)

The neural network based sewer condition prediction model can then be integrated with a comprehensive infrastructure asset management system to aid the municipal agencies in better planning and spending of their limited available budget. Figure 6.1 illustrates a flow chart of the proposed integrated model to make decisions for inspection prioritization using the built neural network model.

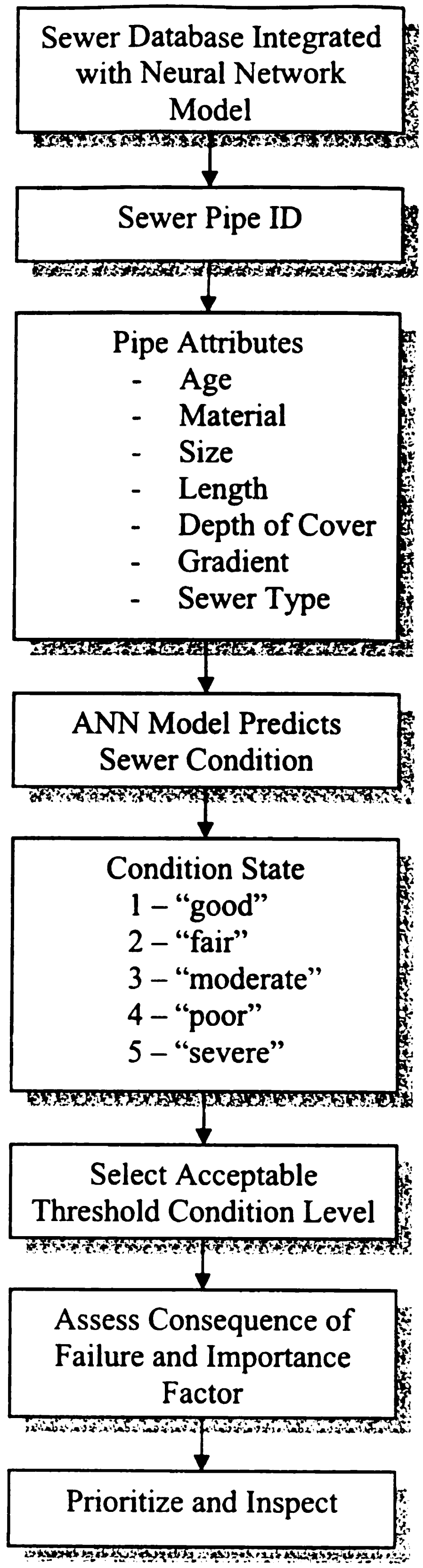

Figure 6.1 – Conceptual Integration of ANN Model

APPENDIX A

INTERNAL SEWER CONDITION GRADES OF DEFECTS - CITY OF ATLANTA

Code	Definition	Condition Grade	Application
CN	Connection	1	Construction
CNA	Connection Abandoned	1	Construction
DC	Dimension Change	1	Construction
JN	Junction	1	Construction
JNA	Junction Abandoned	1	Construction
LC	Liner Changes	1	Construction
LD	Line Deviates Down	1	Construction
LL	Line Deviates Left	1	Construction
LR	Line Deviates Right	1	Construction
LU	Line Deviates Up	1	Construction
MC	Material Change	1	Construction
MH	Manhole	1	Construction
SC	Sewer Shape Changes	1	Construction
CU	Camera Underwater	1	Miscellaneous
FH	Finish Survey	1	Miscellaneous
GO	General Observation	1	Miscellaneous
GOA	General Observation Abandon	1	Miscellaneous
SA	Survey Abandoned	1	Miscellaneous
ST	Start Survey	1	Miscellaneous
WL	Water Level	1	Miscellaneous
ABS	Abandon Service	1	Service
DE	Deposit	2	Service
DEG	Deposit Grease	2	Service
DEJ	Debris at Joint	2	Service
DEP	Defective Plumbing in Bldg	1	Service
DES	Deposit Silt	2	Service
EH	Encrustation Heavy	4	Service
EHJ	Encrustation Heavy at Joint	4	Service
EL	Encrustation Light	2	Service
ELJ	Encrustation Light at Joint	2	Service
EM	Encrustation Medium	3	Service
EMJ	Encrustation Medium at Joint	3	Service
ESH	Scale Heavy	4	Service
ESL	Scale Light	1	Service
ESM	Scale Medium	3	Service
HI	MH Below Grade	1	Service
ID	Infiltration Dripper	2	Service

Code	Definition	Condition Grade	Application
IDJ	Infiltration Dripper at Joint	2	Service
IG	Infiltration Gusher	4	Service
IR	Infiltration Runner	3	Service
IRJ	Infiltration Runner at Joint	3	Service
IS	Infiltration Seeper	2	Service
ISJ	Infiltration Seeper at Joint	3	Service
LO	MH Above Grade	1	Service
MCC	Missing Cleanout Cover	2	Service
OB	Obstruction	2	Service
RF	Fine Roots	1	Service
RFJ	Roots Fine at Joint	1	Service
RM	Mass Roots	3	Service
RMJ	Roots Medium at Joint	3	Service
RT	Tap Root	3	Service
RTJ	Roots Tap at Joint	3	Service
SS	Surface Spalling	3	Service
SSS	Surface Damage Spalling Slight	2	Service
V	Vermin – Rats	1	Service
AD	Area Drain	4	Structural
B	Pipe Broken	4	Structural
BC	MH Cover Cracked or Broken	5	Structural
BCO	Broken Cleanout	3	Structural
BF	MH Frame Cracked or Broken	5	Structural
BJ	Sewer Broken at Joint	4	Structural
CBX	Catch Basin	5	Structural
CC	Crack Circumferential	2	Structural
CCJ	Crack Circumferential at Joint	2	Structural
CL	Crack Longitudinal	2	Structural
CLJ	Crack Longitudinal at Joint	2	Structural
CM	Cracks Multiple	3	Structural
CMJ	Crack Multiple at Joint	3	Structural
CNI	Connection Intruding	4	Structural
CX	Connection Defective	4	Structural
CXI	Connection Defective Intruding	4	Structural
D	Deformed	4	Structural
DB	Brick Displaced	3	Structural
DH	Deformation Horizontal	4	Structural
DI	Dropped Invert	4	Structural
DV	Deformation Vertical	4	Structural
DWD	Driveway Drain	4	Structural
EXP	Exposed Pipe	3	Structural

Code	Definition	Condition Grade	Application
FC	Fracture Circumferential	3	Structural
FCJ	Fracture Circumferential at Joint	3	Structural
FCL	Frame/Cover Leaks	3	Structural
FDD	Foundation Drain	3	Structural
FL	Fracture Longitudinal	3	Structural
FLJ	Fracture Longitudinal at Joint	3	Structural
FM	Fractures Multiple	4	Structural
FMJ	Fracture Multiple at Joint	4	Structural
H	Hole	4	Structural
HOL	Soil Fissures	3	Structural
HSD	Hole in Storm Ditch	4	Structural
JDL	Joint Displaced Large	2	Structural
JDM	Joint Displaced Medium	1	Structural
JDS	Joint Displaced Slight	2	Structural
JX	Junction Defective	4	Structural
LN	Liner Defect	1	Structural
MB	Brick Missing	4	Structural
MFC	Manhole Frame/Cover	3	Structural
MHS	Manhole Structure	3	Structural
MLK	Multiple Soil Fissures	3	Structural
MM	Missing Mortar Medium	2	Structural
MS	Missing Mortar Surface	1	Structural
MT	Missing Mortar Total	3	Structural
OJL	Open Joint Large	2	Structural
OJM	Open Joint Medium	1	Structural
OJS	Open Joint Slight	1	Structural
RLD	Roof Leader Connected	4	Structural
SGL	Surface Damage Corrosion Large	4	Structural
SGM	Surface Damage Corrosion Medium	3	Structural
SMH	Storm Manhole	4	Structural
SSL	Surface Damage Spalling Large	4	Structural
SSM	Surface Damage Spalling Medium	3	Structural
SW	Surface Damage Wear	4	Structural
SWD	Stairwell Drain	2	Structural
SWL	Surface Wear Large	4	Structural
SWM	Surface Wear Medium	3	Structural
SWS	Surface Wear Slight	2	Structural
WWD	Windowwell Drain	2	Structural
X	Collapsed	5	Structural

Code	Definition	Condition Grade	Application
XM	Collapsed Manhole	5	Structural
Z	Multiple	3	Structural

APPENDIX B

DATA SAMPLES USED FOR MODELING

TRAINING FACTS

OUTF LAT LENGTH SIZE CO VC 31-35 36-40 41-45 46-50 51-55 56-60 >60 DEPTH SLOPE OUTPUT

□-------- 1
1 0 215 18 1 0 0 0 0 0 1 0 0 15.9 0.001
3
□-------- 2
1 0 350 18 1 0 0 0 0 0 1 0 0 18.5 0.013
3
□-------- 3
1 0 273 15 1 0 0 0 0 0 1 0 0 9.7 0.005
3
□-------- 4
1 0 416 30 1 0 0 0 0 0 1 0 0 11.4 0.011
3
□-------- 5
1 0 166 30 1 0 0 0 0 0 1 0 0 9.2 0
1
□-------- 6
1 0 241 15 1 0 0 0 0 0 1 0 0 12.6 0.023
3
□-------- 7
1 0 494 30 1 0 0 0 0 0 1 0 0 13.5 0.027
3
□-------- 8
1 0 489 30 1 0 0 0 0 0 1 0 0 9 0.001
3
□-------- 9
1 0 324 15 1 0 0 0 0 0 1 0 0 14.3 0.007
3
□-------- 10
1 0 367 15 1 0 0 0 0 0 1 0 0 10.1 0.01
3
□-------- 11
1 0 404 15 1 0 0 0 0 0 1 0 0 9.3 0.004
3
□-------- 12
0 1 238 8 1 0 0 0 0 1 0 0 0 9.6 0.015
3
□-------- 13
0 1 293 8 1 0 0 0 0 1 0 0 0 10.3 0.008

```
3
□-------- 14
0    1    388    8    1    0    0    0    1    0    0    0    0    8.6    0.01
3
□-------- 15
0    1    332    8    1    0    0    0    1    0    0    0    0    8.9    0.009
3
□-------- 16
0    1    205    8    1    0    0    0    1    0    0    0    0    9.8    0.009
3
□-------- 17
0    1    245    8    1    0    0    0    1    0    0    0    0    8.3    0.003
3
□-------- 18
0    1    162    8    1    0    0    0    1    0    0    0    0    8      0.016
2
□-------- 19
0    1    240    8    1    0    0    0    0    1    0    0    0    8.4    0.006
2
□-------- 20
0    1    254    8    1    0    0    0    0    1    0    0    0    10     0.019
2
□-------- 21
0    1    267    8    1    0    0    0    1    0    0    0    0    12.5   0.008
3
□-------- 22
0    1    360    8    1    0    0    0    1    0    0    0    0    11.3   0.012
3
□-------- 23
0    1    112    8    1    0    0    0    0    1    0    0    0    10.4   0.004
3
□-------- 24
0    1    170    8    1    0    0    1    0    0    0    0    0    7.9    0.012
1
□-------- 25
0    1    249    8    1    0    0    0    0    1    0    0    0    9.7    0.002
3
□-------- 26
0    1    148    8    1    0    0    0    0    1    0    0    0    9.3    0.008
2
□-------- 27
0    1    374    8    1    0    0    0    0    1    0    0    0    12     0
3
□-------- 28
0    1    283    8    1    0    0    0    0    1    0    0    0    8.7    0.005
3
```

□-------- 29
0 1 114 8 1 0 0 0 0 1 0 0 0 8 0.001
2
□-------- 30
0 1 122 8 1 0 0 0 0 1 0 0 0 9.3 0.003
3
□-------- 31
0 1 256 8 1 0 0 0 0 1 0 0 0 9.7 0.018
1
□-------- 32
0 1 202 8 1 0 0 1 0 0 0 0 0 9.3 0.001
3
□-------- 33
0 1 401 8 1 0 0 1 0 0 0 0 0 8.7 0.002
3
□-------- 34
0 1 126 8 1 0 0 0 0 1 0 0 0 14 0.031
3
□-------- 35
0 1 487 8 1 0 0 0 0 1 0 0 0 8.9 0.006
3
□-------- 36
0 1 144 8 1 0 0 1 0 0 0 0 0 8.3 0.004
2
□-------- 37
0 1 290 8 1 0 0 0 0 1 0 0 0 10.9 0.015
3
□-------- 38
0 1 130 8 1 0 0 1 0 0 0 0 0 9 0.002
1
□-------- 39
0 1 84 8 1 0 0 1 0 0 0 0 0 8.5 0.014
2
□-------- 40
0 1 258 8 1 0 0 0 0 1 0 0 0 11.4 0.005
3
□-------- 41
0 1 139 8 1 0 0 0 0 1 0 0 0 11.8 0.001
3
□-------- 42
0 1 226 8 1 0 0 0 1 0 0 0 0 9.2 0.004
3
□-------- 43
0 1 316 8 1 0 0 0 1 0 0 0 0 9.3 0.002
3
□-------- 44

```
0   1   177   8   1   0   0   0   1   0   0   0   0   9.4   0.005
2
□-------- 45
0   1   183   8   1   0   0   0   0   1   0   0   0   12.2   0.002
2
□-------- 46
0   1   440   8   1   0   0   0   0   1   0   0   0   11   0.004
3
□-------- 47
0   1   375   8   1   0   0   0   1   0   0   0   0   9.9   0.001
3
□-------- 48
0   1   394   8   1   0   0   0   0   1   0   0   0   12   0.002
3
□-------- 49
0   1   158   8   1   0   0   1   0   0   0   0   0   11.3   0.005
3
□-------- 50
0   1   372   8   1   0   0   0   0   1   0   0   0   9.9   0.004
3
□-------- 51
0   1   397   8   1   0   0   0   1   0   0   0   0   9.5   0.004
3
□-------- 52
0   1   345   8   1   0   0   0   0   1   0   0   0   10   0.002
2
□-------- 53
1   0   259   8   1   0   1   0   0   0   0   0   0   12.2   0.017
2
□-------- 54
1   0   232   8   1   0   1   0   0   0   0   0   0   19.9   0.057
2
□-------- 55
1   0   437   10   1   0   0   0   1   0   0   0   0   12.1   0.013
1
□-------- 56
1   0   142   8   1   0   0   0   1   0   0   0   0   8.1   0.013
3
□-------- 57
1   0   247   10   1   0   0   0   1   0   0   0   0   11.1   0.01
2
□-------- 58
1   0   212   10   1   0   0   0   1   0   0   0   0   11.8   0.006
2
□-------- 59
1   0   128   10   1   0   0   0   1   0   0   0   0   11.6   0.005
```

1
□-------- 60
1 0 328 10 1 0 0 0 1 0 0 0 0 11.3 0.004
3
□-------- 61
1 0 365 10 1 0 0 0 1 0 0 0 0 9.3 0.001
3
□-------- 62
1 0 230 10 1 0 0 0 1 0 0 0 0 9.2 0.004
3
□-------- 63
1 0 255 10 1 0 0 0 1 0 0 0 0 9.9 0.007
2
□-------- 64
1 0 500 15 1 0 0 0 0 0 1 0 0 13.9 0.011
2
□-------- 65
0 1 139 8 1 0 0 0 1 0 0 0 0 10.5 0.022
3
□-------- 66
1 0 263 18 1 0 0 0 0 0 1 0 0 14 0.053
1
□-------- 67
1 0 256 8 1 0 0 1 0 0 0 0 0 9.1 0.001
3
□-------- 68
1 0 312 18 1 0 0 0 0 0 1 0 0 13.5 0.023
3
□-------- 69
1 0 353 18 1 0 0 0 0 0 1 0 0 17.4 0.019
2
□-------- 70
1 0 405 18 1 0 0 0 0 0 1 0 0 12 0.009
1
□-------- 71
1 0 331 18 1 0 0 0 0 0 1 0 0 11.9 0.009
3
□-------- 72
1 0 190 18 1 0 0 0 0 0 1 0 0 10.7 0.002
2
□-------- 73
0 1 258 8 1 0 0 0 0 1 0 0 0 10.5 0.001
2
□-------- 74
0 1 291 8 1 0 0 0 0 1 0 0 0 8.4 0.002
1

□-------- 75
0 1 202 15 1 0 0 0 0 0 0 1 0 5 0
3
□-------- 76
0 1 232 8 1 0 0 0 0 1 0 0 0 9.5 0.011
3
□-------- 77
0 1 109 8 1 0 0 0 0 1 0 0 0 8.2 0.045
1
□-------- 78
0 1 131 8 1 0 0 0 0 1 0 0 0 12.5 0.001
2
□-------- 79
0 1 219 8 1 0 0 0 0 0 0 1 0 6.8 0.014
2
□-------- 80
0 1 384 8 1 0 0 0 0 0 0 1 0 7.2 0.006
3
□-------- 81
0 1 170 8 1 0 0 0 0 0 0 1 0 6.8 0.018
3
□-------- 82
0 1 176 8 1 0 0 0 0 0 0 1 0 13.2 0.012
3
□-------- 83
0 1 345 8 1 0 0 0 0 0 0 0 1 10.4 0.009
3
□-------- 84
0 1 151 8 1 0 0 0 0 0 1 0 0 7.8 0.003
3
□-------- 85
0 1 352 8 1 0 0 0 0 0 1 0 0 8.7 0.003
2
□-------- 86
0 1 214 8 1 0 0 0 0 0 1 0 0 6.7 0.013
1
□-------- 87
0 1 180 8 1 0 0 0 0 1 0 0 0 5.8 0.003
1
□-------- 88
0 1 500 8 1 0 0 0 0 1 0 0 0 10 0.014
3
□-------- 89
0 1 286 8 1 0 0 0 0 1 0 0 0 6 0.003
4
□-------- 90

0 1 224 8 1 0 0 0 0 1 0 0 0 8.4 0.007
2
□-------- 91
0 1 389 8 1 0 0 0 0 1 0 0 0 9.6 0.001
1
□-------- 92
0 1 282 8 1 0 0 0 0 1 0 0 0 6.5 0.007
2
□-------- 93
0 1 311 8 1 0 0 0 0 1 0 0 0 9.7 0.006
3
□-------- 94
0 1 314 8 1 0 0 0 0 0 0 1 0 11 0.003
3
□-------- 95
0 1 291 8 1 0 0 0 0 1 0 0 0 6.5 0.002
1
□-------- 96
0 1 121 8 1 0 0 0 0 0 0 1 0 6.5 0.03
1
□-------- 97
0 1 267 8 1 0 0 0 0 0 0 1 0 9 0.026
1
□-------- 98
0 1 281 8 1 0 0 0 0 0 0 1 0 10.3 0.002
3
□-------- 99
0 1 129 8 1 0 0 0 0 0 0 1 0 10.4 0.002
3
□-------- 100
0 1 72 8 1 0 0 0 0 0 0 1 0 10.2 0.013
1
□-------- 101
0 1 113 8 1 0 0 0 0 0 0 1 0 9.6 0.012
3
□-------- 102
0 1 80 8 1 0 0 0 0 0 0 1 0 10.9 0.006
1
□-------- 103
0 1 321 8 1 0 0 0 0 0 0 1 0 8.8 0.007
3
□-------- 104
0 1 197 8 1 0 0 0 0 0 0 1 0 9.7 0.016
2
□-------- 105
0 1 216 8 1 0 0 0 0 0 0 1 0 8.2 0.002

3
□-------- 106
0 1 200 8 1 0 0 0 0 0 0 1 0 12 0.029
3
□-------- 107
0 1 290 8 1 0 0 0 0 0 0 1 0 11.9 0.026
1
□-------- 108
0 1 428 8 1 0 0 0 0 0 1 0 0 18.7 0.038
1
□-------- 109
0 1 419 8 1 0 0 0 0 1 0 0 0 7.3 0.006
3
□-------- 110
0 1 217 8 1 0 0 0 0 1 0 0 0 10 0.008
3
□-------- 111
0 1 378 8 1 0 0 0 0 0 1 0 0 9.2 0.013
3
□-------- 112
0 1 278 8 1 0 0 0 0 0 0 1 0 8.6 0.002
3
□-------- 113
0 1 135 15 1 0 0 0 0 0 0 1 0 10.9 0.06
2
□-------- 114
0 1 77 10 1 0 0 0 0 0 1 0 0 4.9 0.037
2
□-------- 115
0 1 311 15 1 0 0 0 0 0 0 1 0 6 0.007
1
□-------- 116
0 1 200 15 1 0 0 0 0 0 0 1 0 5.65 0
2
□-------- 117
0 1 133 8 0 1 0 0 1 0 0 0 0 9 0.011
3
□-------- 118
0 1 331 8 0 1 0 0 1 0 0 0 0 10.2 0.001
3
□-------- 119
0 1 169 8 0 1 0 0 1 0 0 0 0 12 0.008
3
□-------- 120
0 1 282 8 0 1 0 0 1 0 0 0 0 9.8 0.004
3

□-------- 121
0 1 131 8 0 1 0 0 1 0 0 0 0 8.8 0.003
3
□-------- 122
0 1 272 8 0 1 0 0 1 0 0 0 0 9.5 0.012
3
□-------- 123
0 1 194 8 0 1 0 0 1 0 0 0 0 9.4 0.01
3
□-------- 124
0 1 271 8 0 1 1 0 0 0 0 0 0 7.6 0.006
2
□-------- 125
0 1 181 8 0 1 1 0 0 0 0 0 0 6.6 0.002
2
□-------- 126
0 1 192 8 0 1 0 0 1 0 0 0 0 9.8 0.007
3
□-------- 127
0 1 162 8 0 1 0 0 1 0 0 0 0 10.4 0.016
3
□-------- 128
0 1 229 8 0 1 0 0 1 0 0 0 0 12.1 0.004
3
□-------- 129
1 0 96 8 0 1 1 0 0 0 0 0 0 3.8 0.079
1
□-------- 130
1 0 318 8 0 1 1 0 0 0 0 0 0 14.2 0.005
3
□-------- 131
1 0 265 12 0 1 1 0 0 0 0 0 0 9.4 0.014
2
□-------- 132
1 0 374 12 0 1 1 0 0 0 0 0 0 7.4 0
3
□-------- 133
1 0 155 12 0 1 1 0 0 0 0 0 0 7.4 0
3
□-------- 134
1 0 182 12 0 1 1 0 0 0 0 0 0 7.5 0.002
2
□-------- 135
1 0 112 8 0 1 1 0 0 0 0 0 0 19.7 0.12
3
□-------- 136

1 0 139 8 0 1 1 0 0 0 0 0 0 8.1 0.016
3
□-------- 137
1 0 149 8 0 1 1 0 0 0 0 0 0 6.9 0.002
3
□-------- 138
1 0 146 8 0 1 1 0 0 0 0 0 0 6.7 0.003
3
□-------- 139
1 0 298 8 0 1 1 0 0 0 0 0 0 10.7 0.007
3
□-------- 140
0 1 60 8 0 1 0 0 0 0 0 1 0 6.8 0.004
2
□-------- 141
0 1 65 8 0 1 0 0 0 0 0 1 0 5 0.004
2
□-------- 142
0 1 109 8 0 1 0 0 0 0 0 1 0 5 0.007
2

TESTING FACTS

OUTF LAT LENGTH SIZE CO VC 31-35 36-40 41-45 46-50 51-55 56-60 >60
DEPTH SLOPE OUTPUT(DESIRED)
□-------- 1
1 0 362 30 1 0 0 0 0 0 1 0 0 12.5 0.003
3
□-------- 2
1 0 259 15 1 0 0 0 0 0 1 0 0 10.3 0
3
□-------- 3
0 1 208 8 1 0 0 0 1 0 0 0 0 8.8 0.02
3
□-------- 4
0 1 255 8 1 0 0 0 1 0 0 0 0 10.7 0.013
3
□-------- 5
0 1 204 8 1 0 0 0 0 1 0 0 0 10.2 0.002
2
□-------- 6
0 1 134 8 1 0 0 0 0 1 0 0 0 8.7 0.002
2

□-------- 7

0 1 184 8 1 0 0 0 0 1 0 0 0 11.9 0.003

3

□-------- 8

0 1 117 8 1 0 0 0 1 0 0 0 0 9.2 0.006

2

□-------- 9

0 1 227 8 1 0 0 0 1 0 0 0 0 9.5 0.004

2

□-------- 10

1 0 292 8 1 0 0 0 1 0 0 0 0 12 0.019

3

□-------- 11

1 0 253 8 1 0 0 0 1 0 0 0 0 8.3 0.009

3

□-------- 12

0 1 200 8 1 0 0 0 1 0 0 0 0 9.9 0.009

3

□-------- 13

0 1 96 8 1 0 0 1 0 0 0 0 0 9.3 0

2

□-------- 14

0 1 186 8 1 0 0 0 0 1 0 0 0 8.6 0.044

2

□-------- 15

0 1 153 8 1 0 0 0 0 0 0 0 1 9.3 0.002

3

□-------- 16

0 1 201 8 1 0 0 0 0 1 0 0 0 6.3 0.002

1

□-------- 17

0 1 247 8 1 0 0 0 0 0 0 1 0 6.1 0.004

2

□-------- 18

0 1 125 8 1 0 0 0 0 0 0 1 0 10.1 0.005

3

□-------- 19

0 1 175 8 1 0 0 0 0 0 0 1 0 8 0.011

2

□-------- 20

0 1 344 8 1 0 0 0 0 0 0 0 1 10.5 0.012

3

□-------- 21

0 1 197 8 0 1 0 0 1 0 0 0 0 11 0.008

3

□-------- 22

0 1 154 8 0 1 0 0 1 0 0 0 0 9.6 0.021
3
□-------- 23
0 1 235 8 0 1 0 0 1 0 0 0 0 10.6 0.001
3
□-------- 24
1 0 253 8 0 1 1 0 0 0 0 0 0 6.9 0.019
3
□-------- 25
0 1 300 8 0 1 0 0 0 1 0 0 0 8.7 0.004
2

TESTING OUTPUT (@ 40995 RUNS)

OUTF LAT LENGTH SIZE CO VC 31-35 36-40 41-45 46-50 51-55 56-60 >60
DEPTH SLOPE OUTPUT(PREDICTED)

□-------- 1
1.0000 0.0000 362.00 30.002 1.0000 0.0000 0.0000 0.0000 0.0000 0.0000 1.0000
0.0000 0.0000 12.500 0.0029
2.8144
□-------- 2
1.0000 0.0000 259.09 15.000 1.0000 0.0000 0.0000 0.0000 0.0000 0.0000 1.0000
0.0000 0.0000 10.302 0.0000
3.2861
□-------- 3
0.0000 1.0000 208.06 8.0020 1.0000 0.0000 0.0000 0.0000 1.0000 0.0000 0.0000
0.0000 0.0000 8.8012 0.0200
2.7632
□-------- 4
0.0000 1.0000 255.01 8.0020 1.0000 0.0000 0.0000 0.0000 1.0000 0.0000 0.0000
0.0000 0.0000 10.699 0.0130
2.8327
□-------- 5
0.0000 1.0000 204.09 8.0020 1.0000 0.0000 0.0000 0.0000 0.0000 1.0000 0.0000
0.0000 0.0000 10.200 0.0020
2.5039
□-------- 6
0.0000 1.0000 134.05 8.0020 1.0000 0.0000 0.0000 0.0000 0.0000 1.0000 0.0000
0.0000 0.0000 8.7030 0.0020
2.1699
□-------- 7

0.0000 1.0000 184.00 8.0020 1.0000 0.0000 0.0000 0.0000 0.0000 1.0000 0.0000
0.0000 0.0000 11.902 0.0029
2.7097
□-------- 8
0.0000 1.0000 117.08 8.0020 1.0000 0.0000 0.0000 0.0000 1.0000 0.0000 0.0000
0.0000 0.0000 9.2022 0.0060
2.1201
□-------- 9
0.0000 1.0000 227.08 8.0020 1.0000 0.0000 0.0000 0.0000 1.0000 0.0000 0.0000
0.0000 0.0000 9.5009 0.0040
2.8489
□-------- 10
1.0000 0.0000 292.07 8.0020 1.0000 0.0000 0.0000 0.0000 1.0000 0.0000 0.0000
0.0000 0.0000 12.000 0.0190
1.7839
□-------- 11
1.0000 0.0000 253.07 8.0020 1.0000 0.0000 0.0000 0.0000 1.0000 0.0000 0.0000
0.0000 0.0000 8.3020 0.0090
2.3120
□-------- 12
0.0000 1.0000 200.01 8.0020 1.0000 0.0000 0.0000 0.0000 1.0000 0.0000 0.0000
0.0000 0.0000 9.9018 0.0090
2.7588
□-------- 13
0.0000 1.0000 96.026 8.0020 1.0000 0.0000 0.0000 1.0000 0.0000 0.0000 0.0000
0.0000 0.0000 9.3004 0.0000
1.3906
□-------- 14
0.0000 1.0000 186.04 8.0020 1.0000 0.0000 0.0000 0.0000 0.0000 1.0000 0.0000
0.0000 0.0000 8.6008 0.0440
1.3657
□-------- 15
0.0000 1.0000 153.06 8.0020 1.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
0.0000 1.0000 9.3004 0.0020
2.9873
□-------- 16
0.0000 1.0000 201.08 8.0020 1.0000 0.0000 0.0000 0.0000 0.0000 1.0000 0.0000
0.0000 0.0000 6.3013 0.0020
1.9158
□-------- 17
0.0000 1.0000 247.06 8.0020 1.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
1.0000 0.0000 6.1009 0.0040
3.0840
□-------- 18
0.0000 1.0000 125.03 8.0020 1.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
1.0000 0.0000 10.102 0.0050

2.4826
□-------- 19
0.0000 1.0000 175.08 8.0020 1.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
1.0000 0.0000 8.0033 0.0109
2.8503
□-------- 20
0.0000 1.0000 344.06 8.0020 1.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
0.0000 1.0000 10.503 0.0120
2.9880
□-------- 21
0.0000 1.0000 197.00 8.0020 0.0000 1.0000 0.0000 0.0000 1.0000 0.0000 0.0000
0.0000 0.0000 11.002 0.0080
2.8533
□-------- 22
0.0000 1.0000 154.03 8.0020 0.0000 1.0000 0.0000 0.0000 1.0000 0.0000 0.0000
0.0000 0.0000 9.6031 0.0210
2.7178
□-------- 23
0.0000 1.0000 235.03 8.0020 0.0000 1.0000 0.0000 0.0000 1.0000 0.0000 0.0000
0.0000 0.0000 10.601 0.0010
2.9038
□-------- 24
1.0000 0.0000 253.07 8.0020 0.0000 1.0000 1.0000 0.0000 0.0000 0.0000 0.0000
0.0000 0.0000 6.9027 0.0190
2.9997
□-------- 25
0.0000 1.0000 300.02 8.0020 0.0000 1.0000 0.0000 0.0000 0.0000 1.0000 0.0000
0.0000 0.0000 8.7030 0.0040
2.1377

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