UNIVERSITY OF CINCINNATI

Date: 10-Aug-2010

I, Moustafa Abdel Moteleb ,

hereby submit this original work as part of the requirements for the degree of:

Doctor of Philosophy

in Civil Engineering

It is entitled:

Risk Based Decision Making Tools for Sewer Infrastructure Management

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Risk Based Decision Making Tools for Sewer Infrastructure Management

A dissertation submitted to

Division of Research and Advanced Studies
of the University of Cincinnati

in partial fulfillment of the
requirements for the degree of

DOCTOR OF PHILOSOPHY

in the Department of Civil and Environmental Engineering
of the College of Engineering

August, 2010

By

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ABSTRACT

Wastewater utilities in the United States face an aging workforce, higher consumer expectations, stricter environmental regulations, security concerns, and an aging infrastructure. As a result, many utilities have turned to Asset Management for better decision making to prioritize their needs. According to numerous studies that were conducted in the past decade, most notably the USEPA's Clean Water and Drinking Water Infrastructure GAP Analysis Report and the ASCE Report Card, wastewater utilities will need to invest approximately 390 billion in capital infrastructure over the next two decades. Meanwhile, the field of Asset Management is emerging to improve the decision making process to renew, replace, or rehabilitate the nation's infrastructure. Asset management can be defined as set of activities, guidelines, and decision tools that seek to minimize the life cycle costs of capital and O&M spending while maintaining an acceptable minimum level of service (USEPA 2006).

This research provides a road map for the implementation of asset management in wastewater utilities with a strong focus on the critical tools that are needed to identify, quantify, and manage risk associated with the structural failure of sewers. The two components of the Business Risk Exposure; namely the probability and consequences of failure were thoroughly evaluated. Criticality matrices for linear assets were developed using expert opinion. A GIS based criticality tool was developed to identify the most critical assets. The GIS model was developed to eliminate biases and establish a systematic methodology to quantify the impact of failure of an asset. Subsequently, maps were generated showing the critical sewers that the utility needs to focus its efforts on to reduce its risk exposure. Probability curves of sewer failure were developed using historical data extracted from repair history performed between 1997 and 2009. Closed Circuit Television (CCTV) condition assessment methodologies are the basis for the development of deterioration curves used by academics in the U.K., the U.S., Australia, and Canada. Condition based methodologies that are dependent of CCTV data are resource intensive and their output

is subjective. The methods employed in this research to determine the probability of pipe failure are independent of CCTV of the assets. Deterministic models using polynomial regression analysis were developed to describe the deterioration of sewers with age. Probabilistic models were utilized using data fitting and Monte Carlo simulation. Soft computing methods were also used under this research by developing General Regression Neural Network Deterioration Models (GRNNDM) to predict the probability of sewers failure with age.

DEDICATION

This work is dedicated to my father who always wanted me to excel in my education and achieve higher goals. His memory and influence will always live on with me.

ACKNOWLEDGMENTS

I would like to express my sincere gratitude and thanks to my academic advisor, Dr. Ossama Salem, for his guidance, advice, encouragement, and continuous support throughout the development of this work. He always guided me in the right direction with invaluable insights tapping into his vast experience and knowledge in the field of Infrastructure Management and Sustainability. I am indebted to Dr. Suidan for being my mentor and friend; and for giving me the opportunity to work and study at the University of Cincinnati for over a decade as one of his research associates. I am very thankful to the members of my committee: Dr. Heng Wei, and Dr. Larry Gales, for their advice, valuable contributions, and support.

I would like to thank my friends and colleagues: Karen Koran, Jose Padilla, Steve Ziegenfuss, Steve Seibert, and Ed Daly for their encouragement to complete my dissertation. I would like to thank Deputy Director of MSDGC Biju George for launching an Asset Management initiative that inspired me to develop this dissertation while I worked at the District. I would like to thank coworkers at MSDGC: Joe Koran, Rob Kneip, Mike Stevens, Bill Lutz, Jim Curry, and Scott Maring for their expert opinion and input. I would like to acknowledge the valuable contributions of Aimei Chen and Randy Schneider for providing me with data and expert advice related to asset inventory and repair history at MSDGC.

Special thanks to my mother and siblings for their love and support to advance my education. Most of all, I would like to thank to my wife Melissa for her love, support, and continuous encouragement to complete my dissertation. Thanks to my daughter, Sofia, for providing me with a new meaning and purpose to my existence.

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Chapter 1- INTRODUCTION

1.1 BACKGROUND

Numerous studies have been conducted to evaluate the condition of the infrastructure in the U.S. Most notable of these is the Annual Report Card of the American Society of Civil Engineers (ASCE), which examined the shortfall of funding to fix the problems. A challenge to solving infrastructure deficiencies is the poorly met need to optimize spending in a sustainable manner that meets budget constraints, costumers' expectations of a certain level of service, and regulatory requirements. Decision-making tools, financial resources, and new strategies for critical infrastructure maintenance and renewal are needed. In recent years, many entities attempted to provide answers to the rising challenge by implementing guidelines of Infrastructure Asset Management and Sustainability.

The National Research Council of the National Academies (NRC) defines the critical infrastructure as life systems (water, wastewater, power, transportation, and telecommunication systems), without which, other infrastructure systems cannot operate as intended. NRC defines sustainability as the ability of systems to meet the needs of current and future generations by being physically resilient, cost-effective, environmentally viable, and socially equitable (NRC 2009). This research will focus on risk based decision tools for the management of wastewater assets; more specifically, for sewers.

At the end of the 20th century, the United States had 30,000 wastewater treatment and collection facilities (GAO, 2008). Based on the Government Accountability Office (GAO), 41 percent of the wastewater utilities did not generate sufficient revenue to cover the cost of their service.

Roughly one-third of the wastewater utilities deferred maintenance because of insufficient funding while having 20 percent or more of their pipelines nearing the end of their useful life. This highlights the financial challenge that wastewater utilities are meeting today and the increasing needs to invest in a more smart and sustainable way.

According to the 2002 Clean Water Gap Analysis by the US Environmental Protection Agency (USEPA), wastewater utilities will need to invest approximately 390 billion in capital infrastructure over the next two decades. However, if utilities maintain current spending needs, and in light of the recent financial meltdown, funding of all needed investments is not feasible. Wastewater utilities in the United States face an aging workforce, higher consumer expectations, stricter environmental regulations, security concerns, and an aging infrastructure. As a result, many utilities have turned to asset management for better decision making to prioritize their needs.

Between 2000 and 2010, wastewater utilities in Australia, Canada, and Britain, have been successful in implementing a full scale Strategic Asset Management Plans (SAMPs) to formulate improved strategies for maintenance and renewal of their assets. In recent years, wastewater utilities across the U.S. started the implementation of asset management programs to improve the management of sewer lines, treatment plants, pump stations, and other assets. According to the National Mayor's Conference in 2007, 49% of major U.S. cities have begun to develop SAMPs for their water and wastewater infrastructure. Developing SAMPs can take a decade and usually involve the efforts of engineers, economists, and decision makers (Allbee, 2009). Asset Management can be defined as set of activities, guidelines, and decision tools that seek to minimize the life cycle costs of capital and O&M spending while maintaining an acceptable minimum level of service (USEPA, 2006). It is a collection of Best Management Practices (BMPs) that can guide an agency's investments throughout each stage of its asset's life cycle: planning, acquisition, operations, maintenance, renewal, and ultimately, decommissioning and disposal (WEFTEC, 2007). Asset management uses a combination of financial, economic, engineering and other practices applied to physical assets with the objective of providing the required level of service in the most cost-effective manner (IIMM, 2006). Achieving the lowest cost sustainable performance and providing a means to make better acquisition, operation and maintenance, and renewal or replacement decisions are ways to define the outcome of good asset management practices (USEPA, 2010). Asset management evaluates the inventory of assets, assets condition, age, service history, estimated useful life, and criticality; and then prioritizes assets based on a risk factor associated with the asset and its replacement or rehabilitation costs.

1.2 PROBLEM STATEMENT

Improved sanitation and water quality have been cited as one of the main factors contributing to the fight against disease resulting in an increasing life expectancy during the last century (WHO 2010). Sanitary and combined sewer pipes collect domestic sewage from buildings and storm water runoff and convey the raw sewage to wastewater treatment plants for the separation of solids and safe disposal of water to streams. Sewers represent the main component of the wastewater infrastructure systems (Ariaratnam, 2002). In the developed world, more than 90% of the population is supplied with gravity sewers for sanitation (WHO, 2000). Such extensive sewer networks often require intensive maintenance programs to extend their service life. Unfortunately, and similar to other segments of the infrastructure, sewers have been aging and better decision making tools are needed more than ever to formulate strategies for renewal and maintenance (Ana, 2009). The aging of the infrastructure coupled with the lack of a proactive asset management approach result in costly emergency repairs, maintenance costs, and a reduced level of service. The reactive management approach was deemed unsustainable due to the high cost of emergency repairs and due to increasing customer and regulatory pressures (Fenner, 2000). In order to address increased costs, meet higher customer's expectation and stricter regulatory requirements, wastewater utilities began implementing asset management systems to better manage their assets (Vanier, 2001).

The field of asset management provides a paradigm shift from responding to failures with rehabilitation and replacement projects to the prediction of failure before it occurs and mitigates the risk through risk assessment and preventive maintenance strategies (Allbee, 2009). Asset management enables utilities to make systematic decisions on operation and maintenance and capital construction, resulting in efficient management of assets over its whole life cycle. A successful asset management program should provide predictive tools to anticipate sewers failure, assess the risks associated with such failures, and provide prioritization strategies for capital and operating spending.

Condition based deterioration models are needed to predict the remaining useful life of sewers and are crucial to assess the risk associated with failure (Mehle et al., 2001). It is important to determine the factors affecting failure as well as their relative importance or their correlation with the probability of failure. The problem with such models, however, is that they depend on intensive inspection work using CCTV and expert review to assess the condition rating of the assets. Condition based rating using CCTV methodologies are often resource intensive and requires a long period of time, as long as decades. They provide snapshot assessment of the sewers' condition ratings that may become obsolete by the time the CCTV inspection is complete for the entire infrastructure network. Additionally, the output of condition based deterioration models is often a numerical value between one and five describing the asset rating in an abstract and subjective way. This is not the case when using statistical and probabilistic models to predict the failure of sewers. The output of probabilistic and statistical model is a numeric value that describes the probability of failure and is not subject to interpretation. Such probability of failure, coupled with the consequences of the asset's failure, can be used to determine the frequency of maintenance, rehabilitation, and the replacement of a particular sewer.

With funding scarcity, more and more rehabilitation of sewers are deferred and the overall condition of assets is worsening (GAO 2004; Vanier, 2001). Therefore, decision makers in wastewater utilities are in need of prioritization and decision support systems now more than ever. Such decision support systems will aid the utility manager to better address the structural and hydraulic failure of sewers, proactively, while meeting financial constraints, level of service, and regulatory requirements. This doctoral research focuses on the development of deterioration models of sewers as well as developing criticality assessment tool for the management of risk associated with sewer failure. This research will provide a framework for the decision making to formulate capital and O&M strategies to prioritize and optimize competing needs.

1.3 RESEARCH OBJECTIVES

While this research will focus on the critical tools that are needed to identify, quantify, and manage risk associated with linear assets, the probability of failure of sewer pipes as well as the impact of such failure will be thoroughly evaluated. Criticality matrices for linear assets will be developed using expert opinion and Geographical Information Systems (GIS). Maps will be developed highlighting the critical sewers in the collection network. The GIS software (ESRI) will pull attributes from CAGIS to calculate the criticality index of various linear assets. Attributes for MSDGC sewers will be obtained from the Cincinnati Area Geographical Information System (CAGIS) and will serve as the primary source of data for asset inventory data. Historical failure data during the past decade at MSDGC will be collected and manipulated to generate deterioration models. Probabilistic deterioration models will employ techniques such as Probabilistic Neural Networks (PNN), Monte Carlo Simulation, and regression analyses. Probability of failure for linear assets using deterministic, probabilistic, and soft computing methods will be compared. O&M and capital spending strategies will be developed based on risk minimization. A comparison of the methods and developed models as well as a review of the results will be provided.

1.3.1 Main objectives

The following are the main objectives of this doctoral research study:

- Investigate various methods to model sewer structural deterioration, and;
- Develop deterministic, probabilistic, and soft computing models for the deterioration of sewers, and;
- Provide a critique and comparison of the models.

1.3.2 Specific objectives

Specific objectives for this research dissertation:

- Review the existing sewer deterioration modeling techniques;
- Develop deterministic sewer deterioration models using polynomial regression analysis;
- Develop probabilistic sewer deterioration models using Monte Carlo simulation and distribution fitting of data;
- Develop sewer deterioration models using Neural Networks;
- Develop conceptual strategies to optimize both capital and operation spending to maintain, rehabilitate, and renew sewer networks.

1.4 RESEARCH METHODOLOGY

The research methodology used in this study involves both quantitative analysis and analysis of qualitative data. The research methodology combines the review of scientific literature, data collection, statistical analysis, expert opinions and case studies. Research of the literature was conducted to identify the best management practices, national and international, in the implementation of asset management programs in wastewater utilities. Data were collected from the Cincinnati Area Geographical Information System (CAGIS) for attributes related to the collection system in the area as well as the repair history between 1997 and 2009. Data collected from MSDGC serves as the main quantitative source for this dissertation. Researched attributes and factors affecting sewer failure include pipe material, age, soil conditions, depth, size, hydraulic conditions, and construction methods. Data from CAGIS served as the sole source of information to develop the asset inventory for MSDGC. Historical repair data were used to predict future failure of sewers. The data collected is quantitatively analyzed using statistical analysis tools. Statistical software packages including Microsoft Excel, Minitab 15 Statistics (Minitab Inc.), DecisionTools Suite 5.5.1 (Palisades Corporation), and Quantum XL software (SigmaZone Inc.) were used in this study to develop the statistical models. The basis of the conclusions and recommendations of this research study is founded upon the statistical analysis results as well as best management practices available in the literature. Expert opinion and interviews will be used to develop the risk management approach for identifying the critical sewer infrastructure and to validate results obtained for the deterioration models.

1.5 DISSERTATION ORGANIZATION

Literature review on the risk based failure models in asset management of sewers is presented in the second chapter. Publications on asset and infrastructure management, most notably publications by the USEPA, CBO, GAO, and NRC, were reviewed. Various engineering journals and conference proceedings including Water Environment Federation (WEF) and the American Society of Civil Engineers (ASCE) journals and proceedings were searched. The literature was reviewed to identify best management practices and existing sewer failure models- probabilistic and deterministic- in the literature. International journals such as International Water Association (IWA) were searched for relevant research papers. In addition, various best management practices and case studies of existing asset management programs of utilities in Australia, Canada, Europe, and the U.S. were researched. The research methodology and the data collection are discussed in more detail in the third chapter. The fourth chapter will detail the data collection and statistical analysis. Criticality assessment of the sewer inventory for the collected data will be presented in chapter five. Chapter six will explore the use of historical repair data and correlation analysis to develop deterioration models for sewers. The use of

Monte Carlo simulation and probability distribution functions will be reviewed and evaluated in chapter seven. In chapter eight, the use of probabilistic neural networks to develop predictive failure model will be explored. In chapter nine, conclusions and recommendation of this research will be summarized.

CHAPTER 2 - LITERATURE REVIEW

2.1 INTRODUCTION

Numerous studies have highlighted the aging of the infrastructure and the gap in funding its renewal and rehabilitation, most notably: CBO 2001; Water Infrastructure Network, 2001; USEPA GAP Analysis 2002; GAO 2004; ASCE report Card 2001-2010. However, these studies do not propose a rigorous methodology that would improve the efficiency and effectiveness of the decision making process to close the gap in funding. Several protocols for condition assessment of sewers were developed, including the Water Research Centre in the UK (WRC 1986), the Sewer Inspection Reporting Codes from the Water Service Association of Australia (WSAA 2002; 2006), the Pipe Assessment Certificate Program (PACP) in the US by the National Association for Sewers Service Company (NASSCO), and the North American Association of Pipeline Inspectors (NAAPI, 2004) in Canada. The methods mentioned above rely on closed caption television (CCTV) to assess the condition of sewers. Those protocols are becoming the standards in the UK, Australia, and the United States, respectively.

In European countries, CARE-S asset management model for sewers provide decision making tools to rehabilitate and replace sewers (Saegrov and Schilling, 2002). Similarly, the COST-S model for combined sewers in UK (Cashman, 2006) and optimal model-based rehabilitation for sewers in US (Solomatine, 2006) attempt to optimize the decision making process for infrastructure renewal. Deterioration models of sewers, a major component of the asset management model, provide a predictive tool to assess the probability of failure at any given time. Deterioration models, along with a business case analysis, prompt the asset manager/

decision maker to do nothing, extend the service life of the asset through rehabilitation, or decide on a complete replacement of the asset. Condition assessment methods based on CCTV have been previously criticized for their subjectivity due to the dependence on operator skills, accounting of only visible defects, and for their resource-intensive nature. More advanced inspection techniques such as radar and ultrasound may provide less subjective and consistent data; however, their use is not widely available or acceptable for condition monitoring of sewers (Ratliff, 2003; Terry *et al.,* 2006). Statistical models can be developed without CCTV data and can eliminate the subjectivity associated with operators' error and/or inconsistency.

2.2 OVERVIEW

In a study by the GAO, wastewater utilities defer their maintenance because of insufficient funding from revenues generated from user charges and local and federal sources. In the US, the GAO found a significant difference between the actual rate of rehabilitation and the replacement of pipelines in wastewater utilities versus the needs projected by managers. The lack of funding is the most significant factor contributing to the deterioration of sewer infrastructure (GAO, 2004). Reduced federal spending and public resistance to rate hikes contribute to shortfalls of funding. In addition, the reactive approach to asset management in the past has left a backlog of repair and renewal work (WERF, 2000). Approximately half of the utilities in the US rehabilitate or replace 1% or less of their sewers annually and some estimates put the cost of emergency sewer repairs to be 2 to 3 times the cost of planned sewer rehabilitation (Ana, 2007). Sewer networks, in the developed world, serve approximately 90% of the population (WHO, 2000). In the US, approximately 1.2 million miles of sewers are installed (USEPA SRF, 1999).

In addition, water and sewers are the backbone of development for new communities and therefore represent an investment to ensure the well being of future generations.

The deterioration of sewers can be categorized into structural and hydraulic deterioration (Rostum et al., 1999; WRC, 1986). The structural deterioration relates to the weakening of the pipe structural integrity resulting in an eventual collapse while hydraulic deterioration refers to the reduced ability of the sewer pipe to transport sewage resulting in surcharges, spills, or flooding. The consequences of sewer failure include sinkholes, disruption of traffic, back-ups, damage to surrounding infrastructures and pollution of local receiving water bodies (Sveinung, 2006). Disruption of service has a negative economic, social and environmental impact, and can lead to injuries and death. For drinking water, the Urban Institute estimates that 30,000 water main breaks resulting in 300,000 service disruptions occur in the US on an annual basis (Urban Institute, 1981).

2.3 REGULATORY DRIVERS FOR ASSET MANAGEMT

The implementation of asset management in the wastewater utilities is driven by various factors including: 1) Stricter regulations, 2) Aging infrastructure, 3) Higher customers' expectations, 4) Social, economic, and environmental demands 5) Cost effectiveness (Urquhart, 2007). In 1999, the US Governmental Accounting Standards Board issued GASB Statement 34, known as GASB 34. GASB 34 requires state and local governments to report all financial transactions, including the value of their infrastructure assets, in their annual financial report on accrual accounting basis. Two accounting methods are allowed: the depreciated method and the modified method. The modified method takes into consideration the replacement cost of the asset and not just the depreciated value. In addition to GASB 34, the recent financial meltdown led utilities across the globe to implement asset management to reduce the overall life cycle cost of owning their assets. In the aftermath of the credit meltdown, Moody's Standard & Poor downgraded the municipal bonds of seven U.S. cities below investment grade (Standard & Poor 2010). The ability of municipal wastewater utilities to obtain bonding at reasonable rates will play a major role in driving the demand for implementation of asset management even higher in the near future.

2.3.1 The Depreciation Method

The depreciation accounting method of reporting the value of capital assets involves two components: (1) operating maintenance and repairs, and (2) depreciation. Depreciation is the method of accounting for depleting the useful life of assets due to deterioration or obsolescence (USDOT, 2000). It is not intended as a measure of actual deterioration of the asset; deterioration may not occur in a given year while its value increases based on market value. The values of capital assets are reported as acquisition costs minus the total depreciation while routine maintenance and repairs are reported in the statement of activities as expenses. To calculate the net acquisition cost, the acquisition or construction cost of the capital asset is determined and then adjusted to reflect the salvage value. To determine depreciation expense, the net acquisition cost is distributed over the total years of its useful life, usually by dividing net acquisition cost by the estimated years of useful life if the straight line depreciation method is used. The useful life estimate assumes a particular level of service is maintained. Since operation and maintenance costs are considered expenses that are necessary to provide a level of service and not to extend the useful life of the asset, they are reported as expenses. Depreciation costs include a prorated value of any additions or improvements that occur after initial acquisition. In other words, the amount that is depreciated will be adjusted over time if the asset is improved to extend its service life. According to GASB Statement 34, any established depreciation method may be used; and reporting entities may use a combination of depreciation methods.

2.3.2 The Modified Method

In the depreciation method, renewal expenditures are capitalized and depreciated over time using various standard depreciation methods. Under the modified approach, assets initial acquisition costs as well as any improvements to extend their useful life are capitalized; however, they are not depreciated. Any government entity utilizing the modified approach will not have to depreciate infrastructure assets as long as pre-determined conditions are met. First, the reporting government must establish and publish an asset inventory with a condition assessment. Second, the entity must estimate the spending needs to maintain a target level of service. Third, the spending needs to maintain the target level of service must be measured against the entity's actual spending. Fourth, the reporting government must demonstrate that the assets are maintained at or above the acceptable level of service. To meet the requirements of the modified reporting approach, the reporting entity must establish a complete asset inventory, condition assessment of assets, asset valuation, and a complete renewal and replacement strategy. Because GASB Statement 34 requires that governments be able to demonstrate these capabilities, there has been increasing desire by wastewater utilities to establish and implement an asset management plan.

As part of the required supplementary information section of the financial statements, GASB 34 requires the reporting government entity to provide the following:

1. Condition of the assets once every 3 years.
2. Desired level of service that the entity needs to provide.
3. Maintenance records of the assets to meet the desired level of service.
4. Actual O&M costs as compared to estimated needs to maintain the level of service.
5. The basis for condition assessment.
6. Any changes to the reporting basis for tracking condition and spending.

Based on the regulatory requirements of GASB 34, among other factors, the maintenance of sewers in a reactive mode are no longer sustainable (Fenner, 2000). In addition, the reactive approach does not reduce the number of failures in the system and is far more expensive than that of a proactive program (Butler & Davies, 2000).

2.4 ECONOMIC DRIVERS OF ASSET MANAGEMENT

Asset management provides a proactive maintenance strategy reducing the risk of failure by extending the useful life of the asset. By implementing asset management techniques, utilities may reduce emergency repairs; thereby cutting emergency repair costs, staff overtime, and clean up costs (Ana, 2009). Communities that choose not to comply with the GASB 34 financial reporting requirements will not present financial statements in accordance with generally accepted accounting principles (GAAP). Asset management can provide a proactive strategy for not only maintenance but capital construction spending; thereby reducing the overall cost of owning the sewer assets (USEPA, 2002). Asset management is successfully practiced in urban centers and large regional sewer collection systems to improve operational, environmental, and financial performance. Many of these large organizations base asset management planning on sophisticated information systems and resources (EPA, 2002). Even with rate increases, wastewater utilities are faced with shortfalls in funding and often defer the maintenance and renewal of their infrastructure (GAO, 2004). In addition to the EPA and GAO, many other public institutions have highlighted the need to implement the principals of asset management in order for utilities to implement successful operation strategies.

In addition to meeting GASB 34 requirements, asset management will aid utilities in obtaining higher credit rating (GAO, 2004; EPA2002). Better bond rating translates into better interest rates for borrowing which results in significant savings since most public works is financed through issuing of municipal bonds. Lastly, and most importantly, asset management programs will aid utilities to meet federally mandated consent decrees to fix decades-long problems of sanitary sewers overflows (SSOs) and flooding. Since the late 1990's, the federal government has issued numerous consent decrees to wastewater utilities across the US to address their SSOs. During the past decade, jurisdictions in major US cities have negotiated consent decrees with the federal government to resolve SSO-related matters including, but not limited to, Atlanta, GA (1999); Baton Rouge, LA (2001); Hamilton County/ City of Cincinnati, Ohio (2002); Toledo, Ohio (2002); Baltimore, Maryland (2002); Mobile, Alabama (2002); Puerto Rico Aqueduct and Sewer Authority (2003); Washington, D.C. Water and Sewer Authority (WASA) (2003); Los Angeles, California (2004); Sanitation District No.1, KY (2005); Louisville, KY (2005); Knoxville, TN (2005); Baltimore County, Maryland (2005); Indianapolis, IN (2006); Nashville, TN (2007); Lexington, KY (2008); San Francesco, CA (2009); and Kansas City, MO (2010).

2.5 ASSET MANAGEMENT: OVERVIEW

According to the 2002 GAP analysis by the USEPA, wastewater utilities in the U.S. will need to invest approximately 390 billion in capital infrastructure over the next two decades. However, if utilities maintain current spending needs, and in light of the recent financial meltdown, funding of all needed investments is not possible. Wastewater utilities in the United States face an aging workforce, higher consumer expectations, stricter environmental regulations, security concerns, and an aging infrastructure. As a result, many utilities have turned to Asset Management for better decision making to prioritize their needs. Asset management can be defined as a set of rules and guidelines to manage infrastructure capital assets to minimize the cost of owning and operating them while delivering an acceptable level of service (EPA 2002).

Between 2000 and 2010, many wastewater utilities in Australia, Canada, and Britain, have been successful in implementing a full scale Strategic Asset Management Plans (SAMPs) to better formulate strategy for maintaining and renewal of their assets. Wastewater utilities in Australia used SAMPs for at least the past ten years (Ana, 2009). Although the field of asset management is relatively new subject for the water and wastewater industry, it is rapidly developing in is gaining wide acceptance in the U.S. and elsewhere in the world (Schulting & Alegre, 2007). In recent years, wastewater utilities across the U.S. started implementation of asset management programs to improve the management of sewer lines, treatment plants, pump stations, and other assets. According to the National Mayor's Conference in 2007, 49% of major U.S. cities have embarked on an asset management journey for their water and wastewater infrastructure. This effort maybe a decade long and will involve the efforts of engineers, economists, and decision makers (Allbee, 2009). Asset Management encompasses set of activities, guidelines, and decision tools to minimize the life cycle costs of capital and O&M spending while maintaining an acceptable minimum level of service (USEPA 2006). It is a collection of best management practices that can guide an agency's investments throughout each stage of its asset's life cycle: planning, acquisition, operations, maintenance, renewal, and ultimately, decommissioning and disposal (WEFTEC 2007).

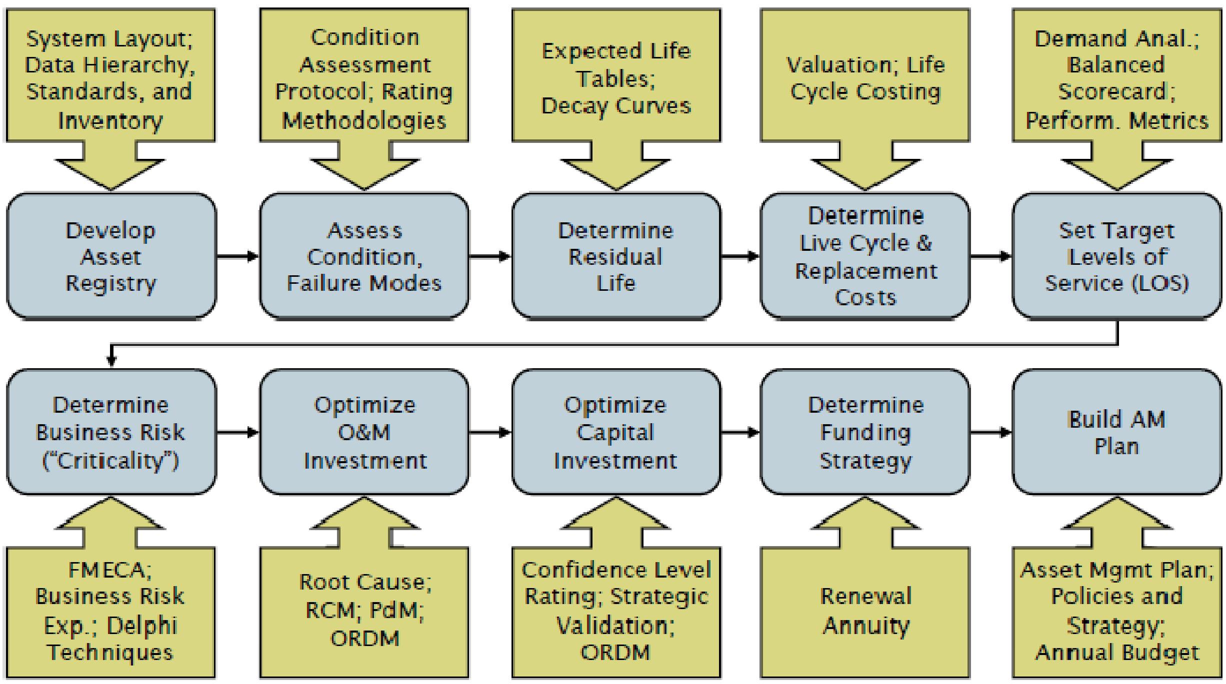


Figure 2.1: Asset Management Overview after (USEPA Workshop 2010)

The International Infrastructure Management Manual defines asset management as the use of a combination of financial, economic, engineering and other practices applied to physical assets with the objective of providing the required level of service in the most cost-effective manner (IIMM 2006). Asset management achieves the lowest cost sustainable performance and providing a means to make better acquisition, operation and maintenance, and renewal or replacement decisions (USEPA, 2006). Asset management evaluates the inventory of assets, assets condition, age, service history, estimated useful life, and criticality; and then prioritizes assets based on a risk factor associated with the asset and its replacement or rehabilitation costs. Figure 2.1 illustrates the steps that are needed to build a strategic asset management plan according to U.S. EPA. Approaches to the implementation of asset management will vary from one utility to the other depending on their needs and capabilities (Lemer, 1999; Vanier, 2001; EPA, 2002; IIMM, 2006). Fundamentally, asset management includes the systematic application of analytical tools such as life cycle cost analysis and risk assessment methodologies (GAO, 2004). A good asset management program will provide the decision maker with the right tools and strategies to balance out the unlimited organizational needs and wants against limited resources, among other constraints.

Management Information Systems such as Geographical Information Systems (GIS), hydraulic computer models such as SWMM and Infoworks, CMMS systems such as Maximo or City Works, provide a wealth of information that can be used for the asset inventory register (Vanier, 2004). The International Infrastructure Management Manual (IIMM, 2006) recommends that the first step in asset management is the development of a complete asset inventory. It is vital to know the critical assets in the utility's inventory to focus on first while building the overall program. For sewers, attributes such as age, material, depth, size, slope, and soil condition are essential to know. Additional information may include asset acquisition cost, depreciation, useful life, and deterioration curve for the sewer. Manholes typically receive an intelligent number that denotes the location of the manhole, the treatment plant it drains to, size and possibly the depth of the manhole. Sewer segments typically receive a unique identifier of a hyphenated number of two manhole numbers.

Condition assessment of the sewer infrastructure is another major step in establishing the asset management program. Condition assessment methodologies available in the literature are dependent on CCTV and operator judgment to establish a condition rating. The more advanced non-destructive methodologies, such as ultrasound, are either not widely available or acceptable in the industry (Tran, 2009). Available condition assessment methods include visual inspection, destructive testing, direct measurements, and response-type devices that are applied either to the interior and exterior to the pipeline. Most condition assessment methodologies in the literature produce a subjective assessment; primarily, a scale of 1 to 3 (WSSA 2002) or from 1 to 5 as in the PACP method, with the condition rating of 1 being perfect or new condition and the highest end of the scale as a failed asset. When a condition assessment of the critical infrastructure is completed, a prediction model of sewer failure should be developed. Figure 2.2 below illustrates an example of sewer deterioration model.

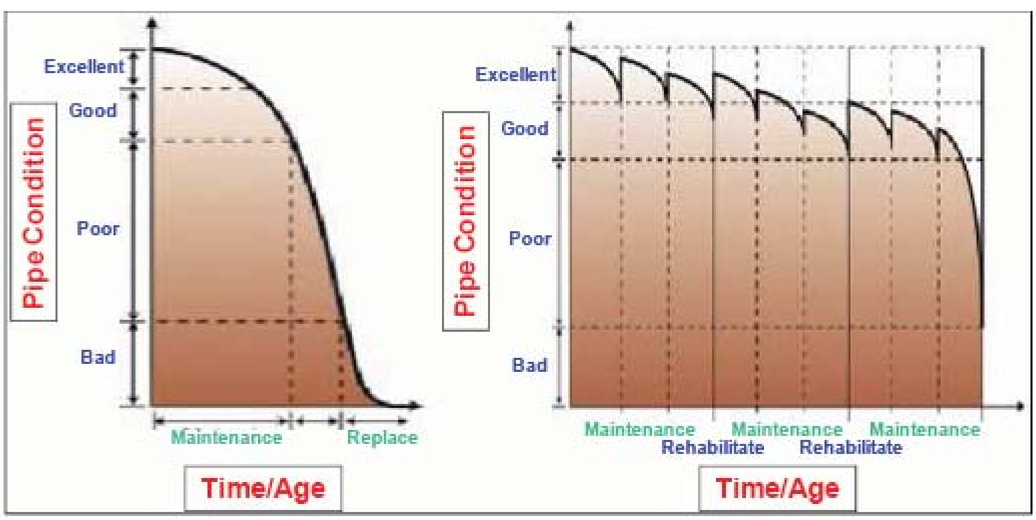


Figure 2.2: Example Deterioration Curves With and Without Rehabilitation

Various methodologies have been described in the literature; they can be primarily categorized into artificial intelligence models, deterministic, and probabilistic models (Morcous, 2004).

Artificial intelligence and neural network models for various engineering problems, including sewers deterioration, have been previously developed (Moselhi and Shehab-Eldeen 2000; Kliener 2004; Singh and Tiong 2005; Wilmot and Mei 2005; Tran 2010). Examples of Deterministic models- both linear and non-linear- can be found in the literature for water mains (Kleiner and Rajani 2001) and for pavements (Lou *et al.* 2001). Probabilistic sewer models, including Markov chain models, can be found in the work of Wirahadikusumah *et al.* (2001) and Mishalani and Madanat (2002).

After determining the risk exposure, which is the product of probability and criticality, the wastewater utility needs to establish an acceptable level of service. The very basic level of service for sewer networks can be defined as the reliable collection of sewage at a minimum cost, while meeting all health and environmental regulations, and ensuring adequate capacity to handle the demand by users, with minimal or no overflows and surcharges (EPA 2002). For wastewater utilities, the definition of level of service will depend on the service segment, affordability, and external demands. For example, the level of service can be defined as capacity assurance for sewers or quality of effluent when measuring treatment efficiency or meeting permit limits, or the amount of time it takes to return a customer's call. Performance measures can help define the acceptable level of service for wastewater utilities. Cardoso et al. (1999) provided a list of performance indicator for sewers to meet structural, hydraulic, economic, social, and environmental requirements.

Another critical element of asset management is the valuation of the assets. Asset valuation should examine the Life Cycle Cost (LCC) of acquiring, operating, maintaining, and ultimately decommissioning and replacing the asset. Infrastructure engineers and managers need to utilize LCC when determining on the rehabilitation or renewal of assets. A risk-based LCC model, to assess failure of each pavement rehabilitation/construction alternative and provides additional knowledge about the uncertainty levels that accompany the estimated life-cycle costs, was developed (Salem, 2003). The Triple Bottom Line (TBL) analysis, an emerging methodology that takes into consideration the social and environmental consequences, in addition to the economic impact of alternatives, has been gaining wide acceptance as the framework of decision making at wastewater utilities. TBL emphasizes social and environmental responsibility to stakeholders rather than focusing on maximizing shareholders' equity.

Another major step in asset management process is to assess the business risk exposure of the utility. Business risk exposure can be measured by evaluating the probability and impact of asset failure. Risk assessment occurs on a critical segment of the infrastructure first since it could be a decade-journey to assess the condition of buried infrastructure (EPA, 2009). After mapping the utility risk matrix and appetite, the next step is to formalize strategies for O&M and capital spending to optimize the process and take the subjectivity out of the decision making. By anticipating the risks associated with asset failure, utilities can plan cost effective maintenance, repairs, and replacement of assets and minimize the overall life cycle cost of owning the infrastructure (Vanier, 2001).

2.6 IMPLEMENTATION CHALLENGES

Natural resistance to change is a barrier to implementing the concepts of asset management to the wastewater utilities; thus, their implementation remains a challenge (Vanier, 2001; GAO, 2004; Schulting & Alegre, 2007). The difficulty in obtaining accurate data related to the asset inventory much less its condition or the prediction of its future condition, is often cited in the literature (Vanier 2001; GAO, 2004; Ana, 2009). There are several possible reasons for this problem including the fact that the wastewater infrastructure is often built over centuries span with limited or unknown data available. Another problem is the inconsistencies of reporting and lack of standardization to document desirable attributes of sewers assets as well as their condition. In turn, the lack of data contributed to the lack of available modeling tools to predict failure patterns to assess the utilities' risks associated with the disruption of service and damage to the surfaces when a sewer structurally fails.

Most wastewater utilities are organizationally divided into operation and maintenance divisions for each different asset type. Most commonly, wastewater utilities will have a treatment division to operate and maintain treatment plants or vertical assets, a collection division to maintain and operate sewers or linear assets, and an engineering division to plan, design, and construct capital projects. Lack of communication among various divisions in an organization can hinder the implementation of asset management. Lack of cross-training and skills among the different division staff within the organization, with competing interests, can result in lack of focus and fragmentation in the implementation phase of asset management. Moreover, the lack of available tools and understanding of data result in the difficulty in developing the right modeling schemes (Vanier, 2001; Schulting & Alegre, 2007). The development of accurate deterioration models for sewers and other vertical assets are the most crucial aspect of asset management (Vanier, 2001; Lemer 2000).

2.7 CONDITION ASSESSMENT OF SEWERS

2.7.1 Overview

Several condition assessment methodologies were developed in England (WRc 1986; 1993; 2004), Canada (McDonald and Zhao 2001; NRC 2004), the U.S. (PACP, 2001); Europe (Cemagref 2003), and Australia (WSAA 2002; 2006). Hydraulic and structural deterioration of sewers are age-dependent and are considered to be a continuous process. Condition assessment methods such as the WRc, WSSA, and PACP methods give a snapshot of the condition rating on a subjective scale basis. For example, WRc assesses the sewer condition on a scale of 1 to 3 with 1 as perfect condition; 2 as fair; and 3 as poor condition. Similarly, WSSA and PACP, in Australia and the U.S., provide a methodology to assign the sewer a condition rating ranging between 1 and 5, with 1 being new and 5 as a failed condition. Similar rating schemes are found in the assessment of deterioration of bridges and pavements where grading scales of 0 to 9 and 1 to 8 were used respectively (Madanat *et al.* 1995; Salem 2003). It can be argued that the use of number in the ordinal rating system can simplify the decision making process at the management level for the purpose of optimizing the maintenance and replacement (Madanat *et al.* 1997; NRC 2003).

2.7.2 Condition Assessment for Sewers in Australia

The Australia Conduit Condition Evaluation Manual (ACCEM) was developed by Sydney Water in 1991, to aid in the development of deterioration curves for assets. Subsequently, the Sewer Inspection Reporting Code (SIRC) and Conduit Inspection Reporting Code (CIRC) methods were developed by the Water Service Association of Australia (WSAA 2002; WSAA 2006). Both the SIRC and CIRC methods divide the deterioration of the condition rating into structural and hydraulic categories. Defects are coded, scored, totaled, and then divided by the length of the sewer for a mean average score. Table 2.1 summarizes the two condition assessment methods by Water Service Association of Australia.

Rating (State)	SIRC (WSAA 2002)		CIRC (WSSA 2006)	
	Structural	Hydraulic	Structural	Hydraulic
1	No apparent need to investigate further.	No apparent need for action.	Appears to be in good condition.	Appears to be in good condition.
2	Consider response on a program basis.	Consider response on a program basis.	Minor deterioration of sewer occurred.	Minor defects are present causing minor loss of hydraulic performance.
3	Urgent need to investigate	Urgent action is needed.	Moderate deterioration of sewer occurred.	Developed defects present causing moderate loss of hydraulic performance.
4	N/A	N/A	Serious deterioration of sewer occurred.	Significant defects present causing serious loss of hydraulic performance
5	N/A	N/A	Failure occurred or eminent.	Failure occurred or eminent.

Table 2.1: Condition Assessment Ratings Definitions by WSSA

2.7.3 Condition Assessment for Sewers in the U.S. and the U.K.

In 2001, the National Association of Sewer Service Companies (NASSCO) developed the Pipeline Assessment and Certification Program (PACP) as a methodology to assess the condition of sewers. The PACP method, amended in 2004, is the U.S. modification of the United Kingdom's TV inspection coding system developed by WRc in 1986. The purpose of PACP is to create comprehensive data to properly prioritize, plan, and renovate wastewater collection systems and create procedures to ensure that each and every rehabilitation project is a success. The WRc developed the Manual of Sewer Condition Classification (MSCC) in 1986. The PACP is a modified version of the MSCC third edition that was published in 1993. Recently, the PACP method has been gaining wide acceptance among utilities in the U.S. as the standards for condition assessment methodology for sewers.

Condition Grade	Condition Description
5	Pipe collapsed or eminent collapse
4	Pipe collapse likely in foreseeable future
3	Pipe collapse unlikely in near future
2	Minimal collapse risk
1	Acceptable structural condition

Table 2.2: Definitions of the Pipeline Assessment and Certification Program (PACP) Condition Ratings

Similar to WRc and WSAA methodologies, PACP depends on CCTV inspections and operator judgment to translate the condition rating into a numerical value ranging between 1 and 5. Wastewater operators need to attend training and attain certification in order to qualify to inspect sewer using this methodology. In addition, open-architecture software packages were developed by various vendors, and approved by NASSCO, to list and quantify the defect scores. PACP method divides the condition rating into two major categories: Structural and O&M. Each defect code in PACP comes with a severity grade from 1 to 5 and when added up, a snapshot condition score is calculated. Manual of Sewer Condition Classification first, second, third and fourth edition, known as MSCC, MSCC2, MSCC3 and MSCC4 (WRc 1986; 1988; 1993; 2004) are assessment methods that are very similar to the PACP method. The PACP started with modifying MSCC3 and NASCCO contends that most of the modifications in the MSCC4 were based on their PACP method. Both PACP and MSCC4 both provide similar approach utilizing CCTV, extensive spreadsheets, software, and operator training, to assess the condition rating of sewers. The MSCC4 and PACP methods are the most common methods for sewers assessment in the U.K., and the U.S., respectively. Seattle Public Utility (SPU) in the United States uses the PACP method as the basis for condition assessment of sewers.

2.7.4 Condition Assessment for Sewers in Canada

The WRc protocol is considered the basis for the development of other sewer condition assessment protocols and guidelines in use in Canada (CNRC 2004). The North American Association of Pipeline Inspectors in Canada (NAAPI) developed training manual on sewer condition classification that is based on the WRc manual. Similar to NASSCO's PACP method in the U.S., NAAPI offers courses and a certification program for CCTV operators and reviewers (NAAPI 2004). An Evaluation of Condition Assessment Protocols for Sewer Management, a report by the Municipal Infrastructure Investment Planning (MIIP) of the Canadian NRC, summaries condition assessment protocols in Canada (Vanier, 2004).

2.8 CONSTRUCTION METHODS

While most of the asset inventory was constructed using an open-cut method, a review of construction methods for sewer installation was conducted. The methods can be primarily divided in to open cut and trenchless. A summary of the methods can be found below.

2.8.1 Open Cut

Open cut methods involve the excavation of a trench using suitable equipment and soil shoring techniques to protect the trench from heaving. Typical trench is excavated using a backhoe and the sides are protected or supported by a trench box. Depending on the depth of the sewer, soil condition, water table level, the sides of the trench could be sloped to stabilize the trench from collapsing. Depending on the material of the sewer, and the soil conditions, a bedding material may be applied at the bottom of the trench. Pipes are lowered, connected, and maintained to grade using a laser guide, and invert elevations are surveyed to ensure accuracy of the grade. After backfilling, compaction of the trench is important to prevent settlement and disturbance to the surface after placing the sewer line in service. Open cut methods are the most widely used for installation of sewers for their practicality and cost effectiveness. Exceptions to that are installations in densely populated areas where the disruption to the surface and traffic outweighs the costs of tunneling or micro-tunneling techniques.

2.8.2 Trenchless Methods

2.8.2.1 Auger Boring

Trenchless technologies are used when the costs of restoring the surface as well as the social, environmental, and economic impact of disrupting the traffic and public access outweighs the additional costs of trenchless methodologies. Trenchless technologies, when applied to the right application, can save time and money. The most common trenchless method used for constructing sewers is auger boring, sometimes known as Jack-and-Bore. In this method, a Jacking pit and a receiving pit are excavated at both end of the sewer installation. A rigid steel or concrete pipe is pushed and spoil is removed in the jacking pit. The lead pipe in the Jack and bore method is equipped with cutters and often times serve as casings for the actual sewer. The advantage of auger boring, other than the minimal disruption to surfaces, is that they provide accurate alignment and grade.

2.8.2.2 Horizontal Directional Drill

This method is more common in installing gas line, fiber optic lines, waterlines, sewer laterals, and force mains, than for installing gravity sewers. The drawback to this method is that it is difficult to control the accuracy of grade when soil condition changes within the alignment. Its use, however, has been increasing in recent years, not only for full pipes, but sewer installations as well. HDD offers many advantages, including efficiency, speed, cost-savings and less disruption to the surface and traffic.

2.8.2.3 Pipe Bursting

In this method, a pipe is pushed through the deteriorated sewer line and replaces it. An expanding head is introduced into the old sewer line and is pushed either hydraulically or through pneumatic means. The new pipe or bursting pipe, is usually larger in size than existing sewer in diameter, gets attached to the expanding device and is pulled through the sewer, replacing it immediately.

2.8.2.4 Tunneling and Micro-tunneling

Tunneling and micro-tunneling are reserved for the large size sewers- main interceptors and trunk lines- that serve as the artery of the collection network to transport the sewage to treatment plants. In tunneling and micro-tunneling, a Tunnel Boring Machine, usually called a mole, is lowered in a shaft and is retrieved in a subsequent one forming the underground sewer. Micro-tunnels refer to the smaller size tunnels that cannot be manned for inspection; they typically range between 48-54 inches in diameter for sewer lines. Tunnels are fairly larger and can have a diameter as large as 40 feet; however, typical sewer tunnels are in the 10-12 feet range in diameter.

2.9 DETERIORATION MODELS FOR SEWERS

2.9.1 Modeling Overview

Modeling can be categorized into deterministic, probabilistic, and soft computing methods such as neural networks and artificial intelligence (Morcous, 2004). Models can be also classified as data driven and expert driven types (Dasu & Johnson, 2003). Deterministic models can be described as empirical or mechanic where parameters are described in a mathematical equation and tested in labs or experiments. Empirical models describe the relationship between variables and the output based on observed data. Almost all the sewers deterioration models found in the literature can be categorized as empirical (Tran, 2007). Other types of models include physical models where a smaller scale of an engineering design, such as a bench scale or a pilot scale, is constructed and monitored to be able to predict the performance of the full scale design. Statistical models are those that use statistical theory to construct the output of the model. Statistical models provide more realistic approach to predict the current and future condition of pipes because their outcomes are explicitly formulated in probability values instead of quantitative values as in deterministic models. Markov models and ordinal regression deterioration models are two common statistical deterioration models that have been used to predict the deterioration of sewers. Most models in the literature are based on CCTV and condition rating methods described earlier. Statistical models that are based on repair data were developed by Seattle Public Utilities (Martin, 2007). The models developed by SPU were based on 15 years of repair data and were developed for concrete and vitrified clay pipes. The accuracy of the model depends primarily on the accuracy and availability of input data. Additionally, the type of modeling method used for deterioration will affect the accuracy of the result. Since the number of sewer deterioration models that were developed in the literature is limited, additional work needs to be done. Also, the limited availability of data related to sewer failure represent a major challenge in developing accurate prediction of future deterioration.

2.9.2 Deterministic Models

Deterministic models are mathematical representations of relationships where no random variables are involved; thus they produce the same output. Deterministic models are used in the domain of perfect information and should be used when the modeler is fairly certain of the accuracy of the input variables. Examples of deterministic models include Newton's law and thermodynamics. Deterministic models, linear and power law models, for water mains and pavements have been used in the past (Kleiner and Rajani 2001; Lou *et al.* 2001). The use of deterministic models- linear and exponential- to predict the deterioration of pipes is preferred by researchers because of their simplicity in describing mathematically the relationship between inputs and the output (Tran, 2010).

2.9.2.1 Linear Models

A linear model was developed to describe the deterioration of infrastructure facilities (Madanat, 1995). The facilities are grouped into cohorts with similar attributes such as size, material and service type. The relationship between asset condition and age for each cohort is described in a linear with condition state *Y*, as dependent variable and age *t*, as the independent variable. Equation (2-1) describes the linear model.

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

Where: i = facility index;

Yi = condition state for facility I;

β_1 and β_2 = parameters to be estimated;

t = facility age;

ε_i = random error term

Linear models are usually calibrated using the least square method with a straight line output depicting the deterioration of asset with time. Linear models are criticized for being too simplistic and for their failure to explain the random failure that occurs in pipes independent of their age (WRc, 1986; Morcous, 2002). Additionally, it is not appropriate to model discrete condition states using linear regression models (Madanat and Ibrahim, 1995; Madanat, 1997).

2.9.2.2 Exponential Models

Similar to linear models, exponential models describe a specific pattern of change between a dependent and independent variables. Deterioration rates of sewers that are constructed in older cities should be considerably higher than those in newer communities (Wirahadikusumah, 2001). Wirahadikusumah developed an exponential model to predict the deterioration of sewers in the City of Indianapolis. The mathematical equation used followed the expression of:

$$Y_i = e^{\beta 1 + \beta 2\, t + \varepsilon_i} \qquad (2\text{-}2)$$

The definition of independent and dependent variable were previously explained in section 2.9.2.1. Similar to linear models, exponential models are often criticized for failure to explain infant mortality or the randomness in assets failure. Another problem is that when dividing the assets into cohorts; the cohorts need to be small enough to be homogeneous yet large enough to cover as many inputs (Kleiner, 2007). Also the complex nature of failure and influences between inputs factors cannot be explained when using this type of modeling (Mishalani and Madanat, 2002).

2.9.3 Statistical Models

Statistical models are tools that can predict the future outcomes through extrapolation of historical data. Statistical models are set of mathematical equations which describe the behavior of an object of study in terms of random variables and their associated probability distributions. They are described as stochastic and random processes as opposed to the deterministic approach described before. Statistical models have been used to describe many engineering problems (Henley and Kumamoto 1992; Johnson and Albert 1999; Kuzin and Adams 2005; Martin, 2007). Statistical models that have one equation are called single-equation models whereas if they contain more than one equation, they are known as multiple-equation models.

2.9.3.1 Ordinal Regression Models

Ordinal regression is a statistical method that is used to predict the behavior of dependent variables with a set of independent variables. In ordinal regression, the dependent variable is the order response category variable and the independent variable may be categorical, interval or a ratio scale variable. In case of sewers deterioration models, ordinal regression re-conceptualize the deterministic regression to predict the probability that a sewer is in a particular condition state based on the values of the contributing factors. The ordinal regression models using the logistic function were developed for sewers deterioration prediction (Davies, 2001; Ariaratnam 2001; Ariaratnam 2006).

2.9.3.2 Markov Chain Models

Markov chain model has been frequently used to predict the deterioration of infrastructure (Morcous, 2002). Markov chain model is a discrete random process with the property that the predicted state depends only on the current state. For example, a sewer pipe that is assigned a condition state of 1 has the probability of *P11, P12, P13, P14* and *P15* to deteriorate to poorer condition states of 2, 3, 4 and 5 respectively. The transition matrix for all probabilities can be described as:

$$\mathrm{P} = \begin{bmatrix} P11 & P12 & P13 & P14 & P15 \\ 0 & P22 & P23 & P24 & P25 \\ 0 & 0 & P33 & P34 & P35 \\ 0 & 0 & 0 & P44 & P45 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \qquad (2\text{-}3)$$

The size of the matrix depends on the number of condition states and the sum of each row is equal to one. Markov chain model ignores the improved condition of assets due to rehabilitation efforts.

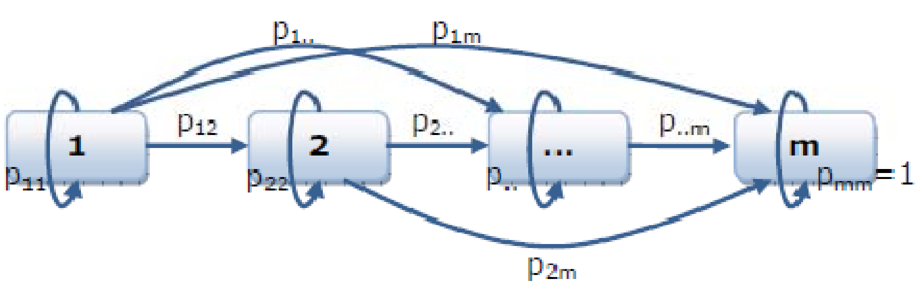


Figure 2.3: Visual Representation of Markov Chain Model

Markov chain model can be used as a condition-based model where the probabilities of the asset deteriorating from one condition state to the other is calculated or can be used as a time-based where the probability distribution of time between states is calculated as shown in Figure 2.2 (Mishalani and Madanat 2002). Calibration of such models for sewers are based on CCTV inspections and many researchers have constructed Markov chain models for the deterioration of storm and sanitary sewers (Wirahadikusumah *et al.* 2001; Kleiner, 2004; Baik *et al.* 2006; Tran 2007; Ana, 2009).

2.9.4 Artificial Intelligence and Soft Computing Models

Artificial intelligence is the branch in computer science that aims at the creation of intelligence of computing machines. Artificial intelligence models are designed to mimic the sapience of Homo sapiens which can be trained to learn and adapt, a feature often used in many engineering models (Moselhi and Shehab-Eldeen 2000; Seo *et al.* 2004; Singh and Tiong 2005; Wilmot and Mei 2005). Artificial intelligence model outputs were classified from pattern recognition within existing data and training and calibrating the machine to predict future events. Artificial intelligence method such as Case-based reasoning (CBR), fuzzy set theory, and NN were used to model the deterioration of infrastructure facilities, including sewers (Kleiner, 2004).

2.9.4.1 Condition Based Reasoning

Condition based reasoning (CBR) models were developed to predict the deterioration of the infrastructure. The replacement of bridges decks based on the existing condition was developed for the Ministry of Transportation in Quebec, Canada (Morcous, 2002). A similar model using expert opinion was developed to predict the condition of sewers (Hahn, 1999). CBR is a problem-solving method that depends on the experience of previous conditions (Aamondt and Plaza 1994) and how the human brain makes judgment (Riesbeck and Schank 1989). The CBR and expert system are criticized for their dependency on the availability of large data and the subjectivity of the inference rules.

2.9.4.2 Fuzzy Set Theory

Fuzzy sets are sets whose elements have degrees of membership. Fuzzy logic is derived from fuzzy set theory to simulate approximate rather than precise reasoning. Fuzzy sets were introduced by Lotfi Zadeh in 1965 and have been employed to mathematically convert linguistic inference rules into fuzzy numbers and rules (Zhao and Chen 2002). Fuzzy set theory have been also used to implement fuzzy expert systems for buried pipes (Makropoulos, 2003; Yan and Vairavamoorthy, 2003; Najjaran, 2004; and Vamvakeridou-Lyroudia, 2005; Kliener, 2006) and to implement fuzzy decision support systems (Chao and Skibniewski, 1998; Liang, 2001; Seo, 2004; Singh and Tiong 2005). Similar to Markov chain models, fuzzy logic and fuzzy decision support systems are criticized for subjectivity.

2.9.4.3 Neural Networks Models

Neural Networks, in modern terms, refer to artificial neural networks, which are composed of artificial neuron or nodes. Artificial Neural Networks (ANNs) are forms of mathematical models that simulate the structure and/or function of biological neural networks. It consists of interconnected neurons and processes. In most cases, ANN is adaptive during the learning phase by changing the structure based on the information flow. Modern neural networks, such as the one used in this research, are non-linear statistical tools for data modeling. They are usually used to recognize patterns in the data, train the network for calibration, and predict future conditions.

Neural Networks can identify complex non-linear relationships between contributing factors and output (Moselhi and Shehab-Eldeen, 2000; Nilsson, 2006), and can adapt and be trained to fuzzy or loosely defined problems (Chua and Goh 2003). NN have been gaining popularity in the field of infrastructure management (Tran, 2007). They have been used to model pavement cracks conditions (Lou, 2001), defect codes in sewers (Moselhi and Shehab- Eldeen 2000), and the deterioration of water main pipes (Luis and Naim 2001; Al Barqawi and Zayed 2006). A feed-forward back-propagation NN model was developed to predict sewer condition based on its contributing factors (Najafi and Kulandaivel, 2005).

2.9.4.4 Probabilistic Neural Network Models

Developed by Specht in 1990, Probabilistic Neural Network (PNN) Models are considered a hybrid technique that uses Bayesian theory and a Parzen-Cacoullos theory on a NN platform to produce the probability distribution of each pattern (Tran, 2007). The main advantage of PNN models is that they are fast to run and do not require much time for training; and can quickly recognize non-linear relationships between contributing factors and the output. The main criticism of PNN models, on the other hand, is that they require extensive data for the construction of accurate models. To test the model, one common method is to randomly select a subset of data to construct the model and a smaller set to test the model. This method has been used in testing deterioration models for bridges (Madanat and Ibrahim 1995), for pavement

(Alsugair and Al-Qudrah, 1998; Lou, 2001) and for the deterioration of sewer pipes (Micevski, 2002; Baik, 2006).

2.10 SUMMARY

Various sewers deterioration models have been used in the literature to assess the condition of sanitary and storm sewers. Most researchers contend that the failure of sewers is a complex process that is not only age-dependent but is random due to other influences. The accuracy of the deterioration model depends on the availability of data related to historic failure as well as the confidence level in the input data. Markov chain method, while criticized for subjectivity in its output as well as the need for extensive CCTV work to build and test the model, are still the most widely available method in the literature. The use of neural networks and probabilistic neural networks to model the deterioration of pipes is increasing. NN and PNN have the advantage of discerning complex non-linear relationships between inputs or contributing factors and the output, specifically the probability of sewer failure under this research. NN models can be complex and their run time will depend on the complexity of the model and the amount of data input to the model. Although PNN models also require extensive data for analysis, the run time is very fast.

In this study, deterministic models using regression analysis as well as probabilistic models using Monte Carlo Simulation, data fitting with probability distribution functions, and probabilistic neural networks, are developed and discussed. A comparison and discussion of the results will be provided as well as recommendations for future work.

CHAPTER 3- RESEARCH METHODOLOGY

3.1 OVERVIEW

The research methodology used in this study involves both quantitative analysis and analysis of qualitative data. The main components of the research methodology include review of the literature, data collection, statistical analysis, expert opinions and case studies. Research literature was reviewed to identify the best management practices, national and international, in the implementation of asset management programs in wastewater utilities, as well as the development of deterioration models for sewers. Data was collected from the Cincinnati Area Geographical Information System (CAGIS) for attributes related to the collection system in the area and the composition of the asset inventory. Researched attributes used to determine the probability of failure of a sewer include pipe material, age, soil conditions, depth, size, and hydraulic conditions, among others. The data collected is quantitatively analyzed using spreadsheets, tabulation, and statistical analysis tools. Probabilistic deterioration curves for sewers were developed, based on historical failure data, using statistical methods, including regression analysis, Monte Carlo simulation, and neural networks. Qualitative analysis collected through expert opinion was used to validate observations from the deterioration models as well as in the development of color-coded maps for the critical sewer infrastructure. The deterioration models obtained under this research using different methodologies are compared to results from previous studies in the literature.

3.2 REVIEW OF LITERATURE

The literature was searched in the areas of asset management, condition assessment methodologies, and deterioration models for wastewater facilities and sewer lines. A number of engineering journals, conference proceedings, and manuscripts, both national and international, were searched for relevant articles, including the American Society of Civil Engineering (ASCE), Journal of Infrastructure Management, Journal of Infrastructure Systems, Water Environment Federation (WEF), American Water Works Association (AWWA), International Water Association (IWA), Urban Water Journal, Water Science and Technology, and Journal of Automation in Construction. Best Management Practices (BMPs) from utilities in the U.S., Australia, and Canada were searched and summarized in the literature search in chapter 2. Probabilistic deterioration models methodologies identified in the literature were used in this research including NN and Monte Carlo simulation.

3.3 GEOGRAPHIC INFORMATION SYSTEM

Unless otherwise mentioned, asset inventory data presented in this research are extracted from the Cincinnati Area Geographic Information System (CAGIS). The City of Cincinnati uses a regional GIS utility application that provides a platform for mapping and data sharing between diverse government agencies, including the Metropolitan Sewer District of Greater Cincinnati (MSDGC). MSDGC currently uses CAGIS- GEN7, on ESRI ArcView platform, as a repository for it assets. The asset inventory serves 800,000 residents in Hamilton County and the City limits over an area of 400 square miles in 33 townships and municipalities. The asset inventory includes 10 wastewater treatment plants treating an average of 180 million gallons a day, more than 120 sewage pumping stations aiding in the conveyance of sewage in low spots in the collection network, more than 200,000 connections, and 3000 miles of sewers. CAGIS houses databases of City and County agencies, including roads, utilities such as gas, water, and sewers, aerial photos, through addresses linked on maps. MSDGC invested 10 years and millions of dollars to geo-code its assets in CAGIS. For linear assets, manholes were assigned a unique intelligent number to denote the manhole's location, depth, and drainage shed, among other criteria. Sewer segments were assigned a number consisting of the two nodes that they are connecting with hyphen in between. Physical and general attributes for sewers in CAGIS include, but not limited to, installation year, material, size, depth, slope, length, shape, type, sewer number, invert elevation, and drainage shed. Geospatial attributes for sewers include, but not limited to, coordinates; nearest address; proximity to right of way, buildings, streams, CSO, SSO, pump stations, treatment plants; jurisdictions; and flood zones. Figure 3.1 below illustrates an example of a geospatial map generated from CAGIS.

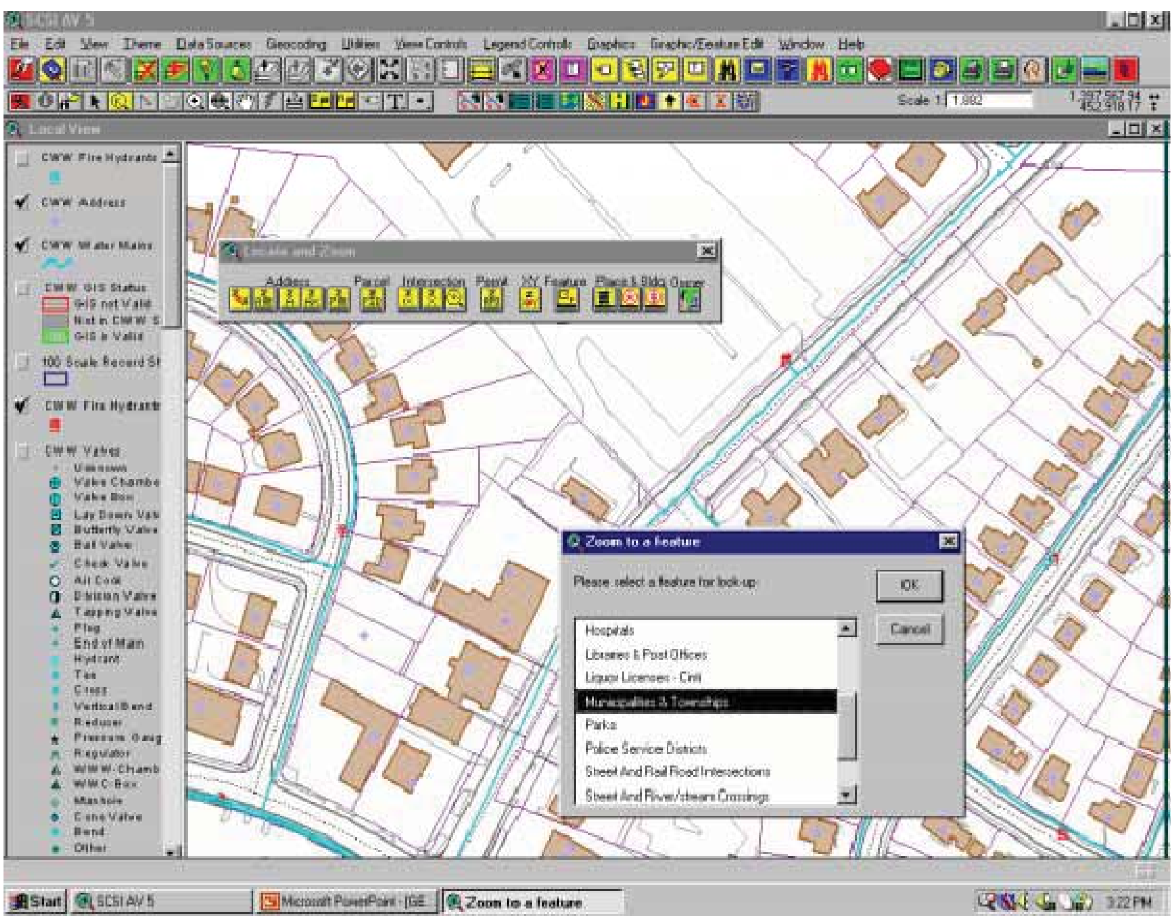


Figure 3.1: An Example Map Using CAGIS.

For the purpose of this dissertation, various data queries in CAGIS were performed to collect information on the attributes of sewers in the network. The attributes collected for sewers include installation year, material, depth, slope, size, length, shape, and drainage shed. Data were then exported to Excel spreadsheets for analysis and manipulation. Figure 3.2 shows a data query conducted in CAGIS by street name.

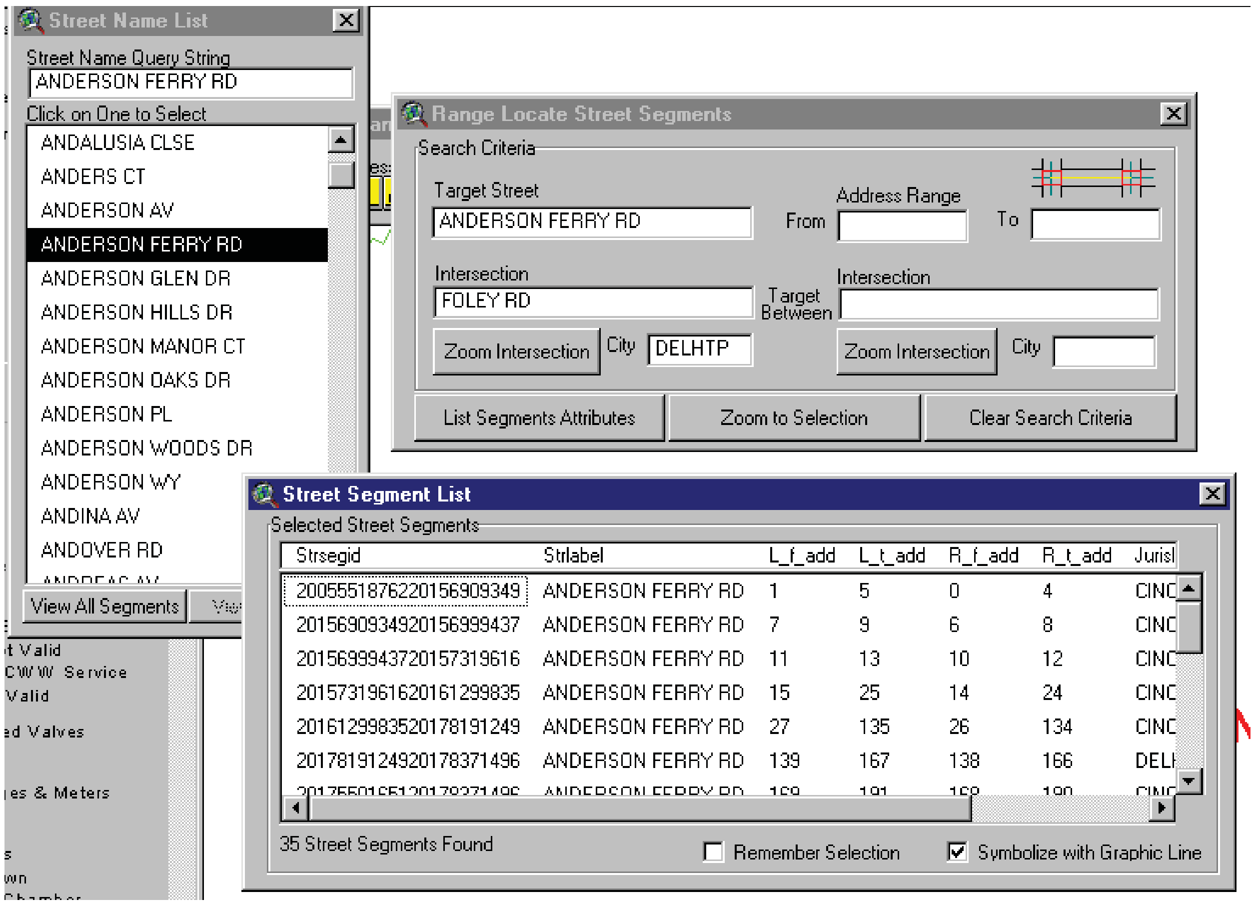


Figure 3.2: Example of Data Query by Street Name in CAGIS

In addition to data queries to construct the composition of the asset inventory, a criticality tool was developed in CAGIS to highlight the critical infrastructure. The purpose of the tool is to provide maps to prioritize the utility's focus for the repair, rehabilitation, and replacement of sewers. The criticality assessment toll took into consideration many contributing factors: Social, environmental, and economic. The contributing factors included the sewer size, wet weather flow, proximity to other utilities, disturbance of roads, traffic disruption, disruption to customers, proximity to buildings, proximity to CSOs and SSOs, proximity to water bodies, and the depth of the sewer.

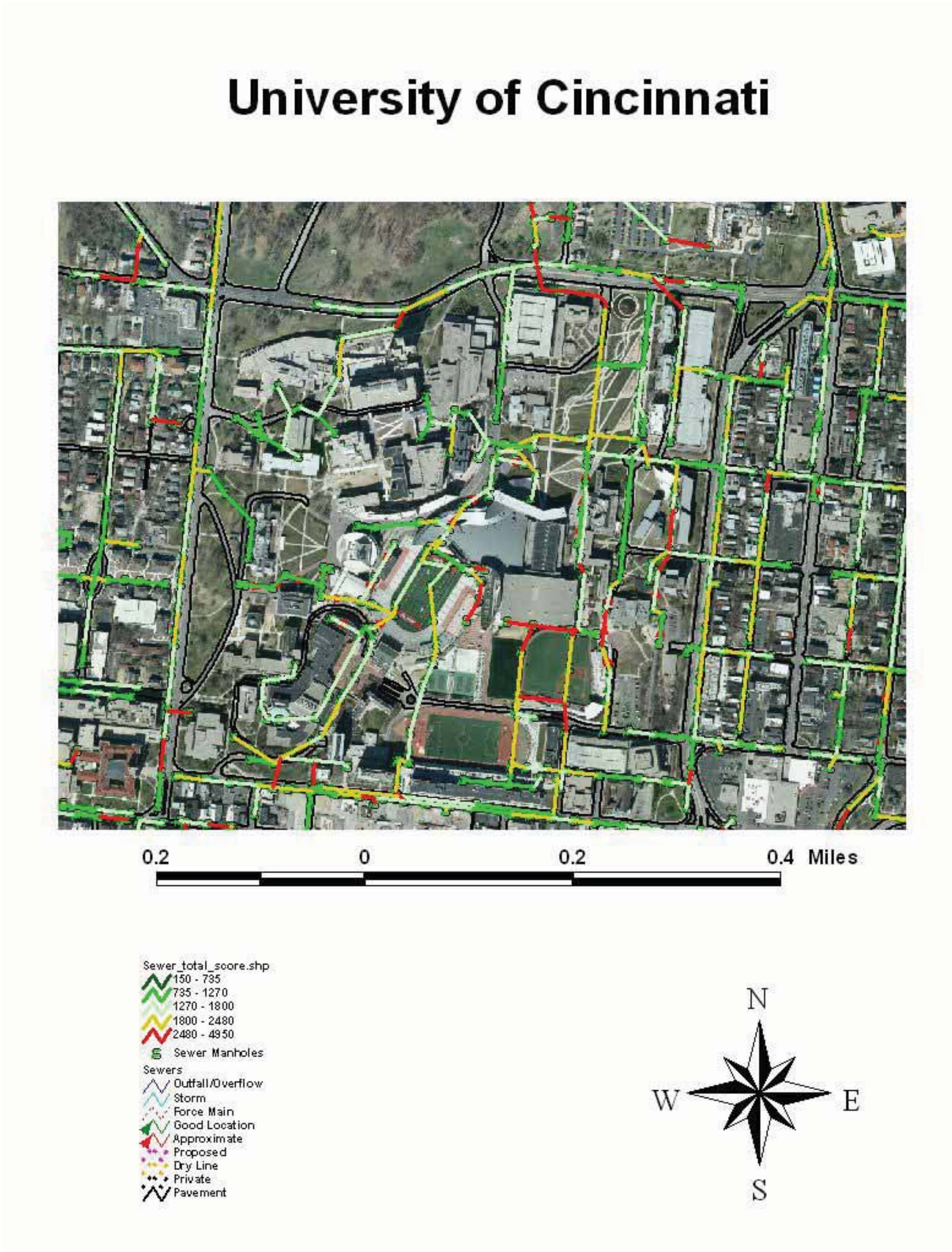


Figure 3.3: Preliminary Map of Critical Sewers on the University of Cincinnati Campus

Relative weight for factors contributing to the criticality of sewers was determined based on expert opinions and a program was written to calculate the risk factors for sewers. Risk factors were translated to layers in CAGIS and criticality maps were developed accordingly. Critical sewers were highlighted in red colors with less critical assets in yellow and green. Figure 3.3 shows an example of a map highlighting the critical sewers.

3.4 DATA COLLECTION FOR DETERIORATION MODELS

The contributing factors to the deterioration of sewers were examined using correlation analysis as discussed in greater details later in this dissertation. As mentioned earlier, the source of data used for asset inventory and the deterioration models were CAGIS and sewers repair database, respectively. CAGIS contained more than 650,000 segments of sewers and a similar numbers of manholes. The database for repairs contained approximately 2,400 repair events occurring between 1997 and 2009. Unfortunately, few parameters were recorded at the time repair was conducted; they include: pipe age, size, material, and slope. Repair events with known pipe age, which was crucial to developing the deterioration curves, totaled 1,526 events. The recorded parameters were examined to determine the correlation between them and the frequency of failure. Not surprisingly, the deterioration of sewers had a strong positive correlation to age and slope. Negative correlation was observed with pipe size and the frequency of failure varied widely with the type of material of the sewer. A discussion on the correlation analysis will be provided in chapter 6 of this dissertation.

3.5 POLYNOMIAL REGRESSION

Polynomial regression analysis was used in this research to generate deterioration models for sewers. Data, and models accordingly, were sorted by material type of pipes and the cumulative frequency of failure was plotted against the age of pipe. The data were then fitted through a polynomial regression to produce the deterioration model. Polynomial regression describes the relationship between an independent variable and dependent variables. Although polynomial regression fits a nonlinear model to the data, it is considered linear, in the sense that the regression function is linear. It is considered to be a special case of multiple linear regression analysis. For parameters estimation, multiple regression analysis can be used in conjunction with the estimation of the least squares associated with dependent variables.

3.6 MONTE CARLO SIMULATION

The Monte Carlo simulation method is used to analyze uncertainty where the goal is to determine how variable inputs, under uncertainty, impact the performance or reliability of the system modeled. Monte Carlo simulation is a sampling method because inputs are randomly generated from probability distributions to simulate the process of sampling from an actual population. In this research inputs were the useful life of various types of pipe material and the probability distributions were determined through fitting of historical data.

Monte Carlo simulation is an iterative method to evaluate deterministic models using sets of random numbers as inputs. A simulation using a million iterations, for most models, can be conducted using computers today in few seconds. Monte Carlo simulation uses random numbers to convert a deterministic model into a stochastic model. Steps of constructing a Monte Carlo Simulation models is as follows:

1. Define the equation to be modeled, i.e., $y = f(x_1, x_2, ..., x_n)$
2. Define a distribution for each variable $(x_1, x_2, ..., x_n)$
3. Generate random inputs, $x_{i1}, x_{i2}, ..., x_{in}$
4. Generate a model output and store the results
5. Repeat steps 2 and 4 for number of iterations
6. Analyze the results

Under this research, Monte Carlo Simulation was used to generate deterioration models of sewers using the statistical data for repair history. The curves were developed specific to various types of material pipes. Since deterioration and age correlated perfectly, other contributing factors such as slope or depth were ignored.

3.7 STATISTICAL ANALYSIS

3.7.1 Weibull Distribution

The statistical model utilized historical repair data and the Weibull distribution among others to evaluate the probability of failure for sewers. The shape parameter (β) of the Weibull distribution was calculated using the @Risk software when the historical repair data was fitted. The two-parameter Weibull model is commonly used in the field of reliability especially when the sample size is small. An alternate method is the one-parameter Weibull distribution; however, it is considered too deterministic. The Weibull-Bayesian model includes variation and uncertainty that might have been observed in the past on the shape parameter.

Applying Bayes's rule on the two-parameter Weibull distribution and assuming that parameters β and η are independent, the following probability distribution function, *pdf,* can be described as:

$$F(T) = \frac{\beta}{\eta}\left(\frac{T}{\eta}\right)^{\beta-1} e^{-\left(\frac{T}{\eta}\right)^{\beta}} \qquad (3\text{-}1)$$

Where:

η: Scale parameter;

β: Shape parameter

The model above assumes that η follows a non-informative prior distribution. This is described as Jeffrey's prior; and is calculated by performing a logarithmic transformation on η. Weibull-Bayesian analysis is conducted as follows:

- Collect the historical failure data.
- Specify a prior distribution for β (the prior for η is assumed to be $1/\eta$).
- Obtain the posterior *pdf* from Eq. (3-1).

The median value, Ť, of the two parameter Weibull distribution is given in Eq. (3-2) below.

$$\check{T} = \eta\,(\ln 2)^{1/\beta} \qquad (3\text{-}2)$$

Other points of the posterior distribution can be calculated as well. For example the 10^{th} percentile of the joint posterior distribution needs to be estimated, equation 3-2 is equated to 0.1. The procedure for obtaining other points of the posterior distribution is similar to the one for obtaining the median values, the value 0.1 substitutes the 0.5 above. This procedure provides the confidence bounds on the parameters, which in the Bayesian framework are called the credible bounds.

In this research, the two-parameter Weibull distribution to fit the historical failure of sewer data was used and the parameters were both calculated by statistical software, a module in the Decision Suite 5.5 called @Risk, by the Palisades Corporation. The Weibull distribution is mostly common in reliability analysis and was found to be the best fit for most of the deterioration model data which we will discuss in a later chapter.

3.7.2 Correlation Analysis

Pearson correlation is considered one of the most common methods used to determine the correlation between two variables. The correlation coefficient, $\rho_{(X,\ Y)}$ is determined by dividing the covariance by the standard deviation of the two variables. The population correlation coefficient $\rho_{(X,\ Y)}$ between the two random variables X and Y with expected values μ_X and μ_Y and standard deviation of σ_X and σ_Y is defined as:

$$\rho_{(X,Y)} = \frac{cov\ (X,Y)}{\sigma X\ \ \sigma Y} \qquad (3.2)$$

The Pearson correlation is defined only if both of the standard deviations are finite and both are nonzero. The correlation coefficient cannot exceed 1 in absolute value and is symmetric; i.e, corr (*X*, *Y*) = corr (*Y*, *X*). The Pearson correlation equals +1 in the event of perfect correlation of a linear relationship between the two variables; equals -1 in the case of a perfect negative correlation; and some value in between -1 and 1 in all other cases, indicating the degree of dependence between the variables. If the correlation coefficient approaches zero, there is less of a relationship. The closer the coefficient is to either -1 or 1, the stronger the correlation between the two variables. In this study, the correlation analysis was conducted using Excel spreadsheets and statistical software including Sigmazone add-on to Excel, Decision Tools Suite, and Minitab Statistics.

3.7.3 Polynomial Regression

Polynomial regression analysis was used in this research to generate deterioration models for sewers. Data, and models accordingly, were sorted by material type of pipes and the cumulative frequency of failure was plotted against the age of pipe. The data were then fitted through a polynomial regression to produce the deterioration model. Polynomial regression describes the relationship between an independent variable and dependent variables. Although polynomial regression fits a nonlinear model to the data, it is considered linear, in the sense that the regression function is linear. It is considered to be a special case of multiple linear regression analysis. For parameters estimation, multiple regression analysis can be used in conjunction with the estimation of the least squares associated with dependent variables.

The general polynomial regression model for an output y, as an n^{th} order polynomial, can be described as:

$$y = a_o + a_1 x + a_2 x^2 + a_3 x^3 + \ldots\ldots\ldots\ldots + a_n x^n + \varepsilon \qquad (3.3)$$

The polynomial regression model can be written as a system of linear equations:

$$
\begin{vmatrix} y_1 \\ y_2 \\ y_3 \\ . \\ y_n \end{vmatrix} = \begin{vmatrix} 1 & x_1 & x_1^2 & . & x_1^m \\ 1 & x_2 & x_2^2 & . & x_2^m \\ 1 & x_3 & x_3^2 & . & x_3^m \\ . & . & . & . & . \\ 1 & x_n & x_n^2 & . & x_n^m \end{vmatrix} x \begin{vmatrix} a_o \\ a_1 \\ a_2 \\ a_3 \\ . \\ a_m \end{vmatrix} + \begin{vmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \\ \varepsilon_m \end{vmatrix} \tag{3.4}
$$

3.8 PROBABILISTIC NEURAL NETWORKS

In 1990, Donald F. Specht developed the first Probabilistic Neural Network model. The figure below illustrates the architecture of any PNN model.

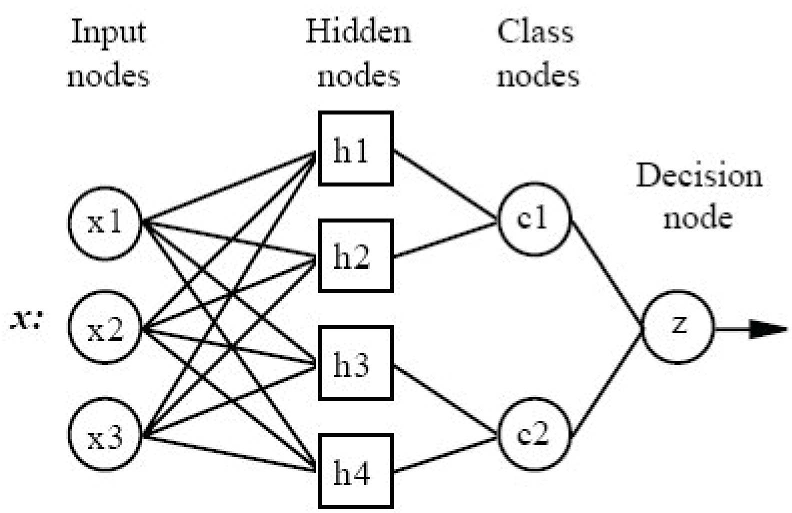


Figure 3.4: PNN Architecture (after DTREG software, Decision Trees for predictive modeling)

All neural network models have the following layers:

1. Input layer: One neuron is used for each contributing factor in the model.

2. Hidden layer: PNN uses one neuron for each output or condition state modeled in the training data set. Each hidden neuron calculates the test case from the neuron's center point.
3. Pattern layer / Summation layer: One neuron is used for each output or condition state modeled. Contributing factors or change in condition states are weighted in the pattern layer and then added up.
4. Decision layer: The decision layer selects the largest vote to predict the target category.

In this research, sewers deterioration models were developed using General Regression Neural Networks (GRNN), a form of PNN. The impact of the size of data set as well as the number of contributing factors on the accuracy of the prediction was examined. PNN models were developed for limited and extensive data sets as inputs. In addition, PNN models were built with only two contributing factors; namely age and material type and as many as six factors. Results of the PNN modeling will be discussed in chapter 8.

3.9 CASE STUDIES AND EXPERT OPINION

Case studies were used throughout this research to investigate best management practices for asset management practices utilities, both nationally and internationally. Examples from Seattle Public Utility in the U.S., the City of Edmonton, Canada, and Hunter Water, Australia were reviewed and used in the literature review and other chapters of this dissertation. Similar approach was used to validate the deterioration models. Condition assessment methodologies and deterioration models used in wastewater utilities in various countries were evaluated and discussed. Expert opinion was used in the development of the criticality matrix and their relative weight for the development of critical infrastructure map for MSDGC. More detail discussion on the use of expert opinion and the criticality matrix for sewers will be provided later in this dissertation.

3.10 SUMMARY

The methodologies used in this research involve both quantitative analysis and analysis of qualitative data. The main components of the research methodology include review of the literature, data collection, statistical analysis, expert opinions and case studies. The findings from this research using different methodologies are compared. Although, similar methodologies for the probabilistic deterioration models of sewers have been implemented in the past, this research utilized repair history rather than condition assessment based on CCTV for the development of the models. GIS was used to extract data for the asset inventory as well for the development of a tool to identify the critical assets based on risk. Expert opinions and case studies were used as examples for best management practices as well in the development of the criticality matrix and the relative weights of importance of the contributing factors.

CHAPTER 4: DATA COLLECTION AND STATISTICAL ANALYSIS

4.1 DATA COLLECTION

Data were collected from CAGIS related to asset inventory included pipe age, material, depth, slope, size, and soil type. Collected data for the criticality matrix included the proximity to structures, proximity to environmentally sensitive areas, depth, location in right of way, proximity to existing overflows (SSO and CSO), and hydraulic conditions. Data for the development of sewers deterioration models were obtained from historical repairs that were conducted between 1997 and 2009 at the Metropolitan Sewer of Greater Cincinnati (MSDGC). Secondary source of data included best management practices and literature from other utilities such as the Seattle Public Utilities (SPU) as well as other utilities in Canada, Australia, and New Zealand.

4.2 ASSET INVENTORY

4.2.1 Overview

The Cincinnati Area Geographic Information System (CAGIS) served as the primary source of data for the distribution of the asset inventory of sewer that are owned and operated by the Metropolitan Sewer District of Greater Cincinnati (MSDGC). The district serves 800,000 residents in Hamilton County and the City limits over a geographic area of 400 square miles in 33 townships and municipalities. The asset inventory includes 10 wastewater treatment plants treating an average of 180 million gallons a day, more than 120 sewage pumping stations to pump the sewage in low spots in the collection network, more than 200,000 connections, and 3000 miles of sewers. The primary focus under this research will be on the sewers, or linear assets, to determine their deterioration patterns, and their criticality in providing service to the customers. CAGIS houses databases of City and County agencies, including roads, utilities such as gas, water, and sewers, aerial photos, through addresses linked on maps. Included in the database, is approximately 2,270 miles of sewers totaling more than 65,000 of sewer segments. Of the 2,270 miles of total inventory, approximately 560 miles were combined sewers and 1,632 were sanitary type; with the remaining pipes as force mains, outfalls, and siphons.

4.2.2 Stormwater Sewers

Stormwater sewers are designed to collect rainwater and convey it to natural streams and rivers. Typically, they are shallow sewers, culverts, and built-up sections that are connected to surface catch basins, traps, swales, or ditches on one end and the stream on the other. Storm water sewers tend to be larger in size since they are responsible for the conveyance of fairly large volumes of water during rain evens. In the U.S., typical storm water sewers material include corrugated metal pipes, polyethylene, and plastic pipe, for the relatively small sizes; and built up sections that can function as small bridges for the large size culverts. Although stormwater is regulated in the U.S. by the EPA, under the National Pollution Discharge Elimination System (NPDES) for sediment control, other environmental concerns includes the transfer of street pollutants such as heavy metals and hydrocarbons into streams. The NPDES permit regulates discharges from municipal separate storm sewer systems (MS4s), construction activities, and industrial activities. Most importantly, the prevention of flooding is a major function of those assets. The prediction of deterioration of stormwater sewers is beyond the scope of this research and will not be discussed in this dissertation except in chapter 2 as part of the literature search. Data for asset inventory that were collected from CAGIS primarily represented sanitary and combined sewers; the deterioration models and asset composition for those assets will be discussed later in this dissertation. Figure 4.1 illustrates the collection system for stormwater as well as sanitary sewers.

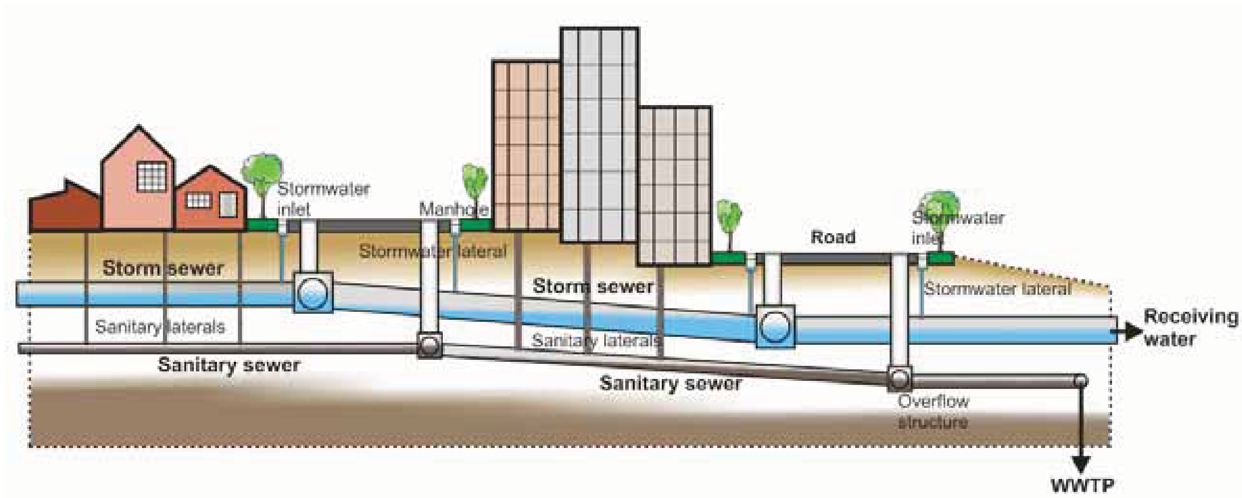


Figure 4.1: Illustration of Storm and Sanitary Sewers (after Ana, 2009)

4.2.3 Sanitary Sewers

Sanitary sewers collect domestic, commercial, and treated industrial waste in an underground network on pipes that uses gravity, for most of the network, to convey the waste to treatment plants for the separation of solids and contaminants from the water; and eventually, to water bodies such as rivers and lakes. Sanitary sewers are usually designed using manning equation to determine their size and slope and based on the demand placed on them. Although they are strictly designed not covey storm or underground water, during rain events, large quantities of that water usually get into sanitary sewers by means of Infiltration & Inflow and through basement and foundation drains of relatively older homes. Wet weather flow can be as high as tens of folds the dry weather flow depending on the condition of the sanitary sewers and their proximity to streams. This surge of flow during wet weather results in Sanitary Sewers Overflows (SSOs). USEPA outlaws SSOs and they are the focus of dozens of consent decrees in major cities across the United States. The asset inventory of sanitary sewers for the data collected for this research will be discussed later in this chapter.

4.2.4 Combined Sewers

The function of combined sewers is to transport raw domestic sewage along with stormwater to wastewater treatment plants for the separation of pollutants and discharge of clean water back to water streams. Combined sewers get overwhelmed, however, during storm events or heavy snowmelt, and overflow, by design or hydraulic failure, resulting in Combined Sewers Overflows (CSOs). CSOs are mandated in consent orders throughout the U.S. for volumetric reduction. CSOs threaten environmental risks to aquatic life and human health because the untreated discharge contains pathogens and competes for oxygen with any forms of life in the water stream. Combined sewers may experience fluctuation in wet weather flow as high as one hundred times the dry weather flow; thus are vulnerable to hydraulic failure. Sanitary sewers that are constructed near water streams sometimes behave as combined sewers during heavy rain events due to infiltration & inflow. In this research, combined sewers will be evaluated for deterioration and failure. Figure 4.2 shows the structure of a typical combined sewer.

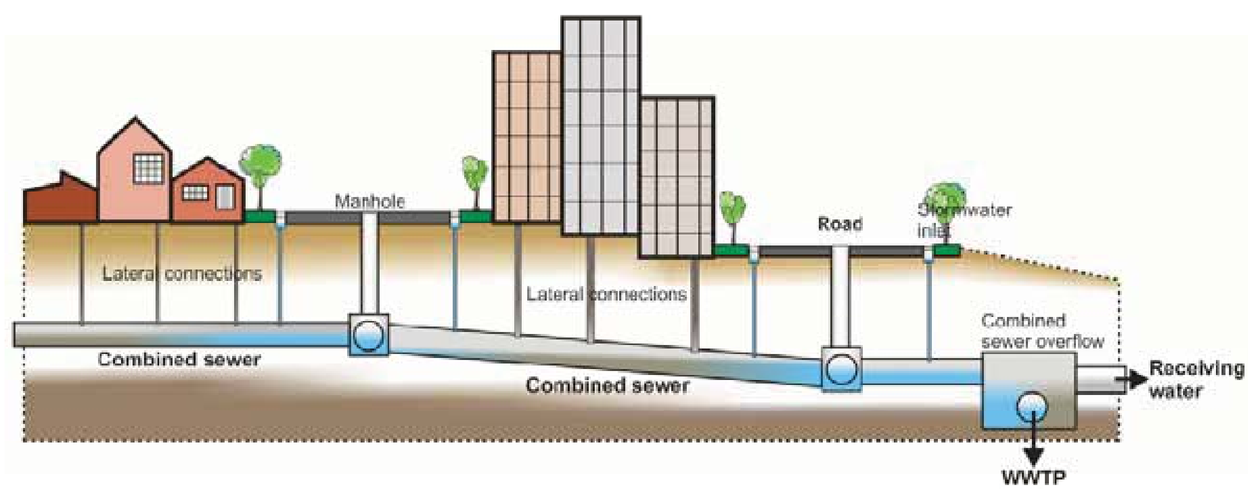


Figure 4.2: Illustration of Combined Sewers (after Ana, 2009)

4.3 DATA ANALYSIS

A criticality matrix for sewers was developed using the data collected from CAGIS. The tool runs on a GIS platform to query and calculate the criticality score to prioritize the assets in terms of their failure consequences. The GIS tool will enable asset managers to generate maps identifying areas of concerns to prioritize O&M and capital construction funding.

To determine the probability of failure, two main types of models for deterioration of sewers were developed; namely, statistical and deterministic. In this study, the statistical analysis was conducted using Excel spreadsheets, statistical software including Minitab Statistics, Sigma zone, and the Decision Tools Suite by the Palisades Corporation. The deterministic model was developed using historical repair data and correlation analysis using Excel. A comparison of the results from the statistical and the deterministic models as well as models developed in the literature will be provided in this dissertation.

4.4 MATERIAL

Various types of material were used for sewers. Within the collected data, sewers were made primarily of concrete, vitrified clay pipes (VCP), polyvinyl chloride (PVC), reinforced concrete pipes (RCP), ductile iron pipes (DIP), brick, truss, segmented blocks, high density poly ethylene (HDPE), and large concrete pipes known as Hobas. Of the approximately 2,270 miles of sewers accounted for in CAGIS, almost 700 miles, which represented one third of the overall collection network, were made of concrete. Concrete although vulnerable to chemical deterioration from hydrogen sulfide often produced in sanitary sewers, can be coated or treated for protection. Although most of the concrete sewers were built in the thirties, forties, and fifties, their use is still common today, especially for large sections or diameter pipes made of pre-stressed concrete. The second most common pipe in the asset inventory was made of vitrified clay. Vitrified clay pipe installation was common in late 1800's and early in the twentieth century and they are less common today. VCP is produced in sections that range between 3 to 6 feet in length and they are superior in terms of chemical resistance to fluctuation in the pH of the wastewater. VCP represented more than 400 miles of sewers in the studied inventory. PVC pipes constituted about 330 mile and their use is possibly most common today's sewers installations. Reinforced concrete pipes were more than 140 miles with the remaining material types constituting a smaller portion of the infrastructure. Figure 4.3 shows the distribution of material types in the data.

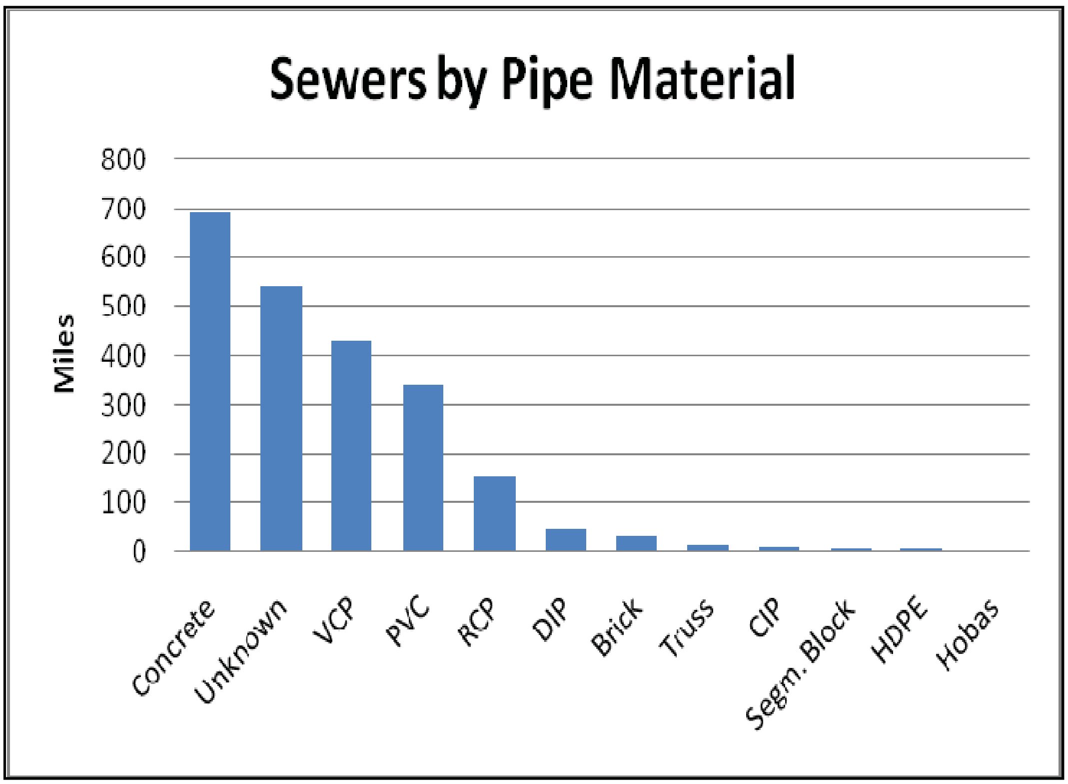


Figure 4.3: Asset Inventory by Material Type

4.5 SEWER SIZES

Sewer sizes in the inventory varied between 6 inches in diameter for collection branches in the network to more than 10 by10 feet square shaped tunnels that served as main interceptors, two conveying sewage from north to south along the Mill Creek, and two carrying sewage from the east and the west to the Mill Creek WWTP. Although 71% of the sewer network fell between 6 to 12 inches in diameter, more than 160 miles of sewers are 48 inches in diameter or more, a category that can be classified as tunnels and micro-tunnels. Due to their size and capacity, most of that large diameter size portion of the assets represents the critical part of the inventory as the impact of their failure would be far more severe than the smaller pipes. Figures 4.4 and 4.5 show the asset inventory by size and the size distribution of sewers, respectively.

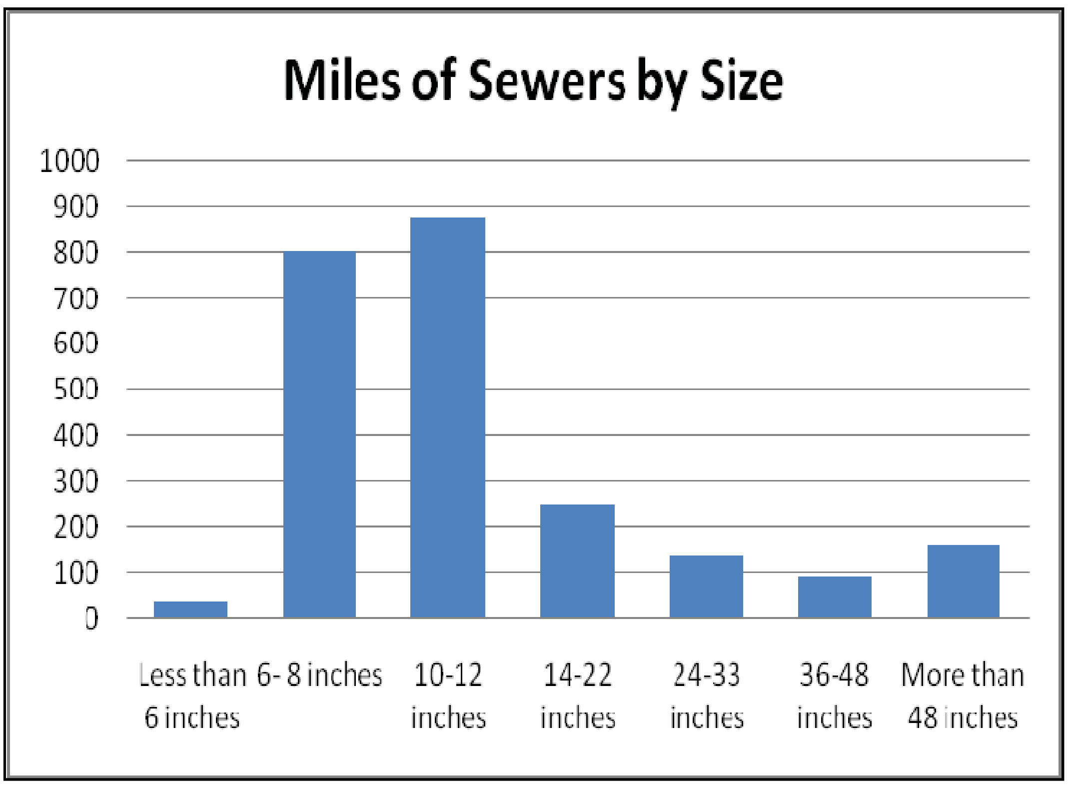


Figure 4.4: Asset inventroy by Pipe Size

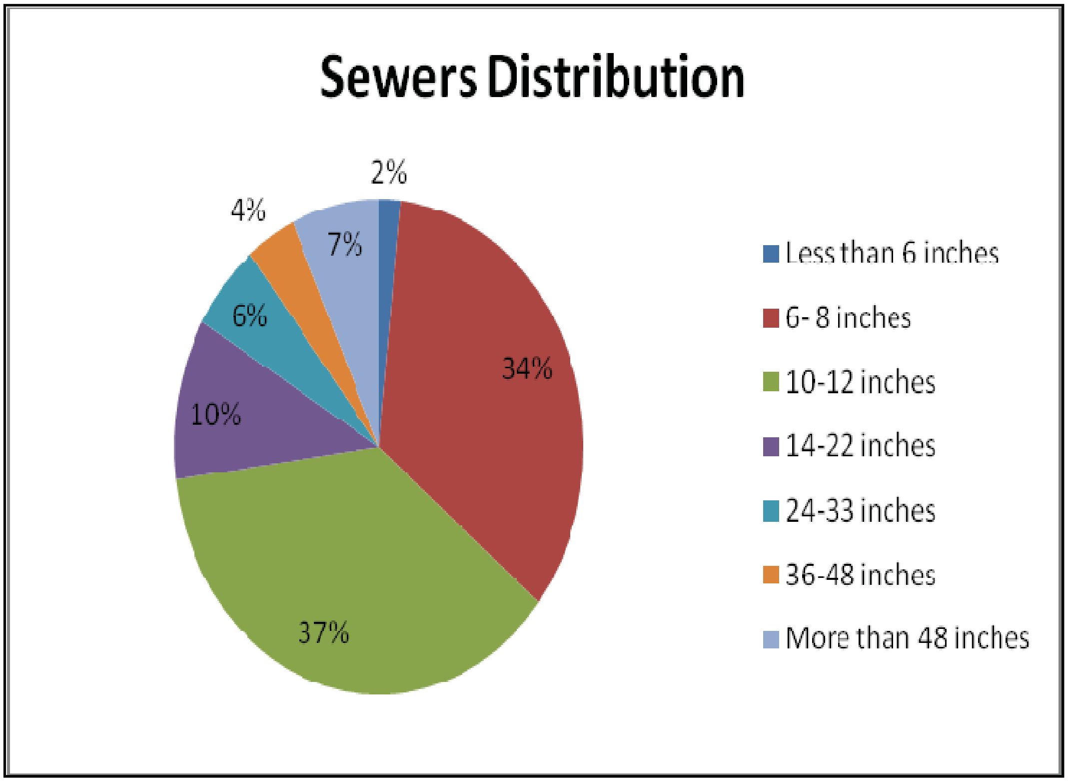


Figure 4.5: Size Distribution of Sewer Infrastructure

4.6 SEWER TYPE AND DRAINAGE BASIN

Sewers within the studied inventory served different functions, primarily as gravity sanitary sewers, and have discharged their sewage into different drainage basins and respectively various treatment plants. Although most of the sewers studied were gravity sewers, other types of sewers were included such as force mains, low pressure force mains (LPFM), outfalls, dry lines, overflow lines, and siphons. Figure 4.6 shows the distribution of sewers by their functional use. Most of the collection network fell n the Mill Creek basin with 54% of the assets followed by the Little Miami basin with 17% of the assets. Sewers network in the Polk Run basin is 7% and in the Sycamore is 5% while the Sycamore treatment plant is significantly larger in size. This could be due to the condition of the sewers in the sycamore basin is in worse condition than that in the Polk Run basin. Figure 4.7 shows the sewer assets tributary to treatment plants.

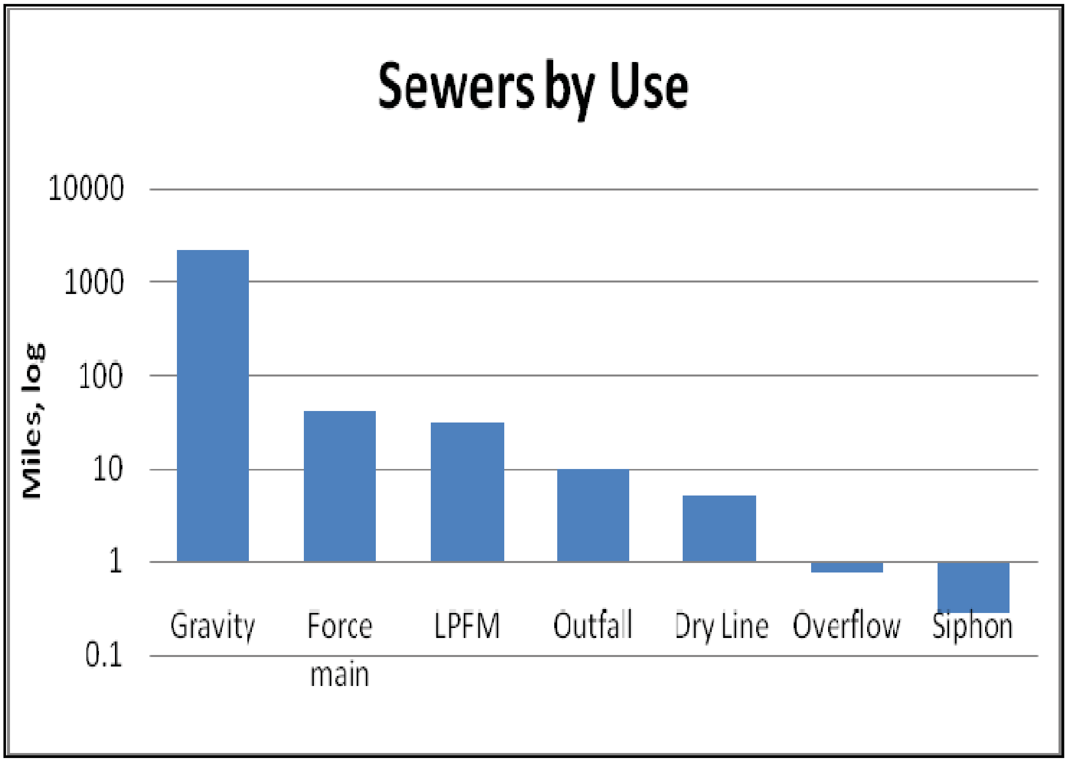


Figure 4.6: Asset Inventory: Pipe Usage

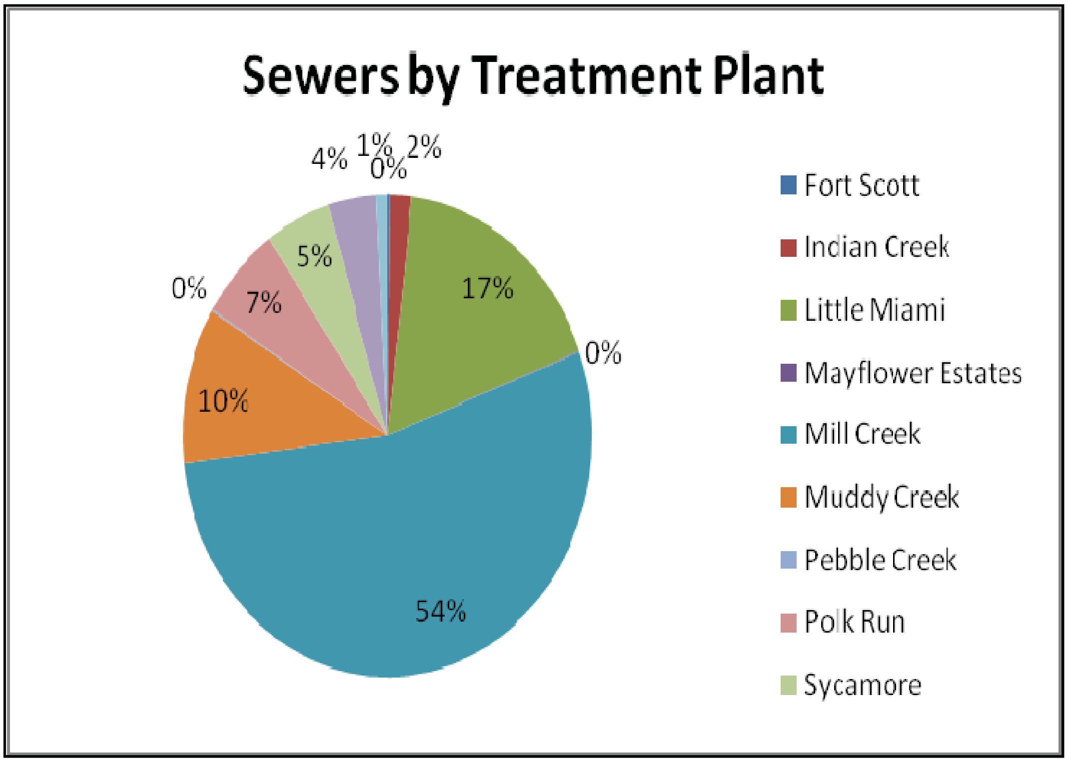


Figure 4.7: Percentage of Sewer Infrastructure by Drainage Basin

4.7 PIPE AGE AND INSTALLATION PERIOD

The average age of sewer in the studied inventory was approximately 79 years, approaching their design useful life. According to EPA GAP report, the design useful life of sewers should be between 80-100 years. Table 4.1 below shows the design useful life of components of the water infrastructure.

COMPONENTS	YEARS OF DESIGN LIFE
Collection Sewers	80–100
Treatment Plants Concrete Structures	50
Treatment Plants Mechanical and Electrical	15–25
Force Mains	25
Pumping Stations Concrete Structures	50
Pumping Stations Mechanical and Electrical	15
Interceptors	90–100

Table 4.1: Design Useful Life According to USEPA

Based on the above, significant portions of the brick, segmented block, concrete and vitrified clay sewers have surpassed their useful life. This highlights the need to extend the useful life of sewers assets through the rehabilitation and sound O&M practices. In addition, since the deterioration of sewers is found, within the result of this research and in the literature, to be strongly correlated with pipe age, the need of asset management practices to predict failure and optimize the decision making to renew the infrastructure, is crucial now more than ever. Figure 4.8 below shows the average age of sewers by material type. Figure 4.9 shows the development of the asset inventory by decade.

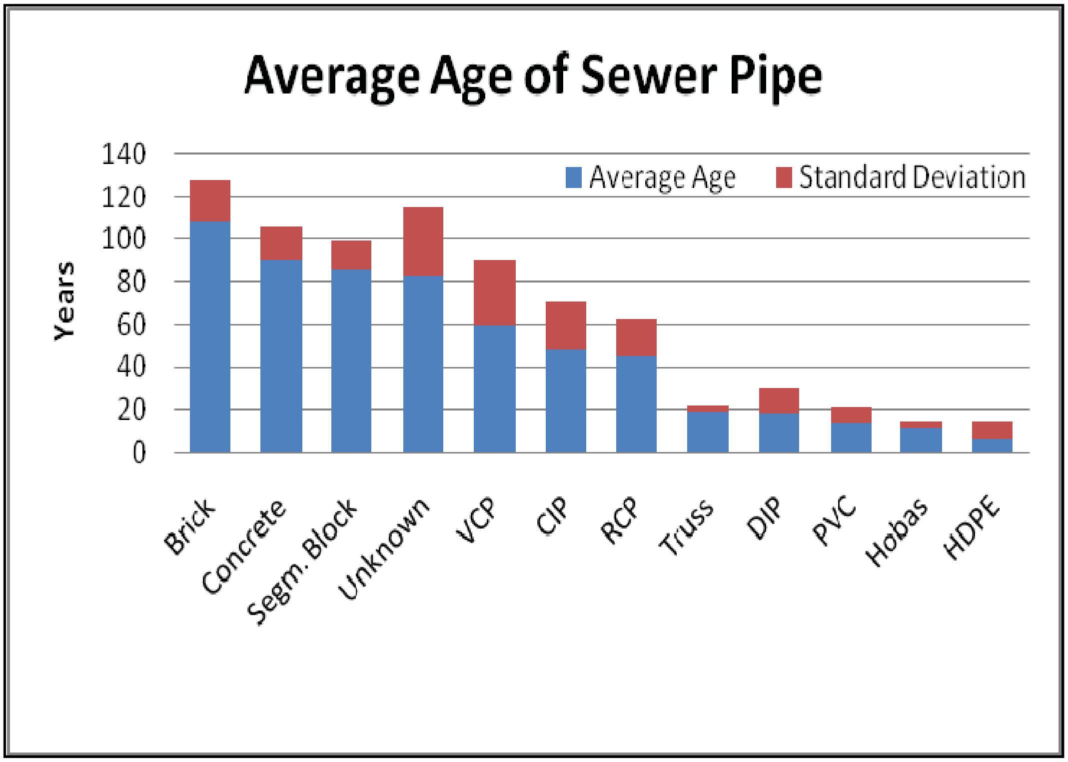


Figure 4.8: Asset Inventory by Pipe Age

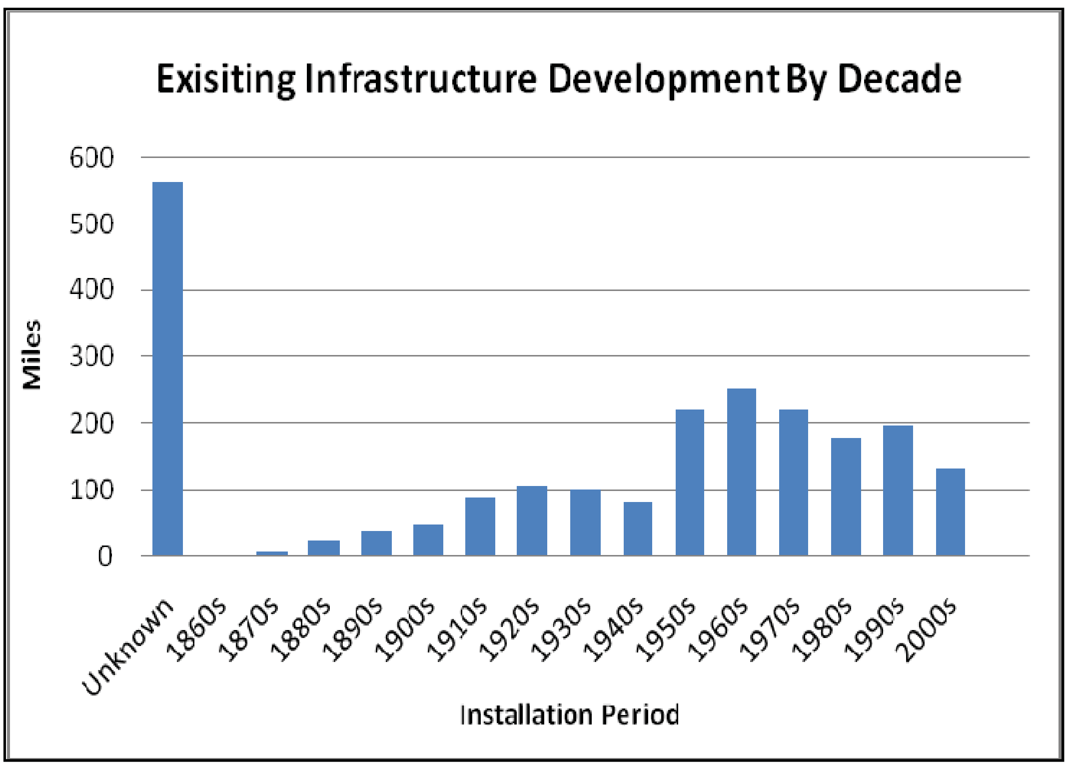


Figure 4.9: Infrastructure Development by Decades

Although installation date of a significant portion of the infrastructure was unknown, from Figure 4.9, a demonstrated slowdown of investments in building the sewer infrastructure can be seen starting in the sixties and continued a relative decline by as much as 100% in the 2000's.

4.8 DISCUSSION

Data from MSDGC CAGIS system were collected to construct both deterministic and probabilistic deterioration models, conduct an assessment on asset inventory composition, and recommend both O&M and capital spending strategy. The data collected was extensive and represented more than 65,000 sewer segments in the Greater Metropolitan Cincinnati area; and included both sanitary and combined sewers. The historical repair data from 1997 to 2009 were collected and analyzed. It is often cited that the lack of confidence and availability in historical data results in making set of assumptions to predict the future failure of underground assets. This is not the case under this research. Historical repair events (representing historical data for sewers failure) were extensive totaling 2,812 events. The pipe's age or installation year was not recorded for all failure events; therefore, the size of the statistical sample was 1796 events.

4.9 SUMMARY

Data were collected from CAGIS related to asset inventory included pipe age, material, depth, slope, size, and soil type. Data from CAGIS were also collected for construction of the criticality matrix, including proximity to structures, proximity to environmentally sensitive areas, depth, location in right of way, proximity to existing overflows (SSO and CSO), and hydraulic conditions. Data for the development of sewers deterioration models were obtained from historical repairs conducted between 1997 and 2009.

The development of the criticality matrix and scoring for sewers depended on expert opinion that included members from various departments at MSDGC. The GIS based tool relied on data related to the physical, hydraulic and spatial attributes of the sewer. The deterioration curves development relied on regression analysis for the deterministic models and on various statistical methods such as Monte Carlo simulation and Probabilistic Neural Networks for the development of statistical models.

The criticality assessment tool as well as results obtained will be discussed in chapter 5. Deterioration models, both deterministic and probabilistic, will be discussed in chapter 6 and chapter 7, respectively. Soft computing methodologies and probabilistic neural network models will be examined in chapter 8.

Chapter 5

CRITICALITY ASSESSMENT OF SANITARY SEWERS USING GEOGRAPHICAL INFORMATION SYSTEMS AND EXPERT OPINION

5.1 INTRODUCTION

Risk assessment of the sewer infrastructure is one of the major steps in establishing the asset management program for wastewater utilities. Risk assessment methods are primarily dependent on CCTV and operator judgment to establish a condition rating of the sewer and estimate the remaining service life of the asset (Tran, 2009). The Business Risk Exposure (BRE) of a utility is measured by the product of both the probability of failure and the consequences associated with this failure for a particular asset. Condition assessment methods include CCTV, visual inspection, destructive testing, direct measurements, and response-type devices that are applied either to the interior and exterior to the pipeline, with CCTV commonly used in both the literature and wastewater utilities in the U.S. Most condition assessment methodologies produce a subjective assessment; primarily, a scale of 1 to 3 (WSSA 2002) or from 1 to 5 as in the PACP method, with the condition rating of 1 for acceptable structural condition and the highest end of the scale as a collapsed pipe. With the subjective condition assessment performed and a condition score developed, another subjective translation to the probability of its failure is recommended by EPA. Technological advances in GIS and high resolution CCTV, however, enable wastewater utilities to better predict sewer failure and quantitatively determine the benefits and costs of renewal alternatives (Boulous, 2010). CARE-S asset management model for sewers in European countries provide decision making tools to rehabilitate and replace sewers (Saegrov and Schilling, 2002). Similarly, the COST-S model for combined sewers in UK

(Cashman, 2006) and optimal model-based rehabilitation for sewers in US (Solomatine, 2006) attempt to optimize the decision making process for infrastructure renewal.

This dissertation provides a critique of such CCTV-based methodologies and provides an alternative approach to addressing risk associated with the failure of sewers. This chapter will focus on the criticality assessment methodology to assess the consequences of failure associated with linear assets. Criticality matrix for the linear assets was developed using expert opinion and ArcMap, a software by ESRI. Maps developed highlighted the critical sewers in the collection network for MSDGC in terms of their consequences of failure. Several attributes were determined to be the contributing factors for criticality; and were compiled, as well as their relative weight, using expert opinion from a panel of professionals in the industry. The GIS software used sewers attributes from CAGIS to calculate the criticality index of various linear assets.

5.2 CONSEQUENCES OF SEWER FAILURE

Consequence of failure can depend on a number of pipe attributes, including depth, number of connected customers, and proximity to critical facilities. Consequence of failure scores of various pipeline assets can be expressed in any user-desired scale, such as high, medium and low impact (Boulous, 2010).

With advances in GIS and other information systems, performing the consequence calculations are becoming less cumbersome. Asset managers can select a particular layer such gravity sewers within the GIS system and calculate distances from the sewer to critical facilities such as rivers, wetlands, hospitals, schools, manufacturing, high density housing, and other contributing factors, to determine the calculated criticality score for each contributing factor.

Criteria	Scoring Matrix					
Sewer Size	S ≤ 12"	12" < S ≤ 24"	24" < S ≤ 36"	36" < S		
Points	25	50	75	100		
Dry Weather Flow	0 ≤ F ≤ 1	F > 1				
Points	(F^3)*100	100				
WWF Capacity - Flooded	None	10 yr. Flood	5 yr. Flood	2 yr. Flood	6 mo. Flood	
Points	0	25	50	75	100	
WWF Capacity - Surcharge	None	10 yr. Surcharge	5 yr. Surcharge	2 yr. Surcharge	6 mo. Surcharge	
Points	0	25	50	75	100	
Street Class[#]	Off Road	7	6	5	4	3
Points	0	10	20	30	60	80
Proximity to Aquatic Life	Outside RZ	Inside RZ				
Points	0	100				
Park/ Recreation Area/ Golf Course	No	Yes				
Points	0	100				
Proximity to Structures	P > 30'	20' < P ≤ 30'	10' < P ≤ 20'	0' < P ≤ 10'	Under	
Points	0	10	50	75	100	
Type of Structure	Single family	Multi-family	Condo	Government	Industrial	School
Points	0	10	50	70	90	100
Location in RR Easement	No	Yes				
Points	0	100				
Depth	0' < D ≤ 33.33'	D > 33.33'	Aerial			
Points	D*3	100	100			
DS proximity to SSO, # of segments	≥ 5th	4th	3rd	2nd	1st	
Points	0	25	50	75	100	
DS proximity to CSO, # of segments	≥ 5th	4th	3rd	2nd	1st	
Points	0	25	50	75	100	
Property Damage	0	1-2	3-4	5-7	8-12	>12
Points	0	6.5	13	25	50	100
Landslide Potential	Low	Moderate	M. High	High	Very High	
Points	0	25	50	75	100	
Location in R/W	No	Yes				
Points	0	100				
Location in Riverfront	No	Yes				
Points	0	100				

Table 5.1: Summary of Contributing Factors for the Criticality of Sewers

[#] Street Class of 2 and 1 received 90 and 100 points, respectively

Other information systems such as hydraulic models and billing information systems can be used to determine the amount of flow and velocity within the sewer as well as how many customers are affected by disruption of its service.

Table 5.1 above summarized the factors influencing the criticality of sewers. The factors were determined based on expert opinion from a panel of professionals in different functions within the organization representing the risk management task force. It is important to note that all the factors and their gradation are measurable from CAGIS. If a contributing factor was decided to be immeasurable from the GIS system, it was then ignored. The decision making process was iterative, similar to that of the Delphi technique, and the factors were divided into economical, social, and environmental to mimic the TBL approach for decision making. Scores were assigned arbitrarily on a sliding scale between 0 and 100 and then added up to measure the overall score using a GIS model. Relative importance of factors was also decided by simply polling experts within the organization, including the risk management team. The model was then calibrated and the contributing factors' scores relative weight of importance was adjusted for a model re-run. Each model run took approximately 5 hours to run and obtain the results of the total criticality score for all the assets within the system. Results were reviewed weekly and adjustments based on experience of the reviewing panel for validation. After few iterations, and expert reviews, the values in table 5.1 were finalized.

5.3 CONTRIBUTING FACTORS

5.3.1 Economic Factors Contributing to Sewer Criticality

Economic Factors that the risk management team of experts determined were primarily affected to replacement and O&M costs. Those factors include sewer size, depth, property damage, proximity to structures, location in Right of Way (R/W), location in Rail Road easement, and proximity of the linear asset to the river front development. All such factors affected the cost of repairs and capital replacements. Replacement and O&M costs typically increase with the increase in the sewer size and depth, the number of private properties it can potentially flood, the closer it gets to existing structures, if it is located within the R/W, if it is located in the RR easement, or if it is placed within the riverfront development area. Next, the expert panel agreed on a sliding scale, of 0 to 100, for the contributing factors and values were arbitrarily assigned to each criterion. For example, sewers were assigned a score of 3 times their depth up to a maximum of 100 points; and 25 points sewers that were less than 12 inches, 50 points for sewers between 12-24 inches, 75 points for sewers ranging between 24-36 inches, and 100 points for larger sewers sized more than 36 inches in diameter. Similarly, sewers within the R/W, within rail road easements, and the riverfront development area received 100 points if they met any of those criteria. Potential property damage was measured by the number of properties that are connected to that particular sewer segment which were theoretically are subject to flooding should the sewer surcharges or floods due to hydraulic limitations. Landslide potential was also considered in the economic factors contributing to sewers' criticality. A layer in CAGIS classified slopes' potential for sliding into low, moderate, moderately high, high, and very high; sewers were assigned a sliding score from 0 points for low potential of sliding to 100 points if the sewer is placed in a very high potential area.

5.3.2 Environmental Factors Contributing to Sewer Criticality

The environmental factors that were considered in the criticality matrix include the proximity of the sewer segment to federally mandated CSOs, SSOs, and aquatic life in the collection system. Again, a sliding scale was used to measure the impact of sewer failure on the existing overflow location by measuring the distance in terms of number of sewer segmented both upstream and downstream of the overflow point. Another environmental factor was the proximity to the riparian zone of streams. While navigable streams are under the jurisdiction of the Army Corps of Engineers and the smaller non-navigable streams are under the states' EPA, disturbance to surface streams require permits from either entity. Due to stricter sediment control measures under the Clean Water Act, any construction activity within the riparian zone of a surface stream is extremely restricted. Accordingly those existing sewers received a higher criticality scores due to their location. Additionally, the proximity of the sewer to streams usually correlates to the potential of overflows to the surface water streams; adversely affecting aquatic and fish life as well as human health. Under this study, all sewers that are located in the riparian zone received the maximum score of 100 points. Moreover, if the sewer segment was less than 5 segments away from an existing CSO or SSO, the segment received the maximum score of 100 points. Other environmental factors related to potential overflow as well as hydraulic failure, due to the limited capacity of the sewer segment in question, were measured using values for the dry weather and wet weather flows. For example, if the sewer was surcharged under dry weather conditions, it received 100 points; similarly, the sewer segment received additional points if it were surcharged under wet weather flow condition; depending on the storm level. If the pipe surcharged under a 6-months storm, it received the maximum score while it received 25 points if it were surcharged under the 10-year storm.

5.3.3 Social Factors Contributing to Sewer Criticality

GIS-based attributes of social factors that are affecting the criticality of sewers were the proximity to parks and green spaces, disruption of service, and disruption to traffic. With respect to parks and green spaces, sewers that are abutting them received the maximum points of 100. The disruption of service was measured by the type of structure abutting the sewer with a single family home receiving the lowest priority and schools receiving the highest. The disruption of traffic was measured by the street class as defined by the state DOT. Table 5.2 summarizes the definition of street classes.

Road Class	Definition	Criticality Points
Class 0	Off Road	0
Class 1	Interstate Highways	100
Class 2	US & State Routes	90
Class 3	Arterial Roads	80
Class 4	Collector Roads	60
Class 5	Local Streets	30
Class 6	Ramps	20
Class 7	Alleys	10

Table 5.2: Street Class Definition and Points Summary

5.4 RESULTS & DISCISSION

Based on the criteria and the scoring matrix discussed above, a GIS model was constructed in ArcMap to evaluate the criticality of sewer assets at MSDGC. The GIS model, contained almost 80 mathematical functions, calculated the scoring for the overall infrastructure. The assets were divided into subsets or geographical areas to reduce the model run time to five hours. In the initial stages, maps were produced and the weighting factors were modified to reflect actual conditions using expert opinion and professional judgment of the risk management team.

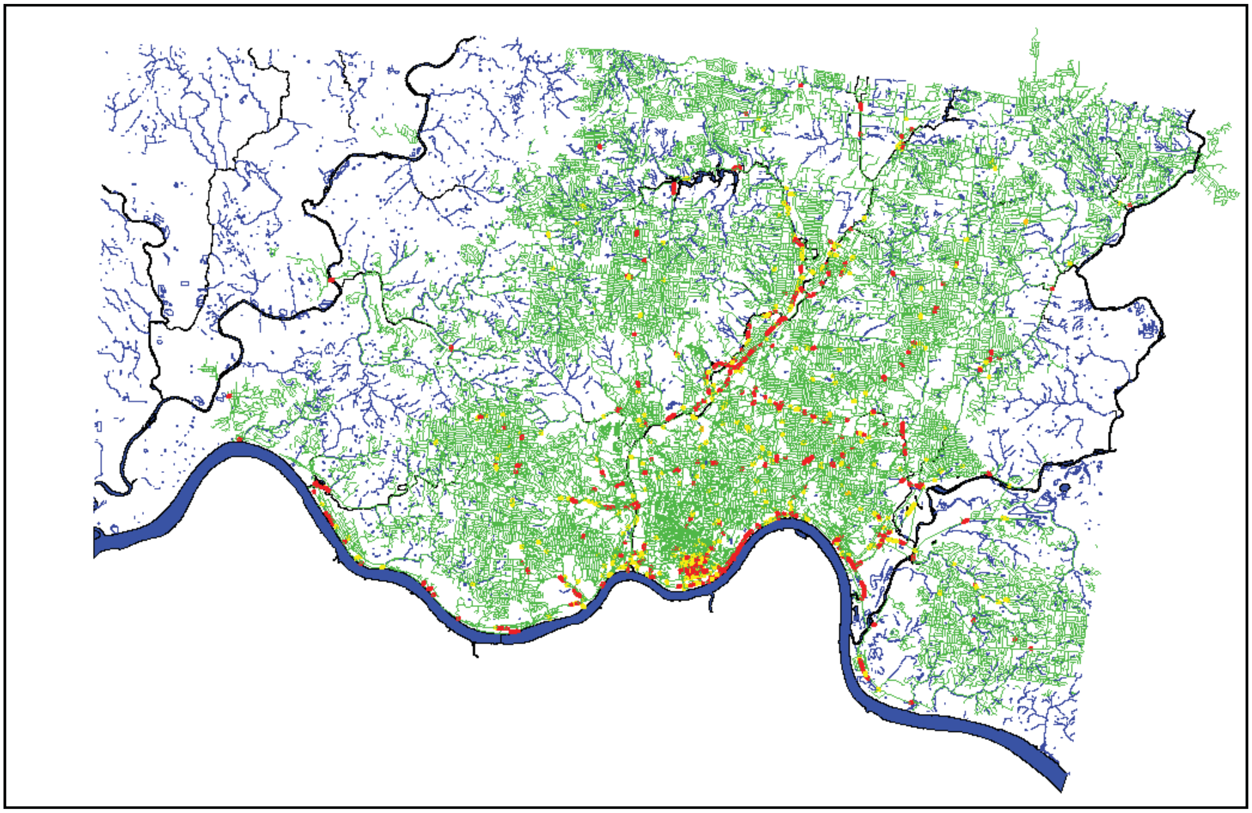


Figure 5.1: Overview of the Assets Criticality

After few numbers of iterations, which can be described as the calibration phase of the GIS model, values were finalized and the results were mapped. Since most utilities replace less than 1% of its assets annually, the top 0.5% of scores was color-coded in red indicating the highest priority, followed by the next 0.5% of scores in yellow indicating a close watch-and-see approach, and 99% of the infrastructure in green indicating non-critical segments of the infrastructure. As shown in Figure 5.5 above, the model highlighted the interceptors along the Mill Creek corridor as well as the interceptors along the Ohio River. Additionally, the model captured main trunks along the Little Miami River due to their size and the environmental sensitivity of the river.

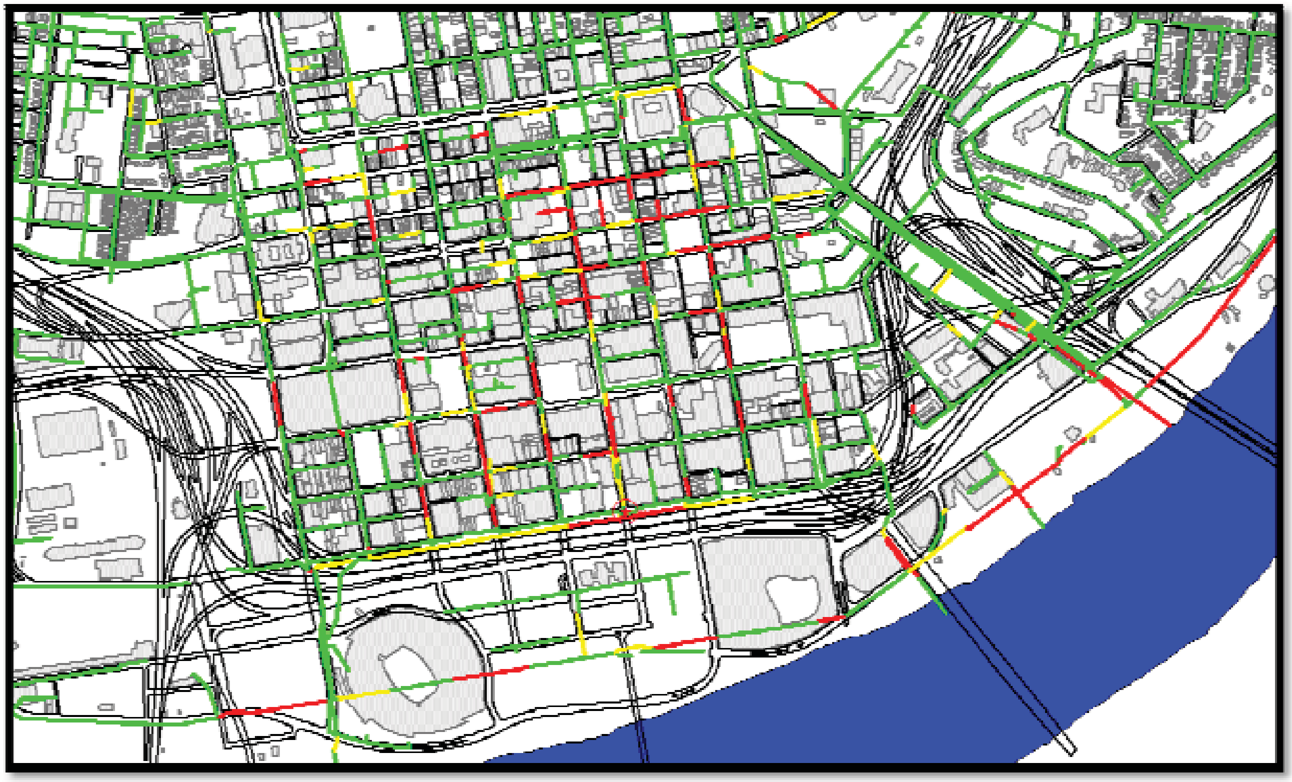


Figure 5.2 Downtown Area Crticial Sewers

Not surprisingly, the model identified the sewers downtown near the riverfront stadium as part of the critical infrastructure for the many factors that they have such as size and proximity to the Ohio River, the riverfront development, as well as the large diameter in size. Other problematic or highly critical areas that are identified by the model included the Camp Washington and south Fairmount and the neighbourhood of St. Bernard; both have been subjected to frequent flooding and are old communities with a relatively older infrastructure. Figures 5.7 and 5.8 illustrate the critical sewers in the camp Washington and St. Bernard areas, respectively.

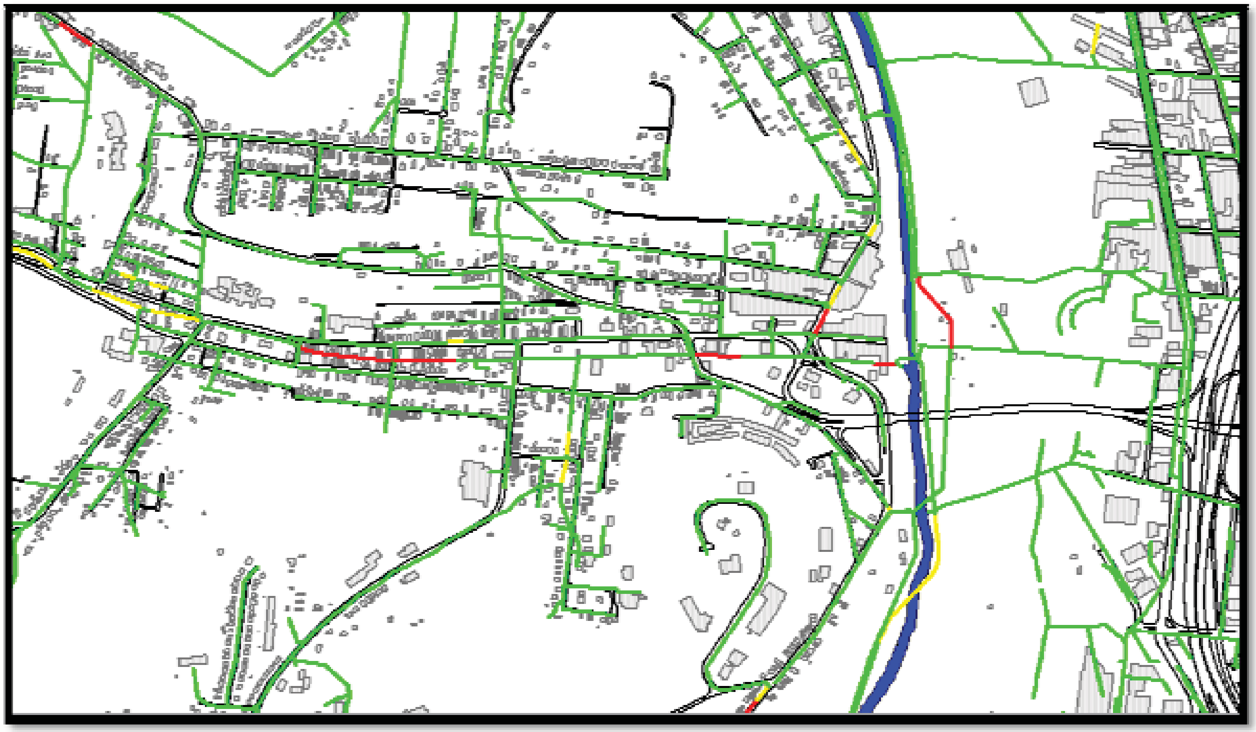


Figure 5.3: Camp Washington Area Critical Sewers

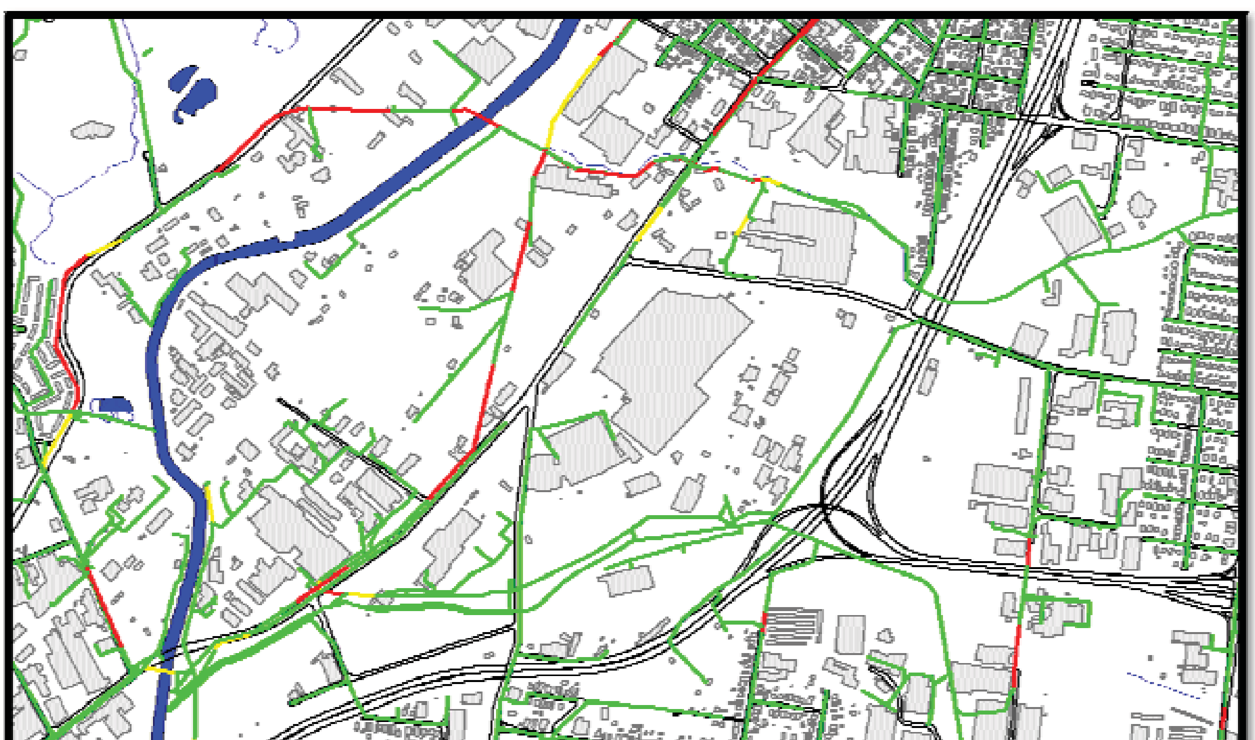


Figure 5.4: Critical Sewers in the St. Bernard Area

5.5 SUMMARY

A GIS-based tool was developed at MSDGC to evaluate the criticality of the linear assets using expert opinion. The tool was fairly accurate in predicting the critical arteries of the collection system and is possibly one of a kind among utilities in the U.S and abroad. The tool once it incorporates the probability of failure will be capable to highlight the critical infrastructure in terms of the overall business risk exposure which is the ultimate goal of developing the tool. GIS was proven to be a powerful tool not only for the purpose of asset inventory but for risk assessment as well.

Although a similar GIS model was previously developed by Seattle Public Utilities (SPU) to assess the criticality of pump stations within their system, the model discussed in this chapter is the first to assess gravity sewers for criticality. In order to provide a complete picture of the risk, MSDGC needs to include the contribution of risk associated with the probability of failure of linear assets and generate, update, and validate the results periodically. The GIS model results for criticality scores was validated by expert knowledge and were successful in identifying critical areas of the infrastructure. In Eaurope, CARE-S, an asset management decision support system, provides decision making tools to rehabilitate and replace sewers (Saegrov and Schilling, 2002). Similarly, the COST-S model for combined sewers in UK attempt to optimize the decision making process for infrastructure renewal. The model produced under this research, when incorporates the probability of failure developed in subsequent chapters, along with a module to calculate Life Cycle Cost of replacing or rehabilitating an asset, will constitute a powerful Decision Support System for wastewater utilities infrastructure management.

Chapter 6

DETERMINISTIC DETERIORATION MODELS FOR SEWERS USING CORRELATION ANALYSIS AND REPAIR HISTORY DATA

6.1 INTRODUCTION

The need for accurate deterioration curves for sewer pipes is crucial to the developmenet of a comprehensive asset management plan. Detrioration curves give insights into the understanding of how sewer pipes lose their functions with age; thus, allowing managers to plan for replacement and O&M strategies. Models developed in the literature can be described as deterministic, probabilistic, and soft computing methods such as simulation and nueral networks (Morcous, 2004; Tran, 2007). This chapter will explore deterministic methods to evaluate the detrioration of sewers, both separate and combined, for the asset inventory that was researched. Failure of sewers are probabilistic events and their deterioration is age dependent as well as many other contributing factors. The contributing factors are primarily divided into physical, environmental, operational, and construction factors (Ana, 2009). Hydraulic conditions such as the pipe capacity, wastewater corresivity, velocity within the pipe, and surcharges are considered factors that affect the hydraulic failure, which are more common than structural failure; however, the focus of this research is the structural detrioration and failure. Deterministic models are mathematical representation of relationships where no random variables are involved; thus they produce the same output. The mathematical equations presented in this chapter are all function of the sewer pipe's age and are based on historical repair data obtained from MSDGC. Deterministic models for infrastructure deterioration have been developed in the past, including water lines and pavements (Kleiner, 2001; Lou, 2001); infrastructure facilities (Madanat &

Ibrahim, 1995; Madanat, 1997); storm water culverts (Tran, 2006; Salem & Najafi, 2008) and sanitary sewers (Wirahadikusumah, 2001). Deterministic models in the literature, however, were primarily developed based on condition assessment ranking methodology, mainly using CCTV. This research explores the use of historical repair data to develop deterministic deterioration models for sewers based on age and material of pipe, and regardless of their condition assessment data.

6.2 SEWER PIPE DETERIORATION

The aging of sewer pipes contributes to the structural and hydraulic deterioration, and ultimately failure; however, age alone cannot explain the probabilistic nature of underground pipes failure. Sewer pipes are usually replaced or "upsized" in reaction to hydraulic failure to accommodate additional development or an increased in the flow due to I&I through structural crack that develop with time. The hydraulic design of sewers determines the size and slope of the sewer as well as how full the pipe will be under diurnal flow conditions. The design flow is determined by the number of population, development and population growth potential, type of land use, soil permeability, drainage area, and the I&I potential that is usually determined using an empirical formula. Proper hydraulic design takes into consideration the hydraulic profile and ground or basement elevations to prevent flooding. For example, if the hydraulic profile of a sewer is higher than ground elevation or the basement elevation, it will result in overflows or flooding of private properties, which deems the hydraulic design improper. Using computer models, and theoretical rain events, the design flow can be determined. Hydraulic models are generally based on two concepts: The conservation of mass and energy. The hydraulic sizing of the pipe diameter and the slope selection is usually determined using manning equation and will depend on the roughness coefficient of the pipe as well as its shape. Additionally, the sizing of the sewer will depend on the assumption of how full the sewer pipe needs to be under the variation in diurnal flow and wet weather conditions. For example, in relatively dry countries with no to modest rain, sewers are designed on the diurnal flow so that the pipe would be approximately one quarter full at minimum flow, half full at average flow, and three quarters at maximum diurnal flow. The pipe will then be allowed to be full under wet weather conditions. In countries with intensive rain events, however, the design approach is different. In the U.S., sewer pipes are designed to be full when handling peak wet weather flows, taking into consideration I&I and the variations of flow and in accordance to the guidelines developed by the regulating state EPA.

Structural deterioration, and ultimately failure, is concerned with the loss of pipe's integrity to perform its intended purpose of conveyance. Such deterioration is dependent on many factors that result in the development of cracks, deformities, and imperfections in the sewer pipe. Sewer pipes are structurally designed to handle the overburden pressures, distribute the loads to the bedding soil, and withstand the stresses within the pipe wall. Structural design of sewers depends on material strength of pipe, stresses acting on the pipe, pipe size, backfill material, depth, length of sewer segments, and installation methods. This research focuses on structural deterioration and failure.

6.3 FACTORS AFFECTING STRUCTURAL DETERIORATION OF SEWERS

The structural deterioration of sewers depends on physical, environmental, construction, operational, and hydraulic conditions. Table 6.1 summarizes the contributing attributes that lead to the structural deterioration of sewer pipes.

Physical	Environmental	Construction	Operational	Hydraulic
Pipe Age Material Slope Size Depth Shape Joints Type	I&I Tree roots Traffic External pressure	Installation method Quality	O&M frequency pH Corrosively	Velocity Capacity

Table 6.1: Summary of Contributing Factors for Structural Failure

While most researchers agree that pipe age is strongly correlated to structural deterioration of sewer pipes, age alone cannot explain early failure of pipes that haven't reached its useful life. As previously discussed, this research found age to be strongly correlated to deterioration and frequency of failure for all sewers examined. While results obtained from this research study showed that the increase in the slope results in an increased deterioration rate, there have been conflicting results in the literature. This research found that the frequency of failure for sewers that have a slope of 20% or higher was three times as much those with less than 1% slope. The findings support previous results obtained from a study of Indianapolis collection system showing increased deterioration with steep slopes (Baik, 2006); and contradicts other observations by others (Baur & Herz, 2002; Ayoub, 2006). This research as well as others' in the literature showed varying deterioration rates of different pipe material. The shape of the pipe is a factor since it impacts how the overburden stresses get transferred to the bedding soil. Bauer & Herz reported that tunnel-shaped pipes had the slowest deterioration rate compared to circular or rectangular shapes. Results related to pipe size are also contradictory in the literature. This research found that pipes between 10 and 12 inches had the highest frequency of failure when compared to larger diameter pipes or even the 6-8 inches in diameter sewers. Some researchers reported that sewer deterioration of smaller pipes is faster than that of larger size (Davies, 2001;

Baur & Herz (2002); Micevski, 2002) while other reported the opposite (Baik, 2006). Most researchers agree that the rate of deterioration decreases with the increase of depth (Fenner, 2000). This is perhaps due to the decreased susceptibility to traffic stresses and fatigue. Failure at the pipe joints is more common in VCP pipes than other material types due to the butting connection of clay pipes (Ana, 2009). Results under this study showed that the frequency of failure of VCP occur relatively late in their useful life and they had longer life when compared to other material type. Construction methods such as trenchless would tend to provide a longer design useful life especially if the pipe in encased. Needless to say, quality of the workmanship, like compaction of backfill soil, under the installation methods also decreases the probability of failure. Moreover, the rate of sewer deterioration can be decelerated by frequent O&M resulting in less accumulation of H_2S, sediment, and any other corrosive material in the sewer.

6.4 DATA COLLECTION AND DETERMINISTIC MODELS DEVELOPMENT

Data used for asset inventory and the deterioration models were collected from CAGIS and sewers repair database, respectively. CAGIS contained more than 650,000 segments of sewers and a similar numbers of manholes. The database for repairs contained approximately 2,400 repair events occurring between 1997 and 2009. Pipe age, size, material, and slope were also obtained from CAGIS when a segment failed and was replaced. Some of the sewers repaired had unknown installation year; thus their age at failure could not be calculated and those data points were not included in the analysis. The total sample size of sewers with known age was 1,796 data points. The known parameters were then examined to determine their correlation with the frequency of failure. The data was sorted by pipe age and the frequency of failure by age was measured and graphed. The cumulative values for failure frequency were normalized to reflect values between 0 and 100, and then plotted with respect to pipe age; and a polynomial regression analysis was conducted to fit the results and obtain survival curves for pipes. The same process was repeated for various types of pipe material and various curves were generated. Generally, the deterioration of sewers was positively correlated to age and slope. Also, negative correlation was observed with pipe size and the frequency of failure varied widely with the type of material of the sewer.

6.5 HYDRAULIC AND STRUCTURAL DESIGN

The main function of sanitary sewers- combined or separate- is to carry the wastewater from customers, residential, commercial, or industrial, to regional wastewater treatment plants for the separation of solids and the discharge of clean water into streams. Hydraulic design aims at determining the size of pipe and slope, as well as how full the pipe will be under diurnal flow conditions. The design flow is determined by the number of population, development and population growth potential, type of land use, soil permeability, drainage area, and the I&I potential that is usually determined using an empirical formula. In the advent of computers, hydraulic design is performed using computer models and theoretical rain events to determine the design flow. The hydraulic sizing of the pipe diameter and the slope selection is usually determined using manning equation and will depend on the roughness coefficient of the pipe as well as its shape. The premise of hydraulic models is based on the conservation of mass and energy. This research is not concerned with hydraulic design or hydraulic failure; rather it focuses on structural failure. Structural design of sewers is concerned with material strength, overburden stresses acting on the pipe, pipe size, backfill material, depth, length of sewer segments, and the construction methods to be used for installation. Structural design elements contributes to a long useful life of the assets; thus, its probability of failure. In summary, both hydraulic and structural design is critical for the longevity of the collection system.

6.6 CONTRIBUTING FACTORS TO SEWER FAILURE

Determining the probability of sewer failure can be determined based on predictive tools, failure history, and CCTV data. The rate of failure is often described as the number of failures per mile per year for various pipe materials and as a function of age (Boulous, 2010). Factors contributing to the failure of sewers can be classified into physical, environmental, operational, and construction factors (Ana, 2009). Physical factors include pipe age, shape, size, depth, length, material, slope, type, and joints type. Environmental factors contributing to failure include groundwater table, I&I, tree roots, soil type, and traffic loading stresses. Operational factors include siltation and sewage type or characteristics. Construction factors include installation methods and quality of work.

In this dissertation, all sewer deterioration curves were developed using historical repair data and were plotted as a function of pipe age and for various types of material. The rate of failure as a function of pipe material, slope, pipe size, and construction methods or installation period was evaluated within the scope of this work. Many other factors, although widely accepted as contributing factors, were not evaluated separately for sensitivity or how much they have contributed to failure because of lack of data. Data presented in this chapter were obtained from CAGIS as well as the repair history for the sewer network at MSDGC. Failure rate for various material types of gravity sewers, both sanitary and combined, was evaluated and the results were plotted in terms of number of failures per mile per year. Segmented block sewers had the highest failure rate followed by VCP, Brick, Concrete, CIP, Truss, HDPE, DIP, RCP, and PVC. Caution should be taking into the interpretation the results as pipes of certain material have different average ages and are at different stages in their useful life. The results should give insights into developing O&M strategies to focus the effort on problematic sewers rather than an endorsement of one type of material versus the other. As reported in chapter 4, the average age of segmented block, VCP and brick types are generally older than PVC and HDPE pipes in the asset inventory examined. Figure 6.1 shows the failure rate of sewers by material.

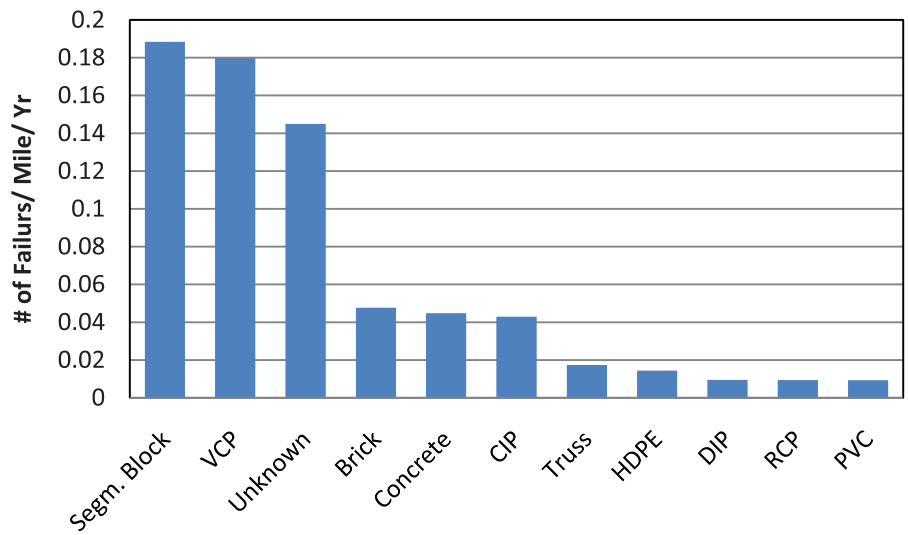


Figure 6.1: Sewer Material and Failure Rates

Similarly, the impact of sewer size of the rate of failure was evaluated using CAGIS and repair history. Figure 6.2 shows the failure rate per mile per year for various pipe sizes. A noticeable increase in the rate of failure was observed for sewers as the diameter increased from six to 22 inches and then tapered off and was reduced for the larger pipes. Theoretically, larger sewers tend to be deeper as they are mainly trunks carrying wastewater from sewer branches and therefore are subject to fewer influences from traffic stresses or tree root damages. The lower rate of reported failure of the 6-8" can be explained due to the fact that a significant portion of that infrastructure are maintained by property owners; therefore, their failure was not reported by the utility.

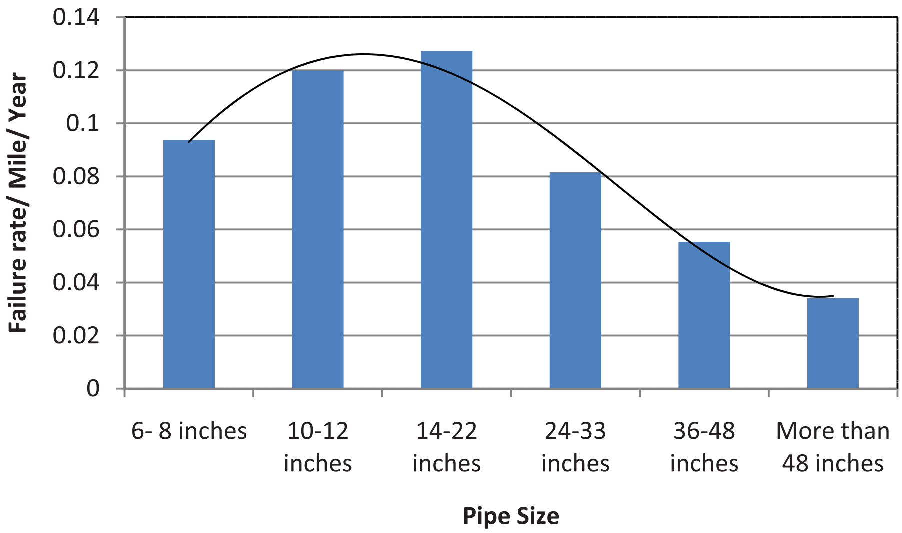


Figure 6.2: Failure Rate by Size Distribution

Within this research, the slope of sewers was found to be strongly correlated to the rate of failure. The rate of failure was exponentially increased for slopes which ranged between 1 and 30 percent. Manning equation in (6-1), which is the theoretical basis of hydraulic design of gravity sewers, shows that the design flow is directly related to the square root of the slope of the pipe; and the increase of the slope will increase the velocity of wastewater in the pipe; thus accelerating its deterioration.

$$V = \frac{k}{n} R_h^{2/3} . S^{1/2} \qquad (6\text{-}1)$$

Where:

V: is the fluids velocity;

K: is a constant;

n: is Manning Coefficient;

R_h: The hydraulic radius;

S: The slope of pipe.

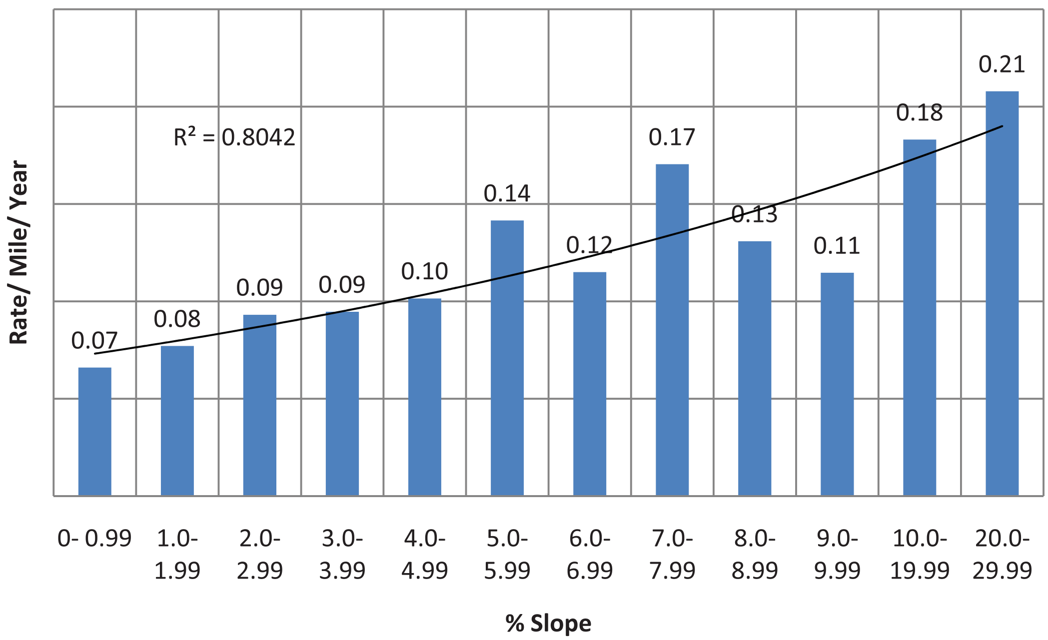


Figure 6.3: Correlation of Slope and failure Rate

Figure 6.3 above shows the correlation between failure and the slope of pipe. The graph shows a strong correlation between failure rate and the slope of sewers. The probability of failure as a function of slope can be described as:

$$P(f) = 0.0671 * e^{0.0868S} \qquad (5\text{-}2)$$

Where:

P(f): Probability of failure;

S: Slope, %

Similarly, the rate of sewers failure was examined in respect to installation periods. This was done primarily due to the fact that some utilities have experienced some irregularity of failure when correlated to age. For example, Seattle Public Utilities (SPU) reported an increased rate of failure for sewers installed in the forties as compared to newer pipes and they attributed the observation to shoddy workmanship in construction techniques that dominated the industry at that time.

Figure 6.4 shows the failure rates for the observed data when plotted against the installation period by decade. From the graph, it can be observed that the rate of failure exponentially increased with age up to pipes as old as 100 years. There was no distinction nor an increase of failure rates for pipes that older than 100 years old. Many factors may have contributed to this anomaly. It is possible that many failures for pipes that are more than 100 years old went unreported since they are installed in older neighborhoods and many abandoned areas. Another reason could be that those old sewers, usually constructed of VCP, Bricks, and Segmented Blocks, are irreplaceable since their material are not widely used today; thus, their repair work is either unnoticed or underreported. Figure 6.4 shows the correlation of rate of failure and the installation period as an indication of construction techniques. For sewers that are installed in the past 100 years and are in service today, the rate of failure is strongly correlated to the sewer pipe's age.

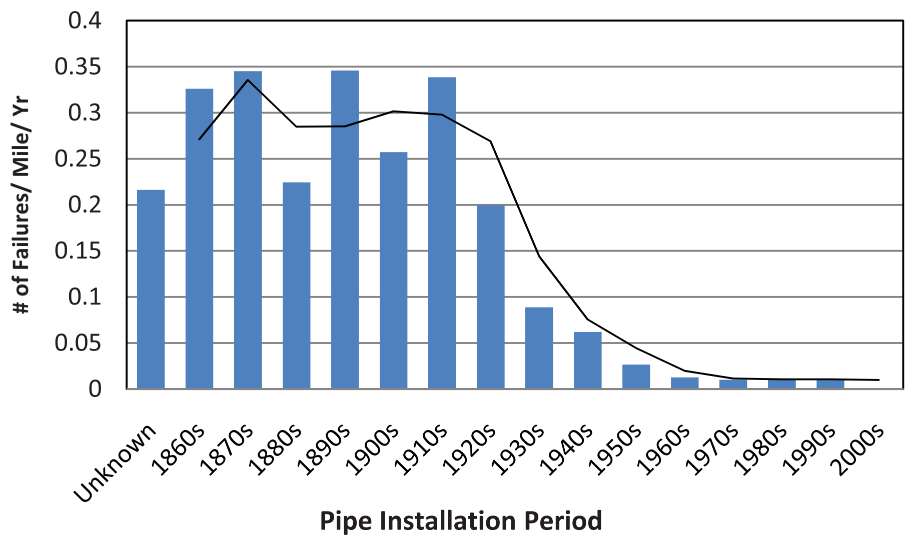


Figure 6.4: Failure Rate for Installation Periods by Decades

6.7 RESULTS & DISCUSSION

Initially all data were analyzed in one data set and sewers were not separated into separate data sets based on material. This was done with the largest sample size which was approximately 1,796 data points to develop a general prediction model for the entire sewers inventory. In subsequent analyses, data were divided into sets based on known or unknown material type and similar deterioration curves were developed. Not surprisingly, a strong correlation between the frequency of failure and sewer's age was observed. The models below are presented based on the sample size from largest to smallest.

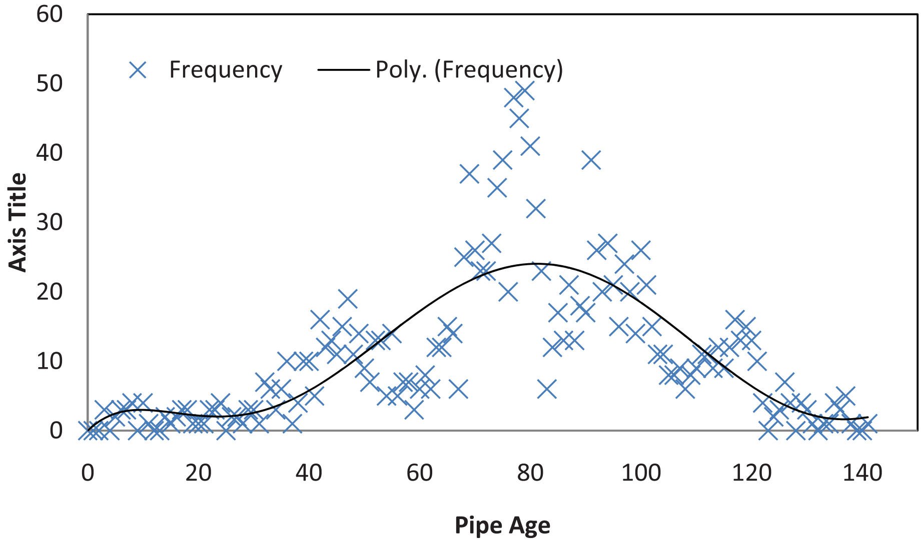


Figure 6.5: Distribution of Failure Frequency for all Asset Inventory

Figure 6.5 shows the frequency of failure for all 65,000 segments of sewers that were examined under this study. Maximum frequency of failure was observed at around 80 years of old which coincides with a similar average age in the asset inventory. Ages of pipes at failure ranged between 3 and 142 years old based on the assets with known age within CAGIS.

The cumulative frequency, normalized between 0 and 100, and plotted against the age distribution is shown in Figure 6.6. It can be shown from Figure 6.6 that a sewer segment that is 80 years old would have approximately 50% probability of being subject to repair or replacement within a given year. Similarly, a sewer that is 40 years old has about 7% probability of structural failure of some sort in any given year.

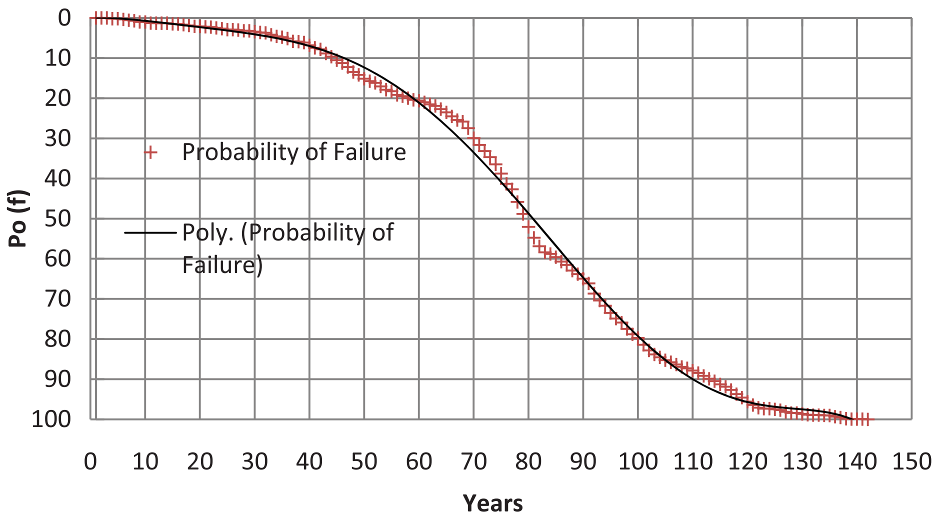


Figure 6.6: Deterioration Curve for All Sewers in the Asset Inventory

Based on Figure 6.6, the probability of failure for all pipes as a function of age can be described as the follows:

$$Po\ (f) = -\ 2E\text{-}07y^5 + 2E\text{-}05y^4 - 0.0009y^3 + 0.0205y^2 - 0.0606y \tag{6.1}$$

Where:

Po (*f*): Probability of Failure;

y: Pipe age, years

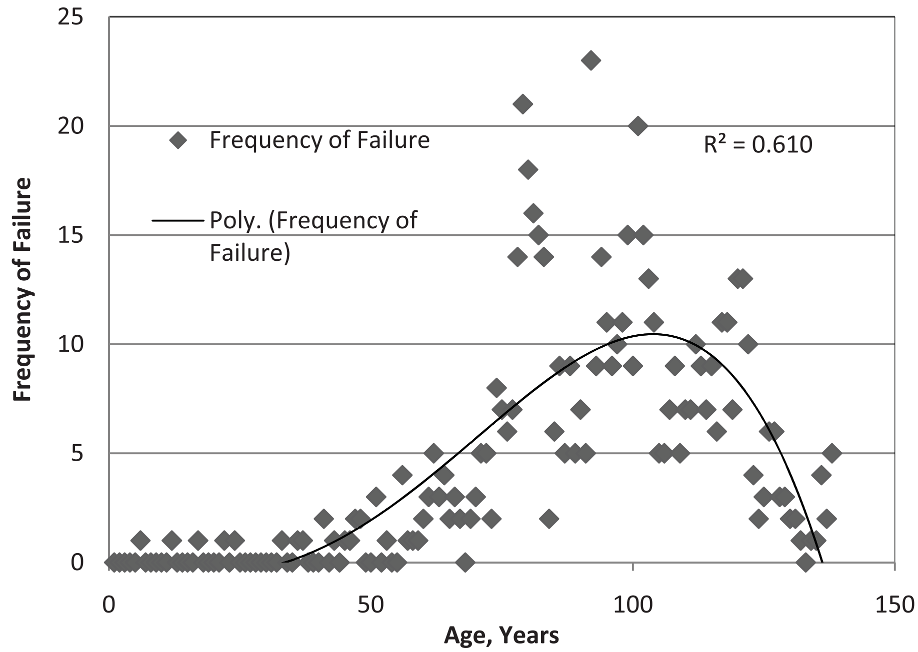


Figure 6.7: Frequency of failure for sewers with Unknown Material Type

The next data set that was analyzed was pipes that are made of unknown material, but known age, which was the second largest data set. The maximum frequency of failure occurred at an older age of approximately 92 years of age. This primarily due to the fact that sewers with unknown material tend to be the ones that are installed long time ago and had no as-built drawings to transcribe into CAGIS. It is important to note that this does not mean that this data set correspond to a superior material but rather the sewers remaining in service today with unknown material represent the portion of that infrastructure that endured with time; thus, the distribution is skewed to the right.

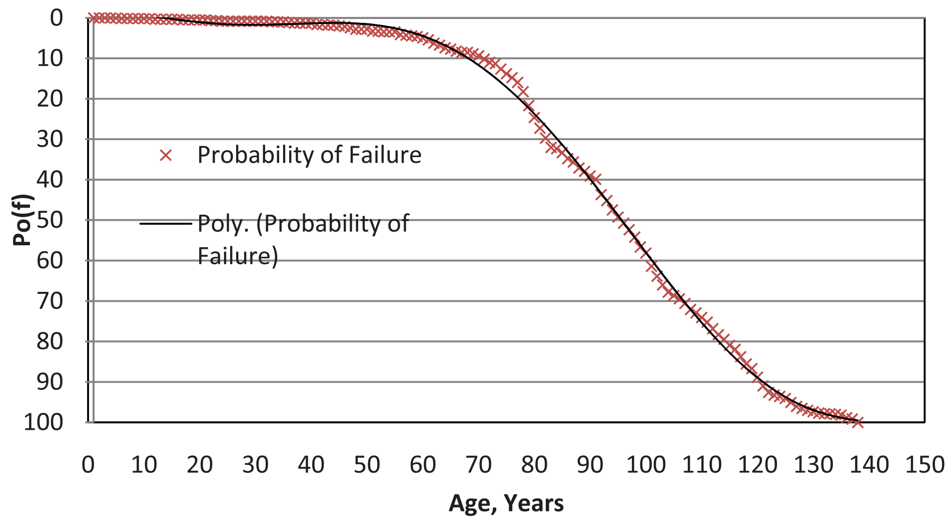


Figure 6.8: Deterioration Curve for Sewers with Unknown Material

Figure 6.7 shows the distribution of failure with time and figure 6.8 represents the detrioration curve for sewers with unknown material. For this subset of sewers, the probability of failure, *Po* (*f*), as a function of age in years, *Y*, can be described as follows:

$$Po\,(f) = -\,2E\text{-}07y^5 + 3E\text{-}05y^4 - 0.0019y^3 + 0.0508y^2 - 0.4037y \qquad (6\text{-}2)$$

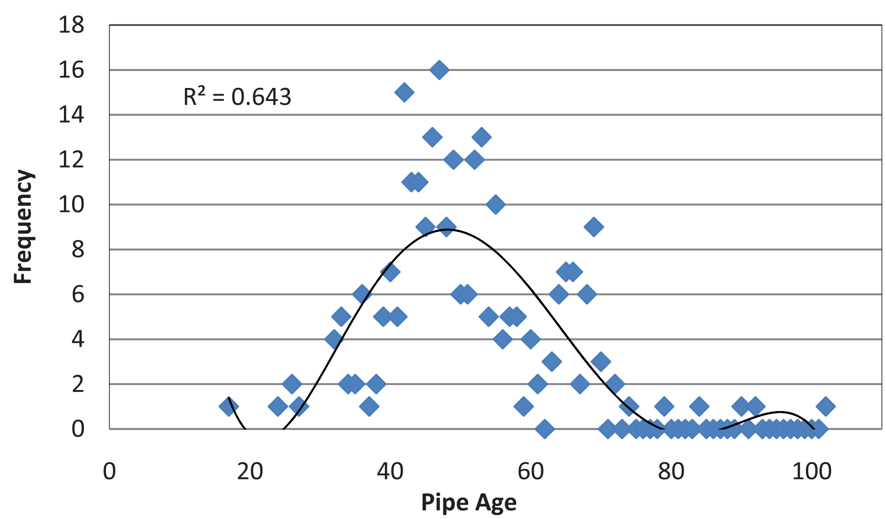


Figure 6.9: Failure Distribution for Concrete Pipes

The next subset of sewers examined was concrete pipes. Although the maximum frequency for concrete pipes occurred at around 50 years of age, caution should be taken into consideration when interpreting the result. This should not mean that concrete pipes have shorter useful life than VCP pipes for example nor should they be treated as less than average when compared to the entire inventory. It is rather that current average age of concrete pipes in the system is relatively younger than the overall average age of sewer within the asset inventory. Since the deterioration curves presented in this dissertation are based on the repair history as of end of 2009, those curves should be updated annually. It can be estimated from the graph that a 30 year old concrete sewer should have a probability of 1% of failure while the pipe deteriorate at a faster rate between 30 and 70 years of age, at which point it may be deemed collapsed. As mentioned earlier, as the inventory of concrete pipes ages, the deterioration curves will also shift to the right; therefore, updating the results annually is recommended.

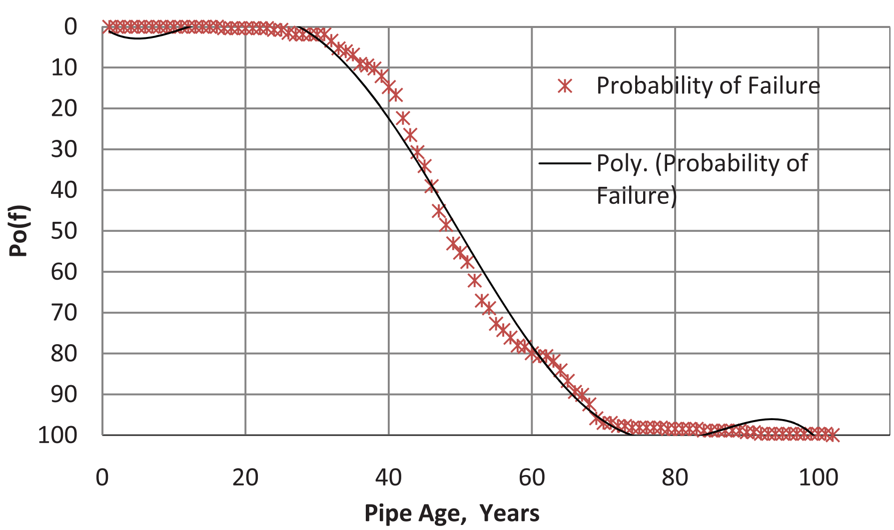


Figure 6.10: Deterioration Curve for Concrete Sewers

For Concrete pipes, the probability of failure as a function of age can be described as follows:

$$Po\,(f) = 9\text{E-}07y^5 - 0.0002y^4 + 0.0104y^3 - 0.2594y^2 + 1.9208y \quad (6\text{-}3)$$

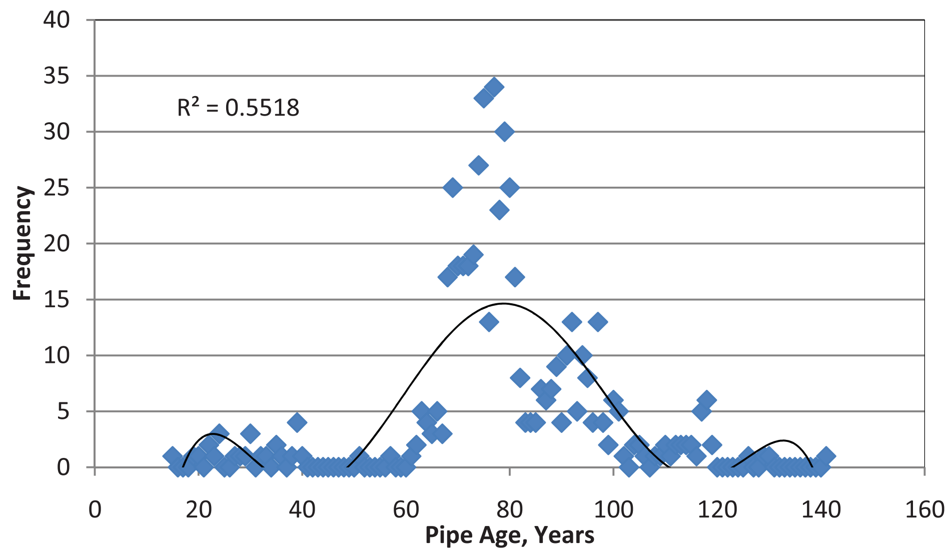


Figure 6.11: Failure Distribution for VCP Pipes

A similar approached was used to develop the deterioration curve for VCP sewers. The maximum frequency of failure was observed at approximately 78 years of age. Figures 6.11 and 6.12 show the failure distribution and deterioration curve for VCP sewers, respectively.

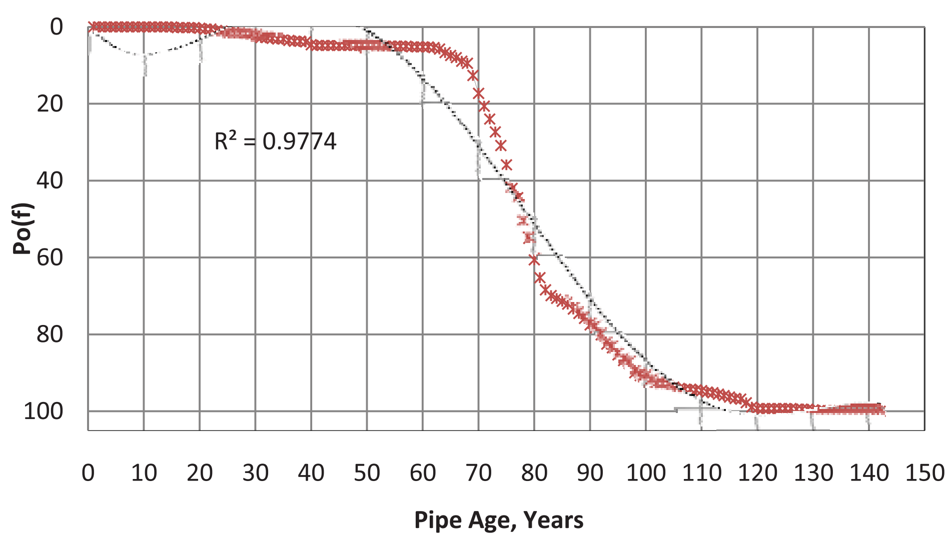


Figure 6.12: Deterioration Curve for VCP Sewers

For VCP pipes, the probability of failure as a function of age in years (y) can be described as follows:

$$Po\ (f) = -\ 2E\text{-}05y^4 + 0.0027y^3 - 0.1239y^2 + 1.7084y \qquad (6\text{-}4)$$

6.8 SUMMARY

Historical repair events extracted from CAGIS were used to develop deterministic deterioration models for sewers. Although other researchers have developed such deterioration models for the deterioration of infrastructure before, this research does not rely on condition assessment methodologies that are based on CCTV. Repair data provided limited attributes such as installation year, repair date, sewer material, depth, size, and slope. No deterministic models for PVC and HDPE pipes were developed because of the lack of sufficient data related to their failure history; however, the general model for all pipes can be used for those pipes. A similar problem was encountered with segmented block and brick sewers. It is recommended that more attributes of the sewers being repaired to be collected and recorded so that will aid in the development of future deterioration models. Polynomial regression analysis, although simple and can be conducted in Excel, provide powerful and meaningful results that will aid asset managers in wastewater utilities in assessing risk associated with linear assets that they own and operate.

Care should be taken when interpreting the results obtained from the deterioration models. The models represent tools to assess the probability of failure and should not be interpreted as one type of material deteriorates faster or inferior to other types of sewers. The data that were used to develop the models represents the sewer infrastructure of the City of Cincinnati and Hamilton County and should be used for risk assessment at MSDGC. It is also worth noting that updating the deterioration models annually could be easily accomplished without spending scarce resources on CCTV and operators training to assess the condition of the entire asset inventory. With the availability of the deterioration models presented in this chapter, CCTV efforts should be selective to target the critical infrastructure and sewers with high consequences to their failure.

Chapter 7

PROBABILISTIC SEWER DETERIORATION MODELING USING DATA FITTING AND MONTE CARLO SIMULATION

7.1 INTRODUCTION

Probabilistic models are useful tools that can be used to predict the future of a particular outcome based on historical events. Statistical models can be described as mathematical equations to describe the behavior of an object of study in terms of random variables and their associated probability distributions. They are described as stochastic and random processes in contrast to the deterministic approach discussed in chapter 6. Statistical models have been used to model the deterioration of storm water pipes (Wirahadikusumah *et al.* 2001; Kleiner, 2004; Baik, 2006; Tran 2007; Salem & Najafi, 2008), infrastructure facilities (Morcous, 2002), pavements deterioration (Salem, 2003), water mains failure (Kleiner and Rajani 2001; Lou *et al.* 2001), and sewers deterioration prediction (Davies, 2001; Ariaratnam 2001; Ariaratnam 2006; Ana, 2009). Statistical models which have one equation are called single-equation models whereas the ones that contain more than one equation are known as multiple-equation models. Most models in the literature were developed empirically based on condition assessment, primarily CCTV-based methods, to predict the failure or deterioration of the studied infrastructure. The reason often cited by researchers for following this approach is the lack of historical data as well as the lack of confidence in the available data. In this chapter, the development of statistical models using historical data of repaired sewers will be discussed. The data were collected from 1997 and 2009 for assets owned and operated by the Metropolitan Sewer District of Greater Cincinnati (MSDGC). For each failure event, the age of the pipe was calculated by subtracting its installation year, extracted from GIS database, from the repair year known from the repair history. The frequency of failure was fitted for probability distributions using statistical software called @Risk, a module of decision making software by the Palisades Corporation called Decision Tools Suite. The cumulative frequency was plotted, then, against the age of the pipe to develop the deterioration curve for the particular data set examined. The overall population was fitted for and the model produced represented the overall sewers in the inventory. Subsets of data were examined to produce the deterioration curves of sewers by material type. The top three fits of cumulative probability distribution functions were determined based on goodness of fit tests and were graphed versus pipe age. Sigma Zone Statistical software was used for Monte Carlo Simulation of remaining service life of sewers. A similar approach was followed where curves were generated by material type and as a function of the pipe age. Statistical parameters for the simulation were determined from the data fitting results and the curves were generated for comparison sake of the two methods. Where the statistical models using data fitting failed to describe the deterioration of the pipe based on its material, and primarily due to the lack of data, the simulation was based on the manufacturer recommendations for useful life of the sewer pipe. This was the case in PVC and Ductile Iron pipes where the installations of both materials have been increasing in the last few decades; thus the availability of historical failure data for that particular type of material is not complete or fully reliable.

7.2 DATA COLLECTION AND STATISCTICAL ANALYSIS

As mentioned earlier, the source of data for the detrioration models that were developed using data fitting of various probability distribution functions were extracted from two databases maintaned by MSDGC. The first database was housed in CAGIS, a GIS information system owned and maintained by the City of Cincinnati and Hamiltion County, which contained attributes for the asset inventory of sanitary sewers in the collection system. This database was the sole source of attributes such as pipe age, slope, material, depth, as well as other physical, hydraulic, and geospatial attributes related to the studied sewers. The second database housed in the collection division of MSDGC which is responsible for the operation and maintainence of the more than 3000 miles of sewers owned by the district. This database housed a historical repair inventory for pipes that failed and repaied since 1997. Although few attributes were recorded in the repair inventory, when coupled with iformation that are available in CAGIS, the data used as inputs to produce the probabilitic models were extensive. More than 1,500 historical repair events for sewers with known installation year; thus known age, wrere captured, manipulated, and used for modeling the structural detrioration. The first step in the analysis was to calculate the pipe age at failure. This was accomplished by knowing both the installation and repair date and the age was approximated to the nearest year. The second step wasusing statistical software to measure the frequency of failure by fitting the frequency of the data using known probability distribution functions. The attributes of the distributions were estimated and the results were plotted against the pipe age. The cumulative distributions were also plotted to produce the detrioration curves of the sewers and estimate the probability of their failure or the remaining useful life of their functional service. When compared with the results obtained in chapter 6 in the determinitic approach, the probabilistic models had very similar output for models with extensive data points; however, they produced smoothed out curves and provided corrections for infant mortality of failure as well as at the endougenous end of the curves. On the other hand, models which had limited data as inputs such as the prediction of failure for PVC pipes, did not adequately describe the deterioration pattern and therefore, their use is not recommended. Other probabilistic models for the detrerioartion of PVC and DIP ipes are recommended and the use of Monte Carlo Simulation was utilized to produce better detrioration curves.

7.3 PROBABILISTIC MODELS USING DATA FITTING

7.3.1 General Probabilistic Model for All Sewers

Using the histroical repair data of all sewers with known age, a statistical model was generated using the @Risk software. Normal distribution was the best fit for the data followed by Weibull and the Logistic distributions. The mean age for sewer pipe failure was 78.8 years with a standard deviation of 25.4 years. Figure 7.1 shows the failure distribution for all the sewers studied. The graph shows that 90% of failures occurred between the ages of 35 and 119 years of age with the highest frequency of failure occurring at age 79.

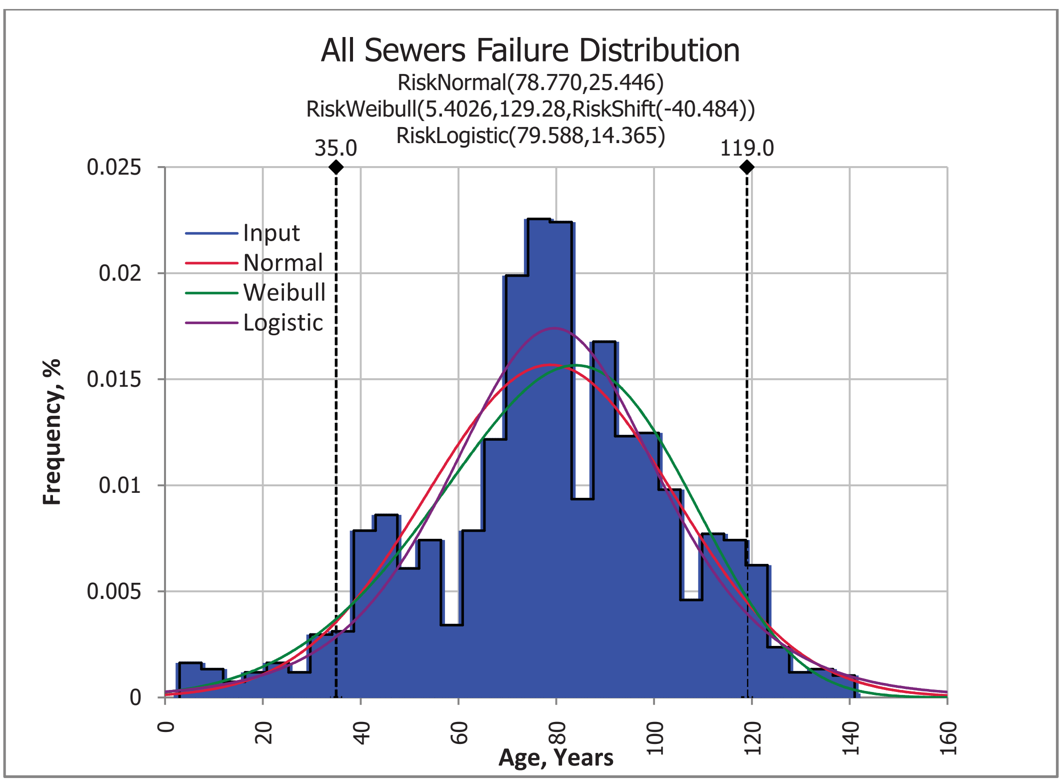


Figure 7.1: Failure Distribution for All Sewers

Normal distributions generally follow the following form:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \text{Exp}\left[\frac{-(X-\mu)2}{\sigma 2}\right] \quad (7.1)$$

By substituting the values for the mean and standard deviation that were obtained through the data fitting, the distribution of sewer failure as a function of age for all sewers under this study can be expressed as:

$$Po\ (f) = 0.0156785 \text{ Exp } \left\{- (Y - 78.88)^2 / 647.2\right\} \quad (7.2)$$

Where: Y, pipe age in years

The cumulative distribution of failure, or the probability of failure as a function of pipe age, representing the deterioration curve for all pipes, is shown in figure 7.2.

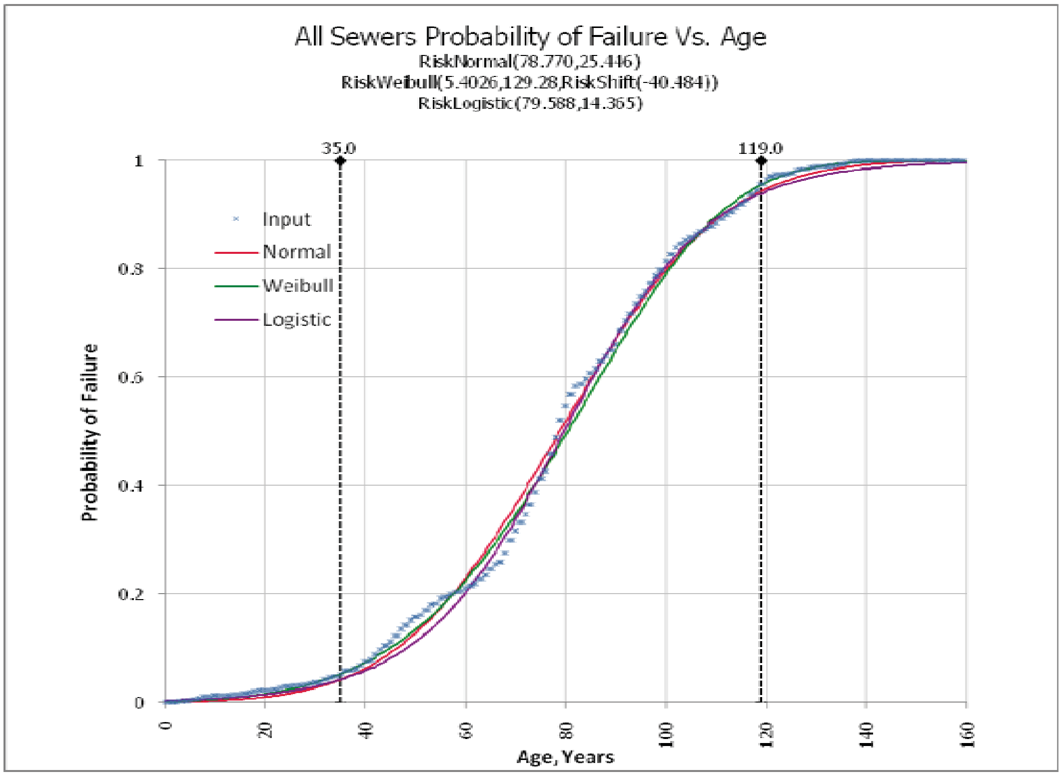


Figure 7.2: Probability of Failure Curves for All Sewers in the Asset Inventory

Figure 7.2 can be used to estimate the remaining useful life of a linear asset or assess the probability of its failure. For example, it can be demonstrated that a sewer line takes approximately 20 years to deteriorate by 2% and lasts for another 20 years at the end of its useful life before it structurally collapse. The values for probability failures can be generated using only the sewer's age and, coupled with its failure consequence or the criticality score developed in chapter 5 can be used to assess the risk of the asset's failure at any given year of operation. Accordingly, the wastewater utility can determine its O&M and capital construction strategy based on the risk values.

7.3.2 Probabilistic Model for Concrete Sewers

A similar approch was used to produce the detrioration curves for concrete sewers.

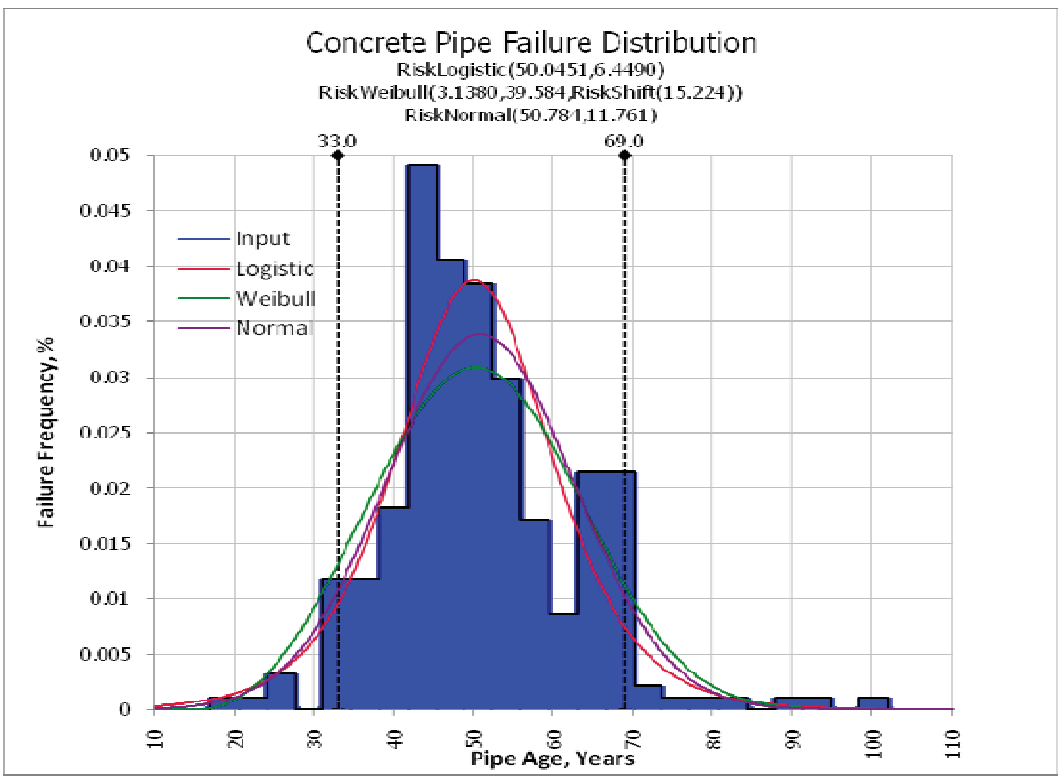


Figure 7.3: Failure Distribution for Concrete Sewers

Based on the above model, the probability of failure for concrete sewers, therefore, can be described as:

$$Po\ (f) = \int_0^y [1 / (1 + e^{-y})] \qquad (7.3)$$

Where y: Concrete pipe age

The deterioration curves for concrete sewers are described in Figure 7.4. The graph shows that 90% of failures occurred between the age of 33 and 69 years old with the most frequently observed age of 50 years. The interpretation of the concrete deterioration model should take into consideration that concrete pipe installations have been established more than 100 years ago; therefore, it is not likely that the deterioration curves will shift dramatically in the future when the model is updated.

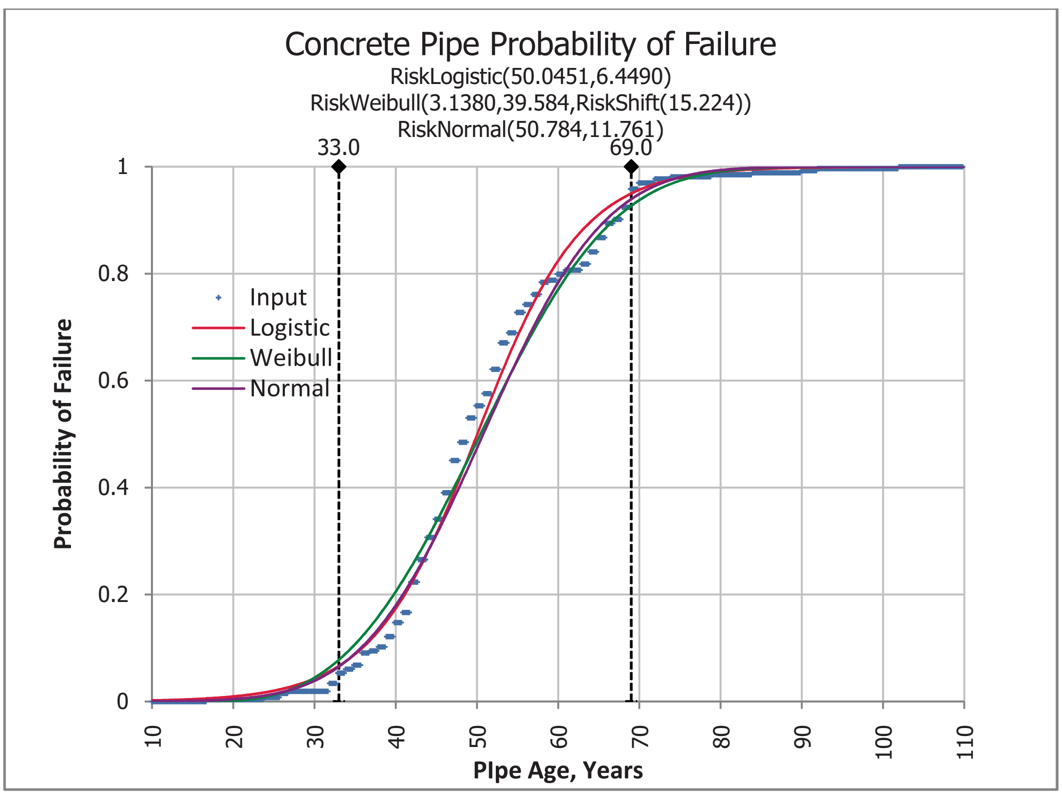


Figure 7.4: Probability of Failure Curves for Concrete Sewers

7.3.3 Probabilistic Model for PVC Sewers

The probabilistic deterioration model for PVC pipes, on the other hand, showed an infant mortality mode of failure; primarily, due to the lack of data. PVC sewers installations have been more recent when compared to other type of material and records of PVC failure are scarce due to their young age and relatively good condition in the collection system that was studied. Figure 7.5 shows the distribution of PVC pipe failures. The model inaccurately showed an average useful life of pipes at 16.4 years and that a pipe aged between 29 and 30 years of age has an 80% chance of failure. The use of this model is not recommended and it is only included to show the shortcomings of probabilistic models in absence of a good statistical sample size.

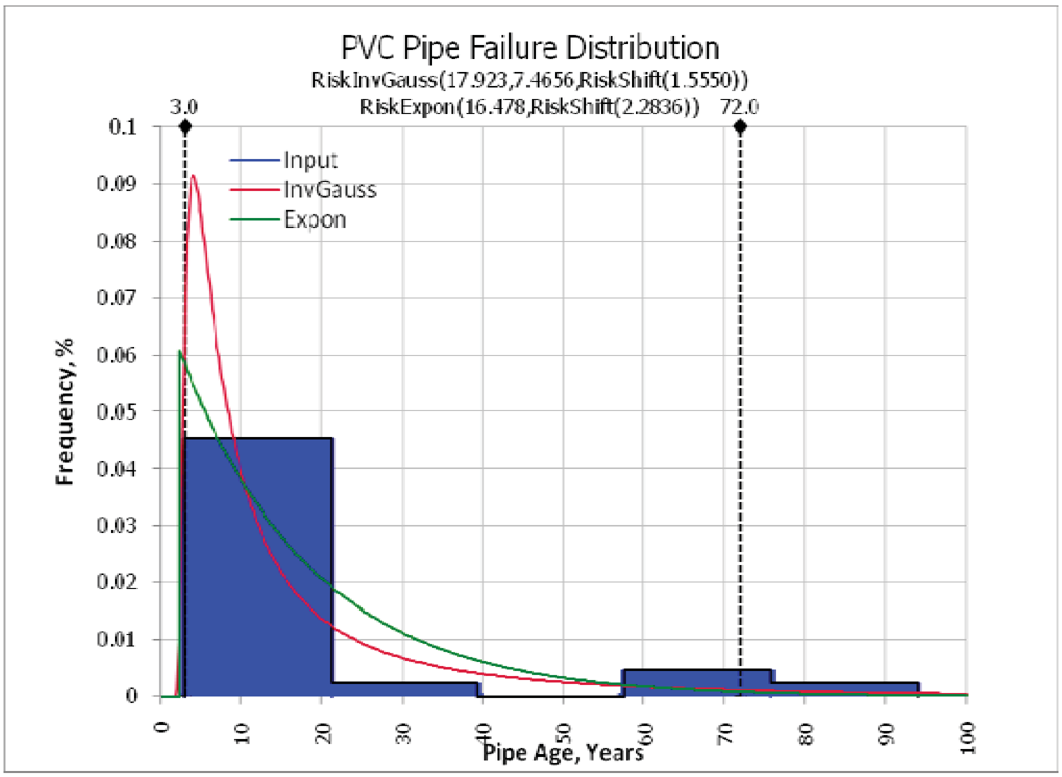


Figure 7.5: Failure Distribution for PVC Sewers

The exponential distribution function of PVC pipe failure can be described as:

$$Po\ (f) = 1 - e^{-\lambda y} \qquad (7.4)$$

Where y is pipe age in years; $\lambda = 1/\mu = 0.0607$

Figure 7.6 shows the probabilistic deterioration model for PVC sewers. As mentioned above the model is unrealistic due to the lack of failure data of PVC pipes. The use of Monte Carlo simulation is recommended using manufacturer's recommendation of useful life which will be discuss later in this chapter.

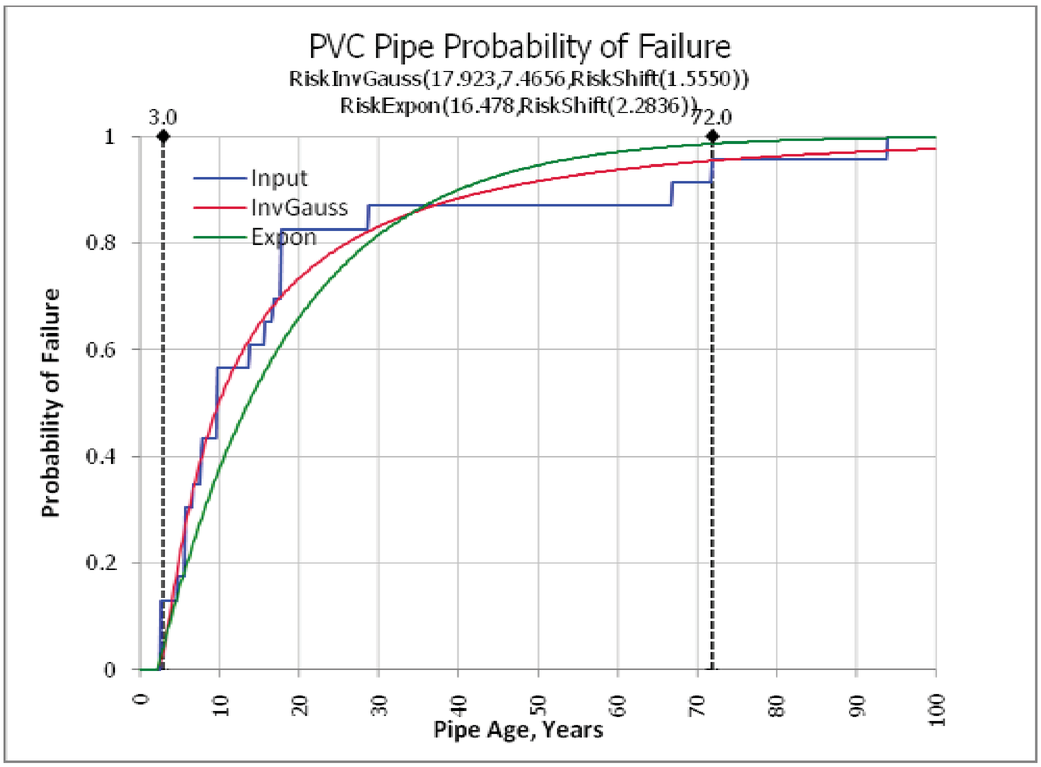


Figure 7.6: Probability of Failure Curves for PVC Sewers

7.3.4 Probabilistic Model for VCP Sewers

Using the @Risk software, the VCP frequency of failure occurred most frequently at age 79 years of age. The distribution showed that 90% of failures took place between 57 and 111 years of the pipe's age. Assuming the normal distribution shown in Figures 7.7 and 7.8, the probability of failure for VCP sewers can be written as:

$$Po\ (f) = 0.009323 \text{ Exp } \left\{- (Y - 79.07)^2 / 291.4\right\} \quad (7.5)$$

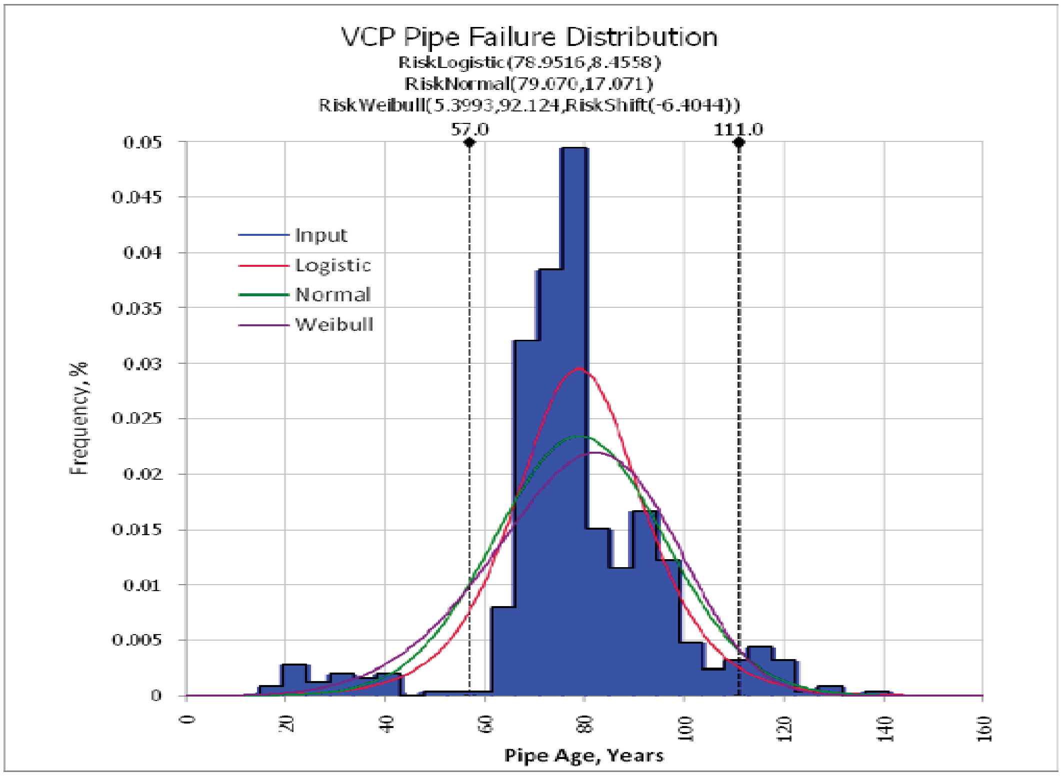


Figure 7.7: Failure Distribution for VCP Sewers

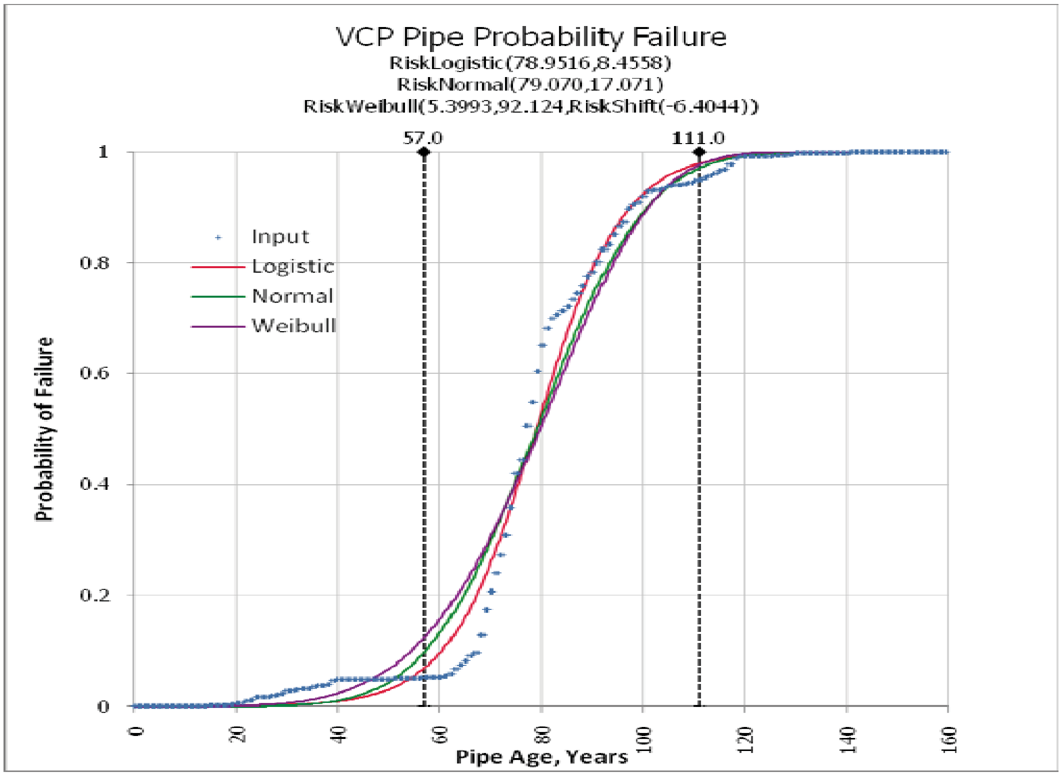


Figure 7.8: Probability of Failure Curves for VCP Sewers

7.3.5 Probabilistic Model for Sewers with Unknown Material

Similarly, the historical repair data for sewers with unknown material were fitted using the statistical software and best-fit curves were obtained. The frequency of failure was most intensive between the age of 93 and 94 and the data showed that 90% of the failure occurred between the ages of 60 and 124 years. Figures 7.9 and 7.10 show the best probability distribution functions to fit the data as the cumulative probability curves for sewers with unknown material, respectively.

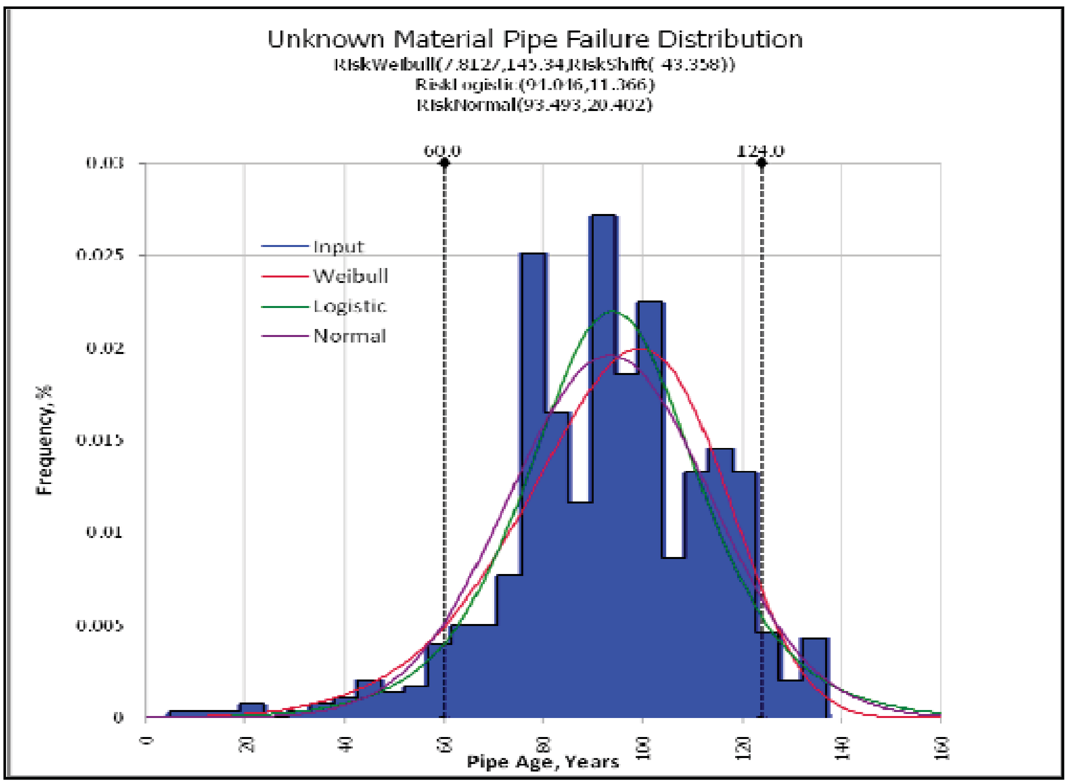


Figure 7.9: Failure Distribution Sewers with Unknown Material

The probability of failure of sewers in the model describing the deterioration of sewers with unknown material using the Weibull Distribution can be written as:

$$Po\ (f) = 1 - e^{-(y/\ 7.8127)145.34} \qquad (7.6)$$

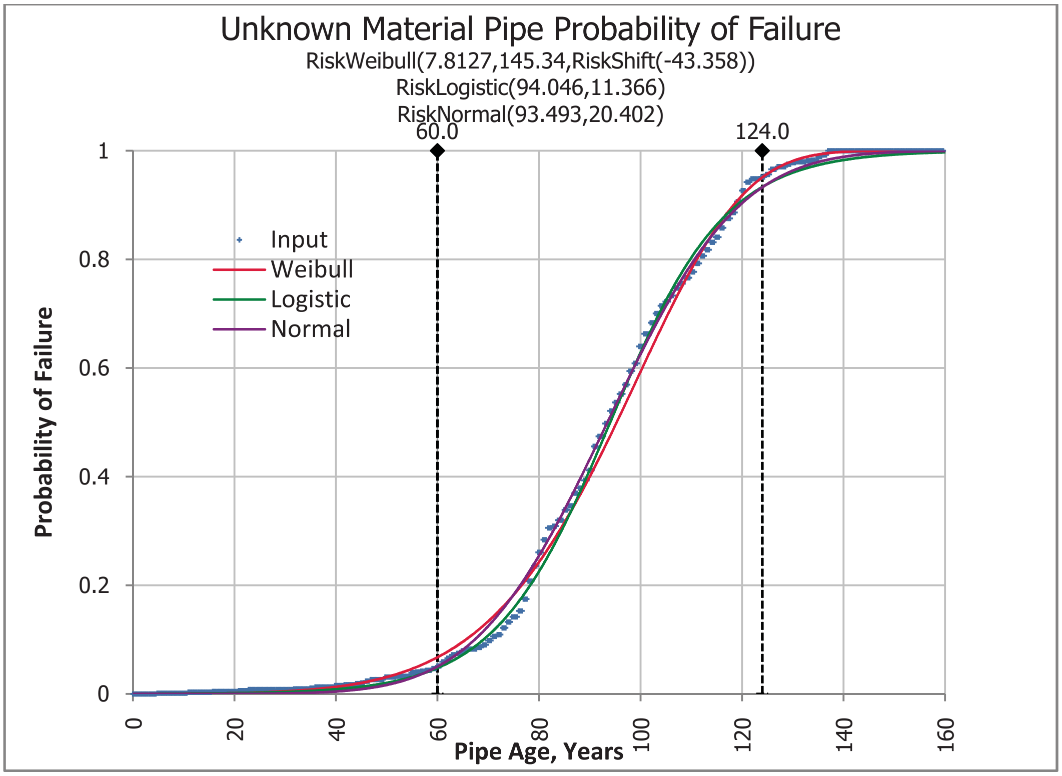


Figure 7.10: Probability of Failure Curves for Sewers with Unknown Material

7.3.6 Probabilistic Model for Segmented Blocks and Brick Sewers

Similar to the previous models the repair records of segmented block and brick sewers were fitted using the @Risk module. The model did not show good fit due to the lack of data given that this segment of the infrastructure tends to be the older sewers in the collection system. The probabilistic model showed that segmented block and brick sewers failed most frequently at the ages of 98 and 99 years of age; that 90% of the failure occurred between 31 and 138 years of age. Figure 7.11 and 7.12 show the distribution of failure and the cumulative probability of failure for brick and segmented block sewers, respectively. The probability of failure of brick and segmented block sewers, using the normal distribution function, can be described as the following:

$$Po\ (f) = 0.03806 \text{ Exp } \left\{- (Y - 98.88)^2 / 564.87\right\} \qquad (7.2)$$

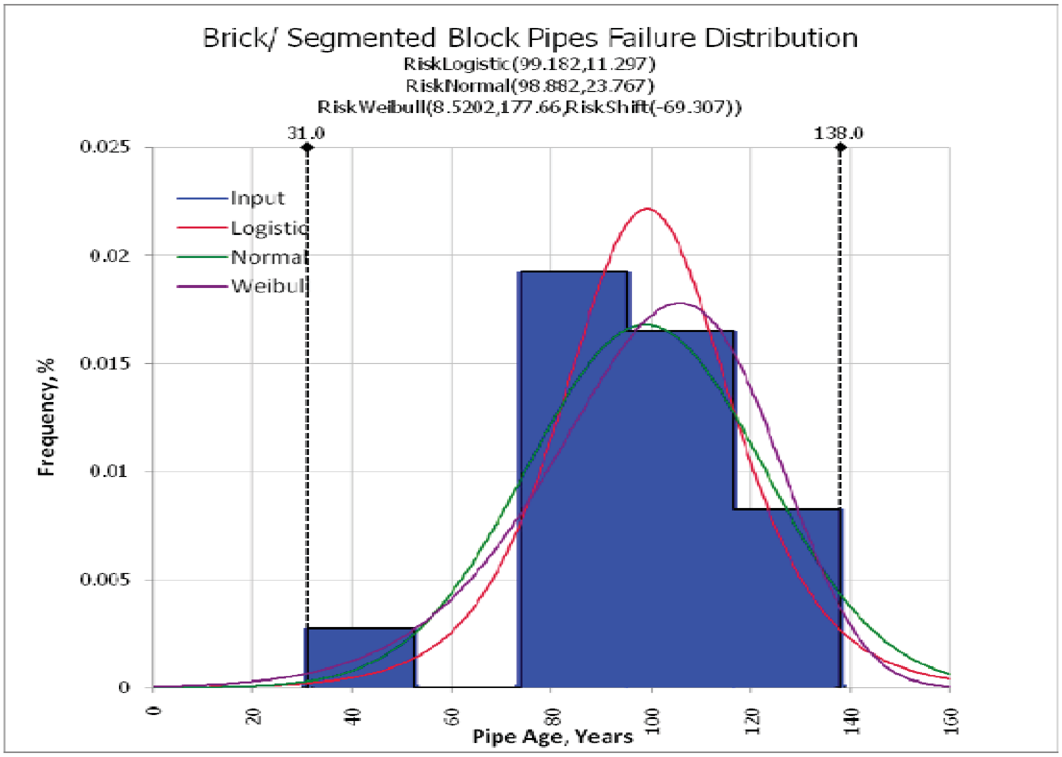


Figure 7.11: Failure Distribution for Brick and Segmented Blocks Sewers

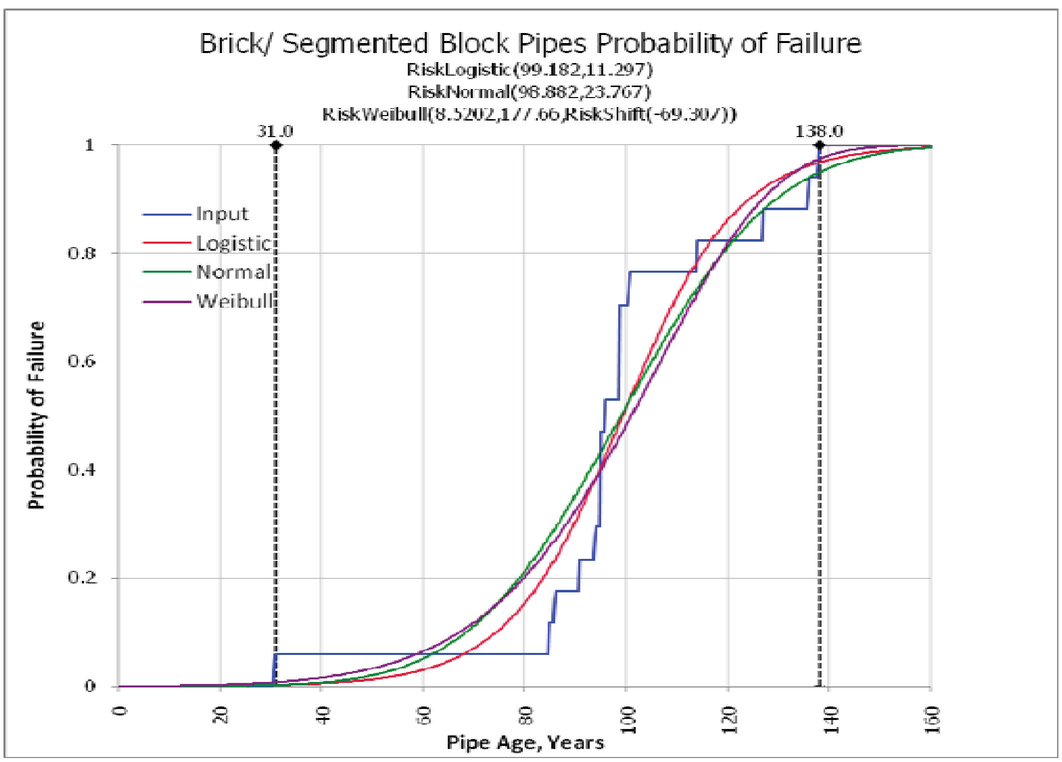


Figure 7.12: Probability of Failure Curves for Brick/ Segmented Blocks Sewers

7.4 PROBABILISTIC MODELS USING MONTE CARLO SIMULATION

Monte Carlo simulation method is another way to analyze uncertainty to determine how the sewer pipes deteriorate with age. Monte Carlo simulation is a sampling method because inputs are randomly generated from probability distributions to simulate the process of sampling from an actual population. In this research inputs were the useful life of various types of pipe material and the attributes for the probability distributions were determined from historical data fitting. The decay curves of sewers or deterioration as the pipe ages were developed through Monte Carlo Simulation using Sigma Zone software for statistics. Since deterioration and age were found to be correlated perfectly, other contributing factors such as slope or depth were ignored. Parameters for the probability distribution functions were estimated from the results obtained from the data fitting previously discussed.

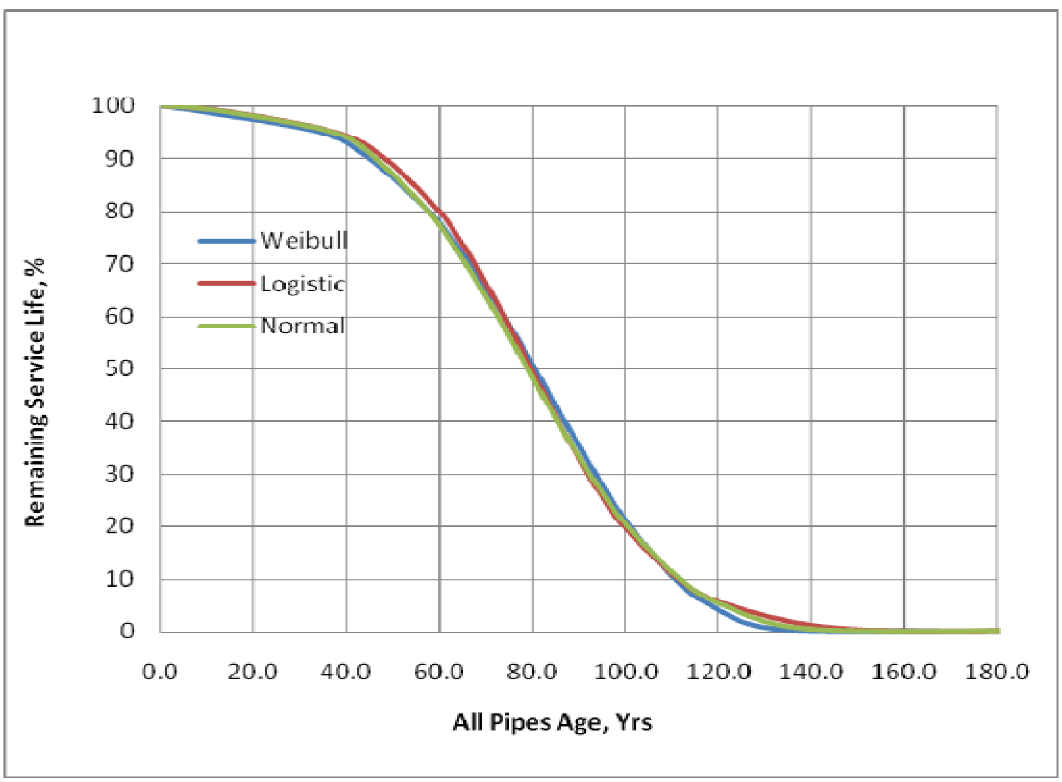


Figure 7.13: Monte Carlo Simulation of Survival Curves for all Pipes Inventory

The simulation software randomly selected one million values inputs to the model and the distribution functions were selected according to results of the data fitting. Due to their fast nature for running the statistical model at high number of iterations, the detrioration curves generated had far better smoothing effect for the output detrioration curves. Figure 7.13 represents the general model for deterioration of all sewer pipes examined under this study. The results obtained are identical to the results obtained in Figure 7.2. For example, a sewer pipe had 80% probability of failure at age 100 years in Figure 7.2 while the simulation results showed 20% remaining service life for the same age.

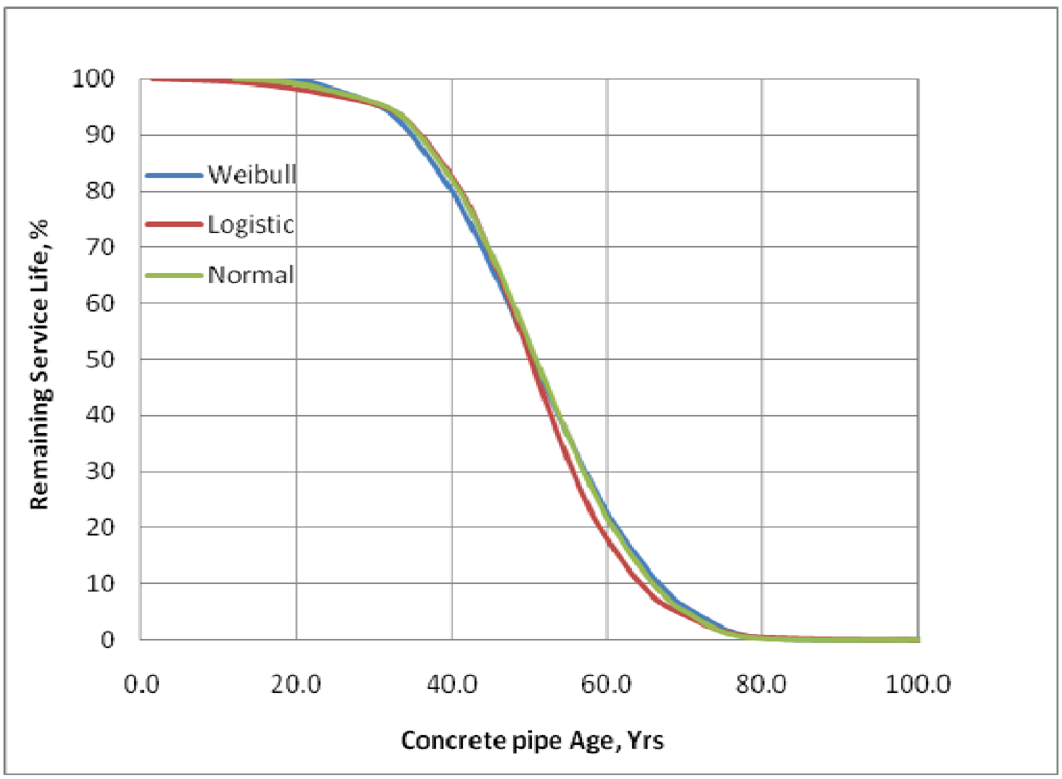
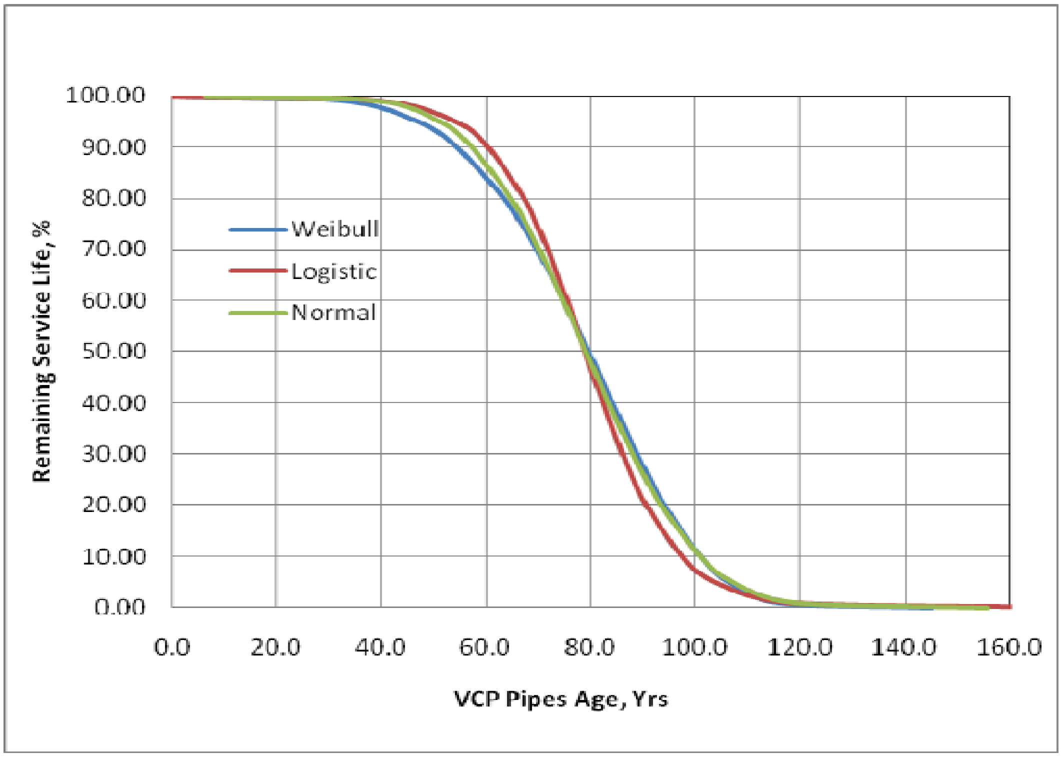
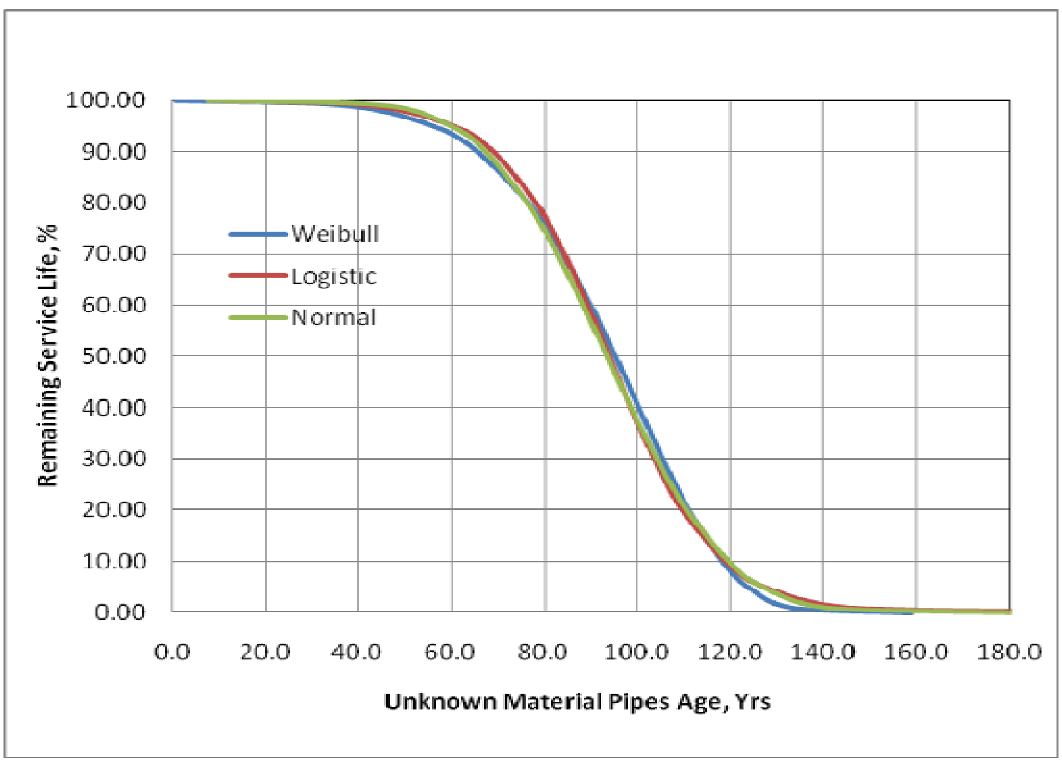


Figure 7.14: Monte Carlo Simulation of Survival Curves for Concrete pipes

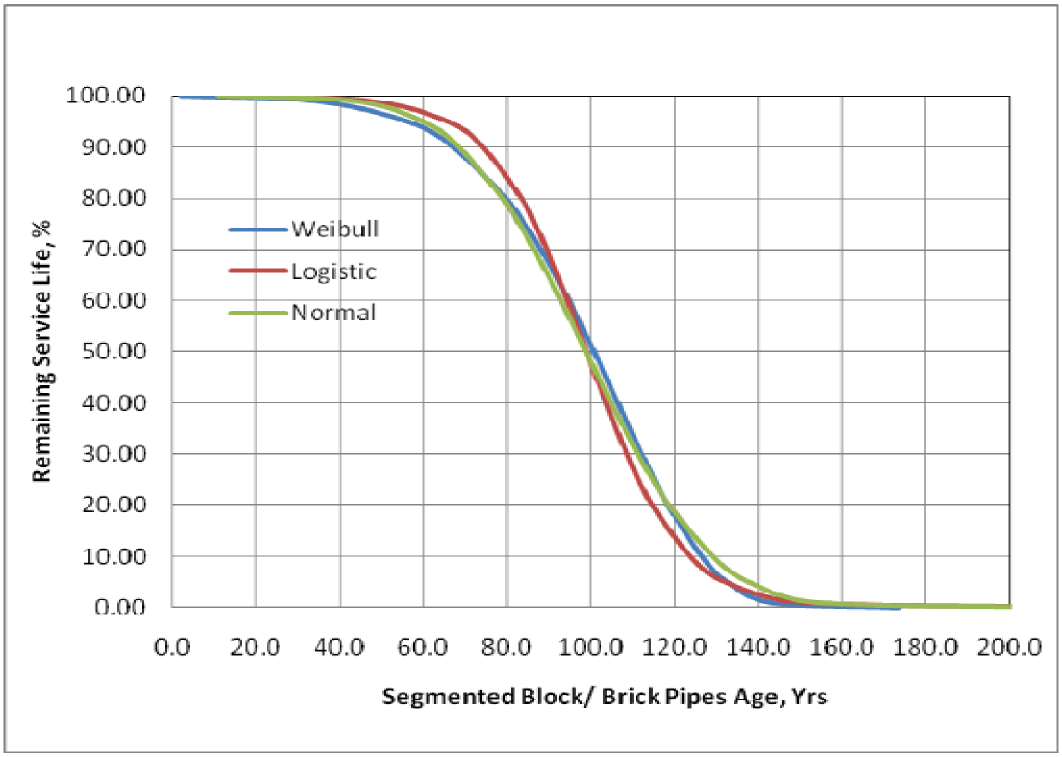
Figure 7.14 through 7.17 demonstrate the detrioration curves for Concrete, VCP, Unknown Material, Segmeneted Block, and Brick sewers, by plotting the remaining service life against the pipe's age. Results of these models were identical to the previously discussed data fitting results.



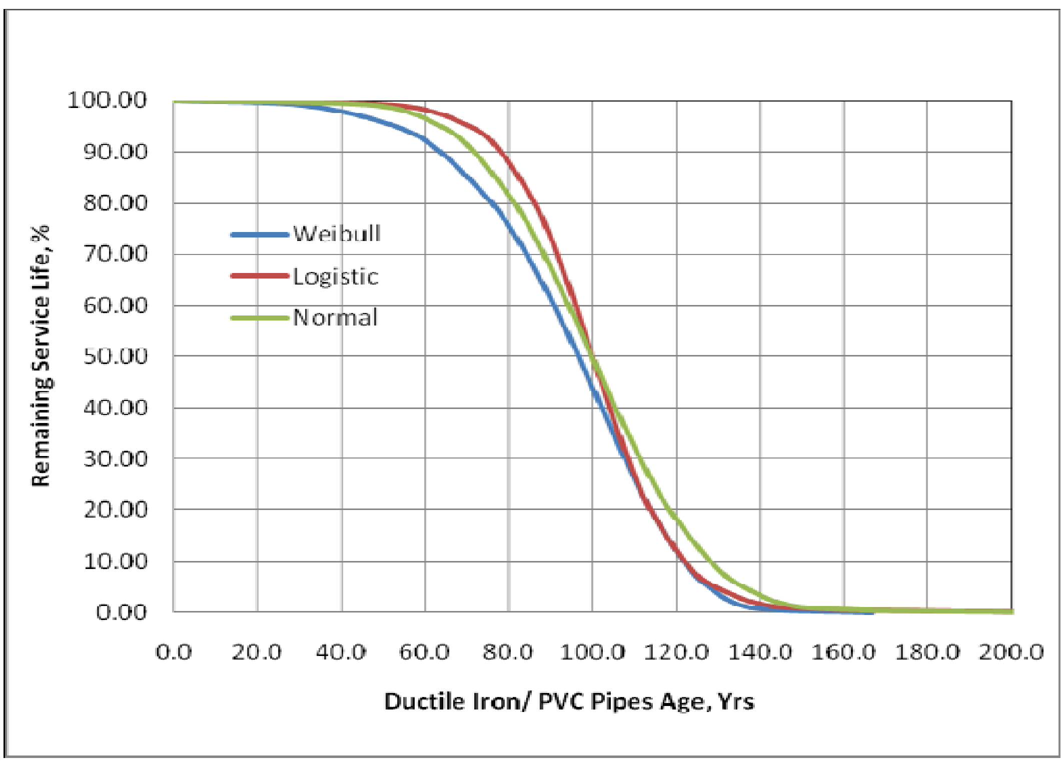
7.15: Monte Carlo Simulation of Survival Curves for VCP pipes



7.16: Monte Carlo Simulation of Survival Curves for Pipes with Unknown Material



7.17: Monte Carlo Simulation of Survival Curves for Segmented Block and Brick Pipes



7.18: Monte Carlo Simulation of Survival Curves for Ductile Iron and PVC Pipes

The data simulation in Graph 8.18 are based on manufacture suggested life of 100 years for both PVC and Ductile Iron pipes and the standard deviation for all pipe inventory at MSDGC. All other data presented above are based on data fitting models derived from MSDGC CADGIS and asset failure history.

7.5 SUMMARY

Two statistical software packages were used for the development of the probabilistic deterioration curves under this research. A module of Decision Tools Suite, called @Risk, was used for data fitting and parameter estimation while the Monte Carlo simulation was conducted using Sigma Zone for statistics. Both software packages provided powerful tools for the risk-based decision making approach to determine the deterioration rate of sewers infrastructure.

Various probabilistic deterioration models were developed using historical repair data for the asset inventory that was studied under this research. Two distinct probabilistic methods were used to generate the models. Distribution fitting of data was used utilizing known probability distribution functions to estimate the distribution functions parameters by fitting the historical repair data. Best distribution fits were determined and a mathematical equation describing the model was developed. The second probabilistic method investigated was the Monte Carlo Simulation method. Simulation results produced high resolution curves due to the high number of iterations, one million iterations in specific, which served as an input to the model. Monte Carlo simulation model for PVC and Ductile Iron sewers was far more accurate and reliable than the ones produced through data fitting due to the limited availability of repair data on those two types of material. A similar conclusion can be made for models that were produced for segmented blocks and brick sewers. While the data fitting models produced good results, the simulation models produced better tools under conditions where limited or no availability of data were present.

Chapter 8

USE OF NEURAL NETWORKS FOR THE PREDICTION OF SEWER FAILURE

8.1 INTRODUCTION

A number of General Regression Neural Network Deterioration Models (GRNNDMs) have been developed under this research study to examine the failure of sewer pipes. The output of the probabilistic models from Chapter 7 coupled with other contributing factors such as pipe slope, age, material, size, and depth were used as input factors to a computer constructed GRNN. The main difference between GRNN and PNN is in the type of output produced with the former a numeric value and the later categorical. Two main types of inputs were evaluated: numerical and categorical and the availability of data was varied between limited number of data points and extensive input data points. In addition, the number of contributing factors was varied from two to six to examine the impact on the model output. The models were produced using, Neural Tools, a module of the Decision Tools Suite 5.5 by the Palisades Corporation. The software allowed more than 16,000 variables to be analyzed; however, the constructed models contained only two to six variables. The software allows the user to define all the variables within the dataset, numerical or categorical, that are input to the model, then train the network for pattern recognition, and subsequently make the model prediction. The structure of the NN model and type of regression within the model could be varied by the user. The outputs were measured against the calibrated model and the predictions were deemed good if the prediction value fell within 30% from the model. Neural network are most suitable to handle noise in data, recognize patterns, and adapt to circumstance to make accurate predictions. Based on mimicking the human brain through interconnected neurons, the applications of neural network is expanding to all kinds of applications. Their applications have been implemented in quality control, defense, intelligence and data mining, disease prediction, pharmaceutical, protein sequencing, highway maintenance program, as well as other engineering applications. This research extends the use of neural networks to the predictions of sanitary sewers failure and their deterioration with age.

8.2 BACKGROUND

Developed by Donald F. Specht in 1990, PNN combines Bayesian theory and a Parzen-Cacoullos theory on a NN platform to produce the probability distribution of different pattern. The advantage of PNN models is that they are fast in terms of run time and do not require much time for training; and can quickly recognize non-linear relationships between contributing factors and the output. The disadvantage of PNN models, however, is that they require extensive data for the construction of accurate models. Artificial Neural Network (ANN) is a form of mathematical models that aims at simulating the structure and/or function of biological interconnected neural networks. Generally speaking, ANN is adaptive during the learning phase by changing the structure based on the information flow.

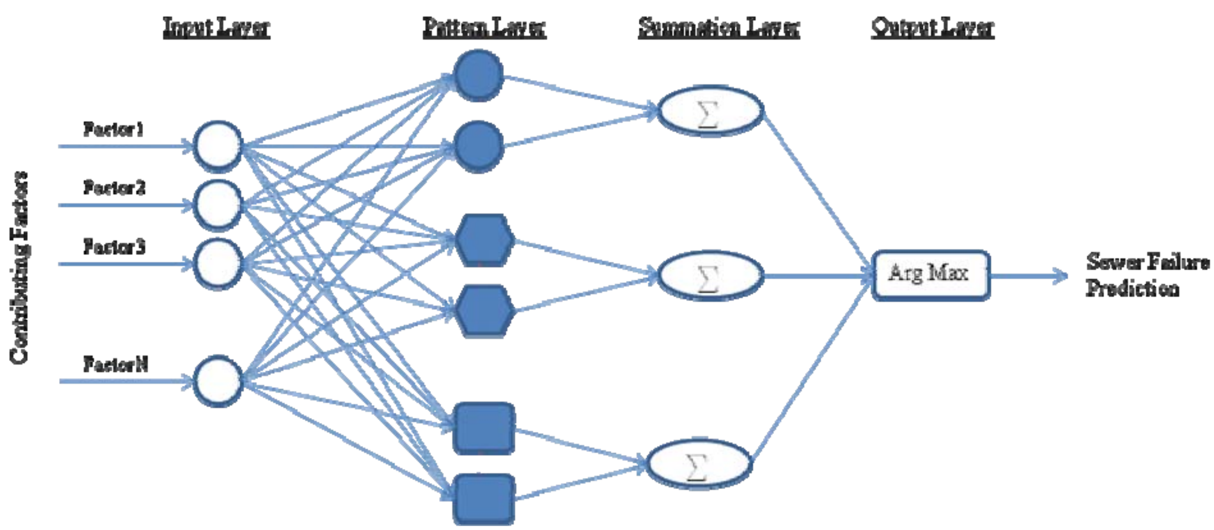


Figure 8.1: Topology of the General Regression Neural Network Deterioration Model (GRNNDM)

Modern neural networks, such as the one used in this research, are non-linear statistical tools for data modeling. They are usually used to recognize patterns in the data, train the network for calibration, and predict future conditions or a numerical value.

One common method to test the model is to randomly select a subset of data to construct the model and a small set to test the model (Tran, 2007). For the models developed in this chapter, 80% of the input data were used to construct the model while the remaining 20% were used to test it. A similar approach for testing models was previously used in testing deterioration models for bridges (Madanat and Ibrahim 1995), in pavement (Alsugair and Al-Qudrah, 1998; Lou, 2001) and for the deterioration of sewer pipes (Micevski, 2002; Baik, 2006). Based on the results obtained by data fitting and other independent factors such as pipe slope, soil type, among other factors, as input to the GRNN model, the GRNNDM computer generated models in this study were obtained.

8.2.1 Topology of the GRNNDM

Figure 8.1 shows the architecture of the GRNNDM which consists of interconnected neurons representing four layers: input, patter, summation, and output. As mentioned earlier the number of input factors was varied and models were developed for two, three, and six input parameters. Each pattern node was responsible for recognizing trends associated with one variable and the results were passed on to the summation node. The output layer could contain more than one output such as the case when using PNN for a Markov chain model with five different condition ratings.

8.2.1.1 Input Layer

The input layer consists of a number of neurons that are equal to the number of contributing factors. No calculations are processed in the input neurons and the data is simply passed forward to the pattern neurons, in this case the pipe age and slope for the first model developed in Figure 8.2 and 8.9.

8.2.1.2 Pattern layer

This layer is different in GRNN when compared to PNN models. In the GRNN models, the layer consists of only two neurons for each variable. One neural is called a numerator and the other denominator. The numerator adds up the weighted values for factors while the denominator adds only the weights. In PNN models, on the other hand, the pattern layer has one neuron for each input factor.

8.2.1.3 Summation Layer

This layer has one neuron for each contributing factor in the training dataset. The neuron adds up the values from the pattern layer incorporating relative weights and passes on the results to the output or decision layer.

8.2.1.4 Output Layer

In GRNN models, the decision layer incorporates a numerator summation neuron and a denominator to produce the predicted value. In PNN models, on the other hand, the decision layer selects the largest vote to predict the target category or model output.

8.2.2 PNNDM Training

Training of the PNNDM was done using 20% of the input by storing the training data in the network and assigning their values into the neurons in the pattern layers. A correct prediction is counted if the predicted probability of pipe failure is within 30% of the known probability in the training data. The training of PNNDM in this study was done using 20% of the input data points for the training of the model with the remaining 80% of each data set used for network training.

8.3 RESULTS AND DISCUSSION

The first model that was developed tested the use of NN under the condition of data limited availability. Twenty data points from the output of the probabilistic model produced through data fitting, discussed in chapter 7, were used as inputs to the GRNNPM. Only sixteen data points were using for training and model development and four points were used for testing. Although the limited data model did not produce the typical deterioration curves similar to the ones that were obtained in chapters 6 and 7 of this dissertation; and rather produced a linear deterioration model, the predicted values fell within the model tolerance limits of 30% for three data points and one data point failed to meet the model tolerance criteria. The model had 52 trials to maximize the good predictions and the run time was only few seconds. This type of modeling technique in not recommended when data is not available or limited. The model is presented to demonstrate the shortcomings of NN models as compared to other probabilistic modeling techniques. Graphs 8.2 through 8.8 demonstrate the limited data model output, calibration, calibration accuracy, validation, and output accuracy. Table 8.1 summarizes the results obtained for the limited data model.

Configuration	GRNN Numeric Predictor
Independent Numeric Variables	1 (Pipe Age)
Dependent Variable	Numeric Var. (Probability of Failure)
Training	
Number of Cases	15
Number of Trials	52
% Bad Predictions (30% Tolerance)	0.0000%
Root Mean Square Error	0.01120
Mean Absolute Error	0.008975
Std. Deviation of Abs. Error	0.006705
Testing	
Number of Cases	4
% Bad Predictions (30% Tolerance)	25.0000%
Root Mean Square Error	0.01818
Mean Absolute Error	0.01499
Std. Deviation of Abs. Error	0.01029
Name	Neural Tools to Predict Failure
R-Square (Training)	0.9846
Root Mean Sq. Error (Training)	0.03473
Root Mean Sq. Error (Testing)	0.02638

Table 8.1: Summary of the model results under limited availability of input data

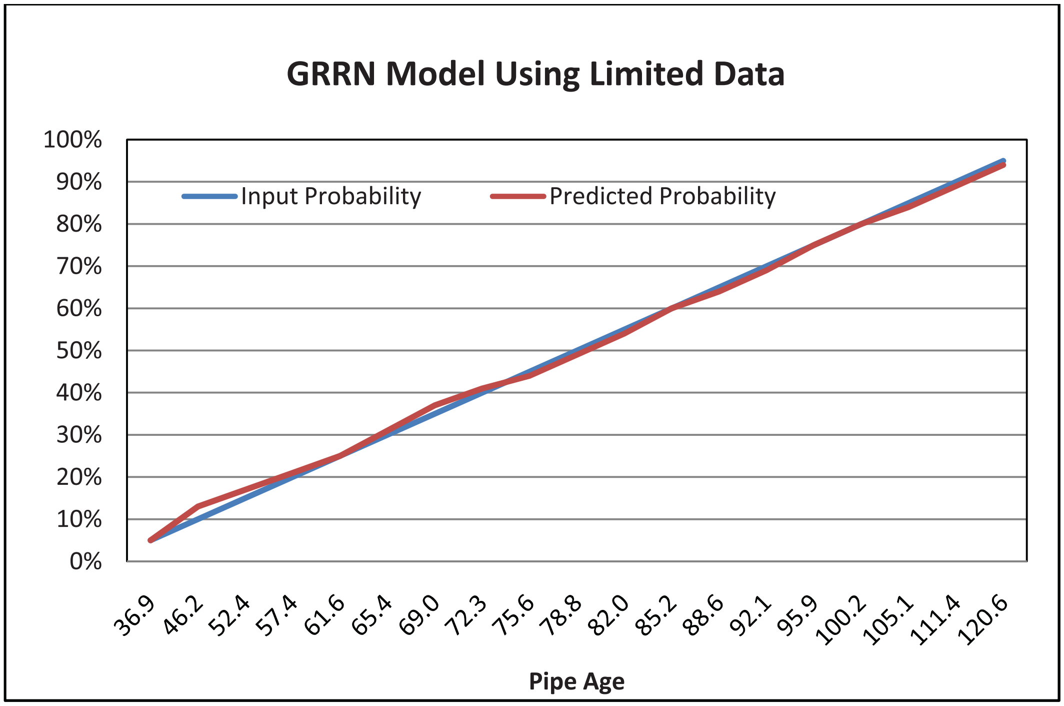


Figure 8.2: GRRN Prediction Using Limited Data with (20 Data Points) for Probability, Age, and Slope

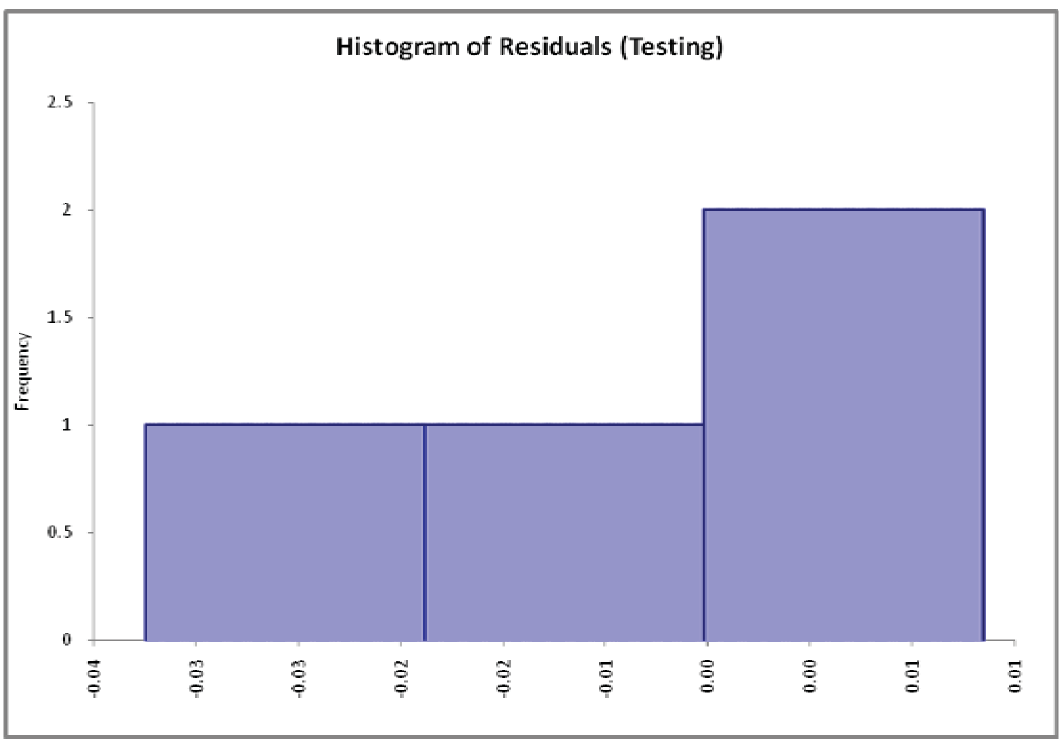


Figure 8.3: Testing Residuals with Limited data of Probability, Age, and Slope (4 Data Points)

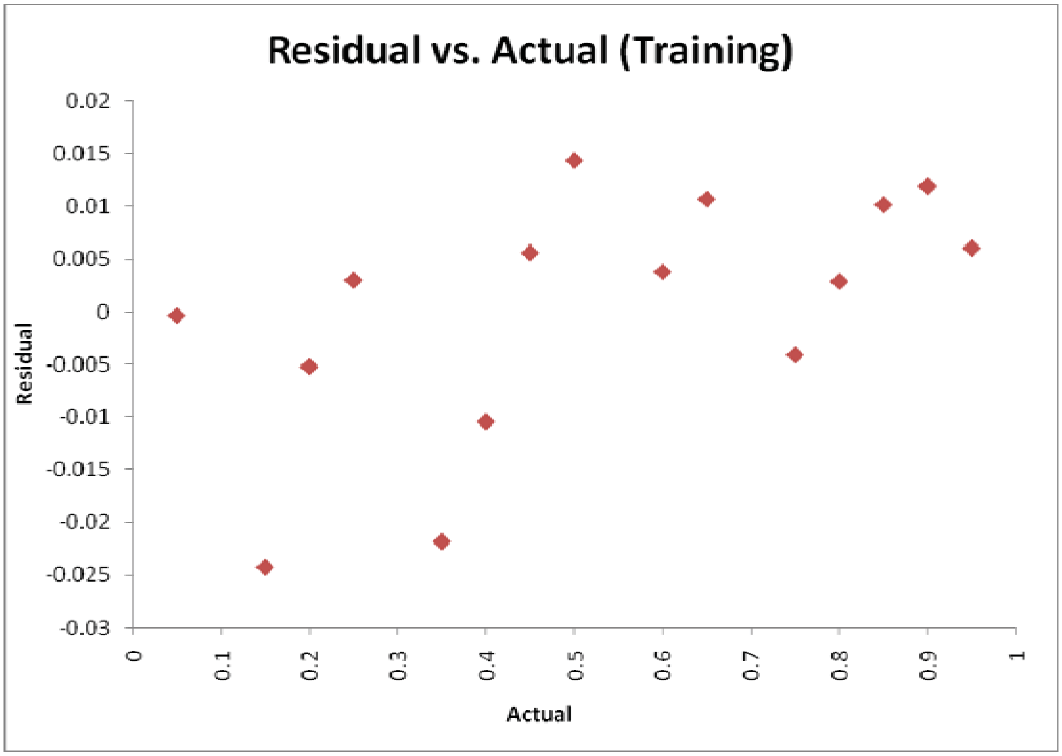


Figure 8.4: Training Residuals for Limited Data of Probability, Age, and Slope

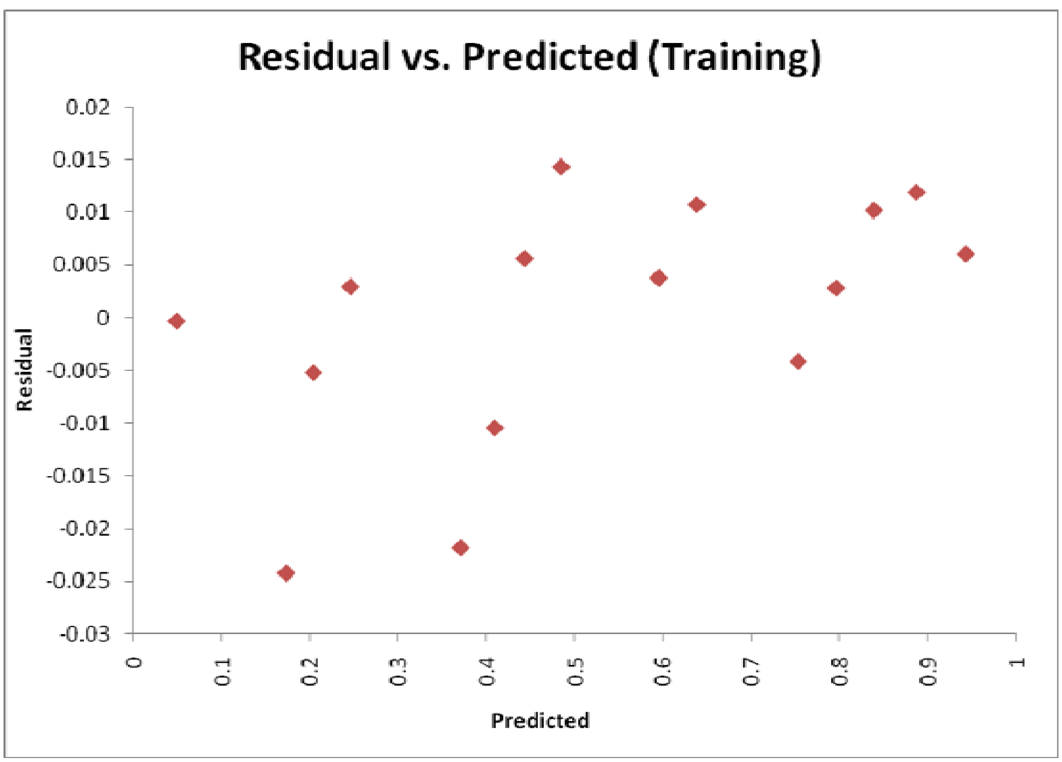


Figure 8.5: Prediction Residuals for Limited Data of Probability, Age, and Slope

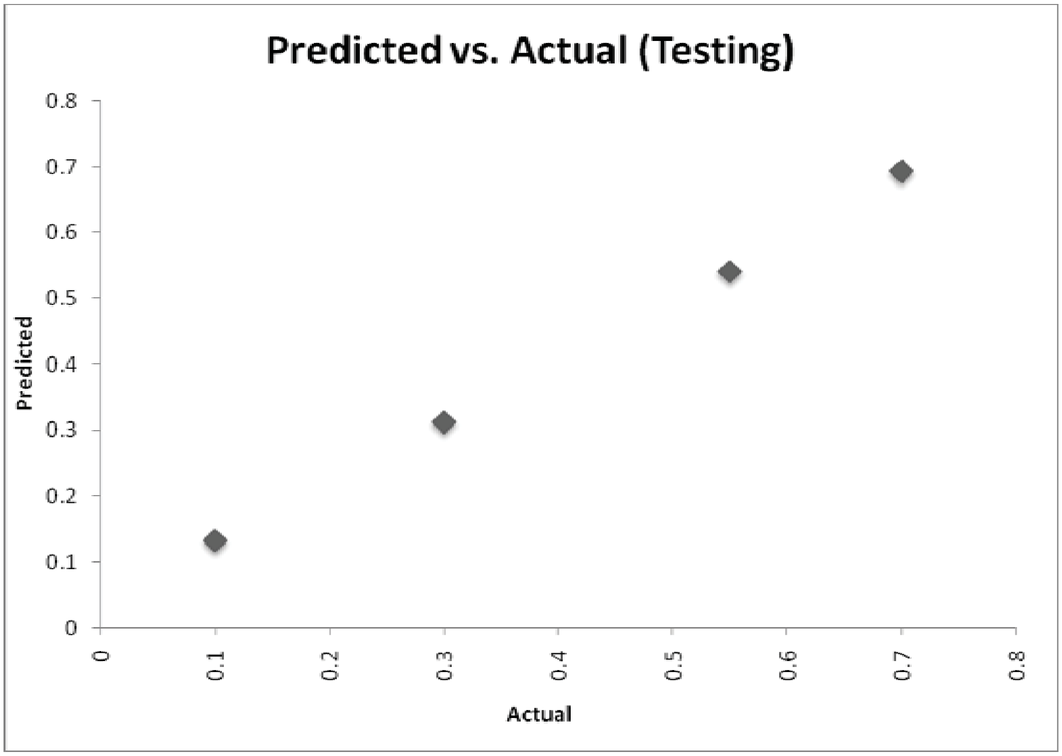


Figure 8.6: Limited Data Model Validation

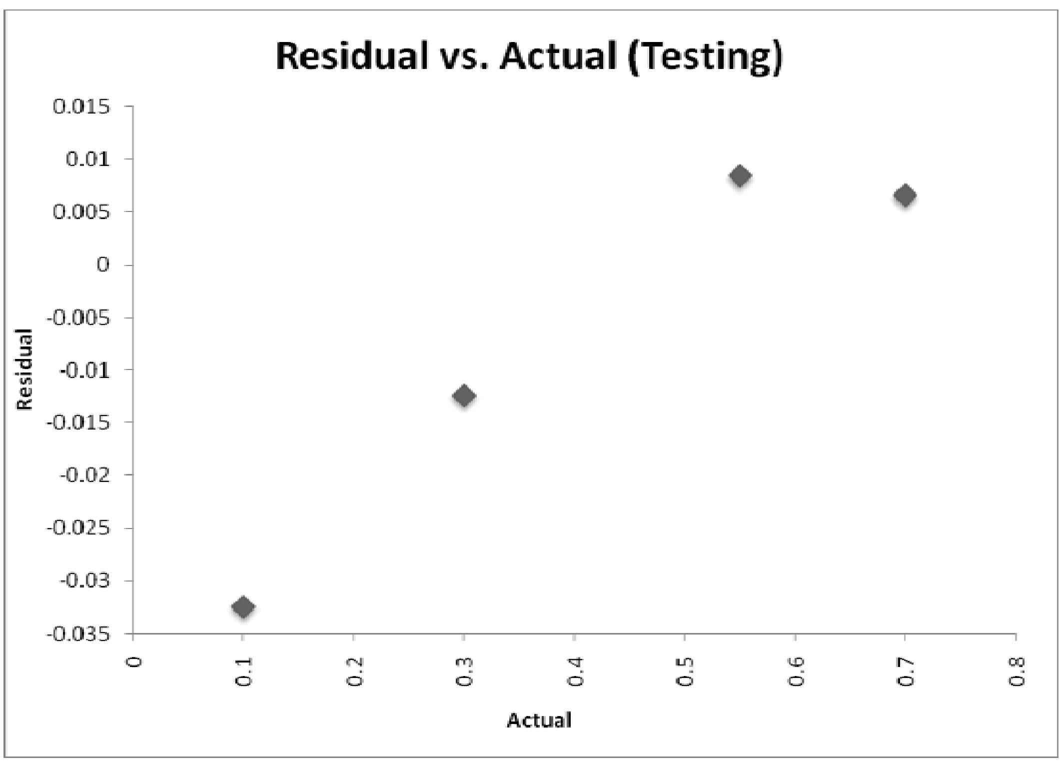


Figure 8.7: Limited Data Model Calibration Accuracy

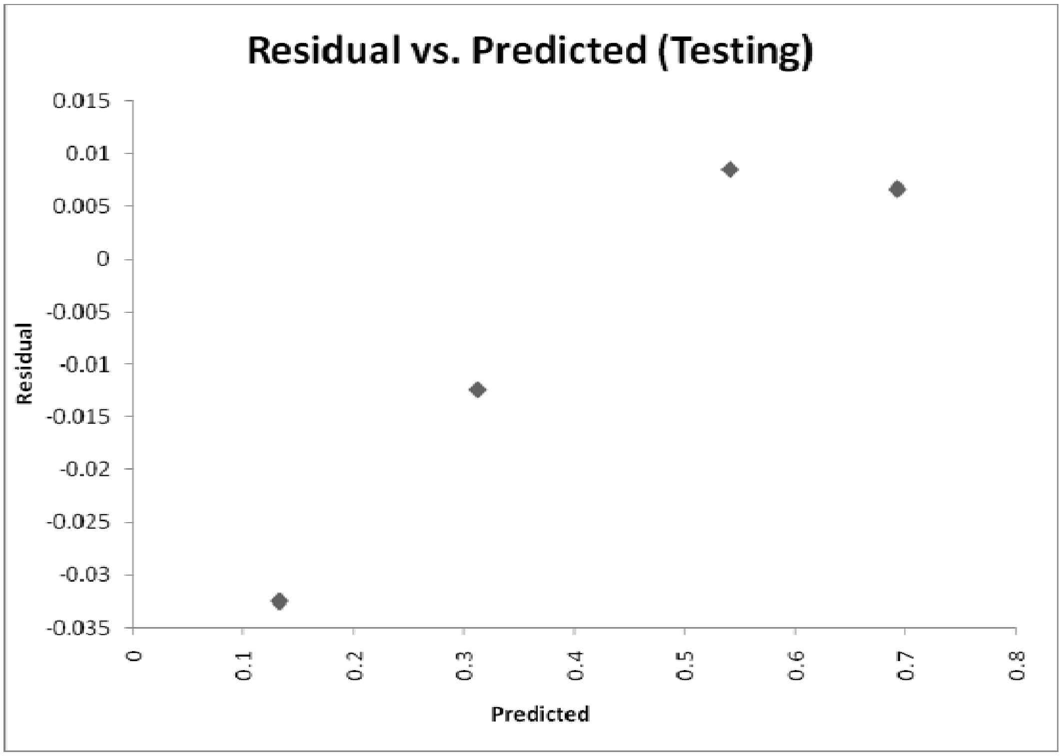


Figure 8.8: Limited Data Model Output Accuracy

Next, extensive input data points were used to develop another NN model using the same GRNNDM architecture. The data input were extracted from the probabilistic model for all sewer pipes obtained in chapter 7 and the sewer age and slope served as additional two contributing factors. The model incorporated pipe age and slope as inputs and measured the probability of failure as the single output for the model. Similar to the limited data model, 20% of the input values were used for testing and validating the model and the remaining 80% were used for training. Figures 8.9 through 8.14 show the model output, calibration, validation, and testing, as well as tolerances for each phase. The results of the model as well as the model configuration and parameters are summarized in table 8.2 below. Overall, the model included 1.25% of bad prediction during training and 7.5% during the testing phase. The model provided excellent results that strongly correlated with the output of the previously obtained probabilistic model described in chapter 7.

Configuration	GRNN Numeric Predictor
Independent Category Variables	None
Independent Numeric Variables	Pipe Age and % slope
Dependent Variable	Probability of Failure
Training	
Number of Cases	320
Number of Trials	52
Reason Stopped	Auto-Stopped
% Bad Predictions (30% Tolerance)	1.2500%
Root Mean Square Error	0.002925
Mean Absolute Error	0.001733
Std. Deviation of Abs. Error	0.002357
Testing	
Number of Cases	80
% Bad Predictions (30% Tolerance)	7.5000%
Root Mean Square Error	0.002849
Mean Absolute Error	0.001759
Std. Deviation of Abs. Error	0.002241

Table 8.2: Extensive Data Model Results Summary (3 Numeric Data Inputs)

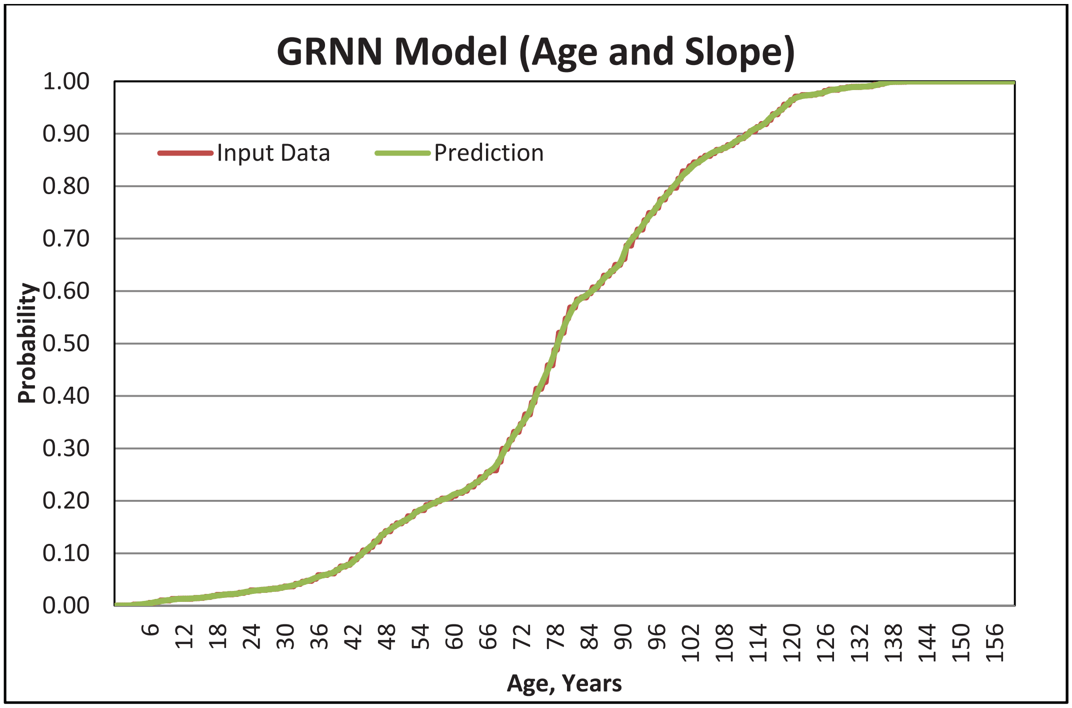


Figure 8.9: GRRN Prediction Using Extensive Data (400 Input Data Points) for Probability, Age, and Slope

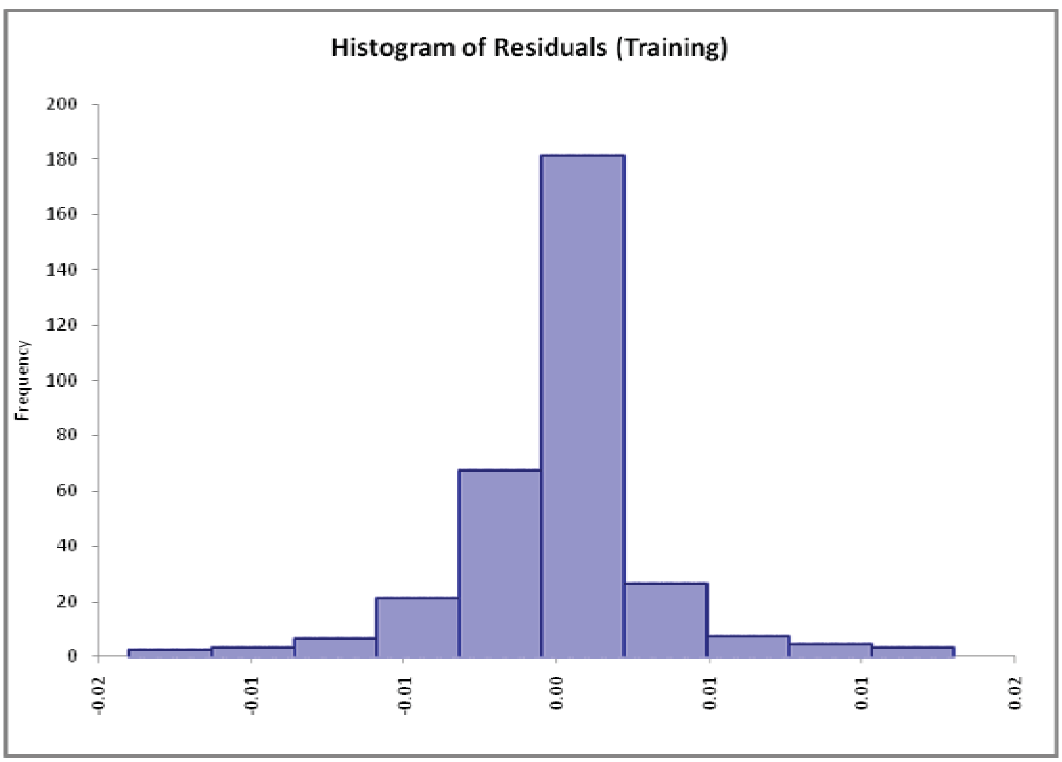


Figure 8.10: Network Residual Training Using Extensive Data for Probability, Age, and Slope

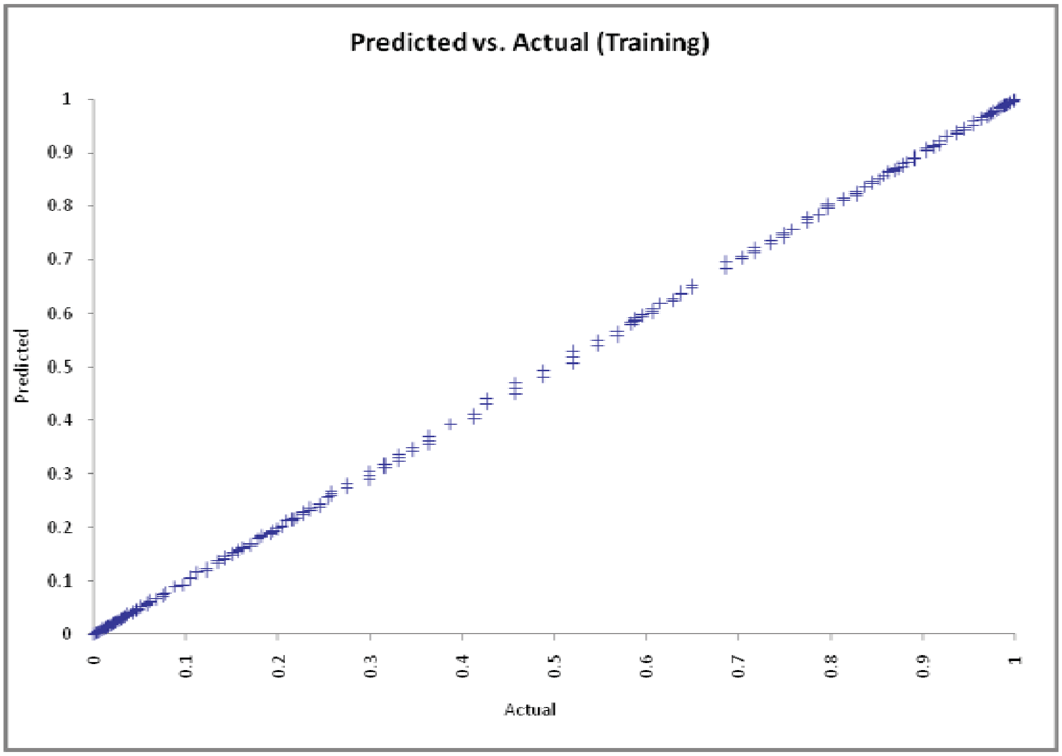


Figure 8.11: Calibration of Model with Extensive Data (Probability, Age, and Slope)

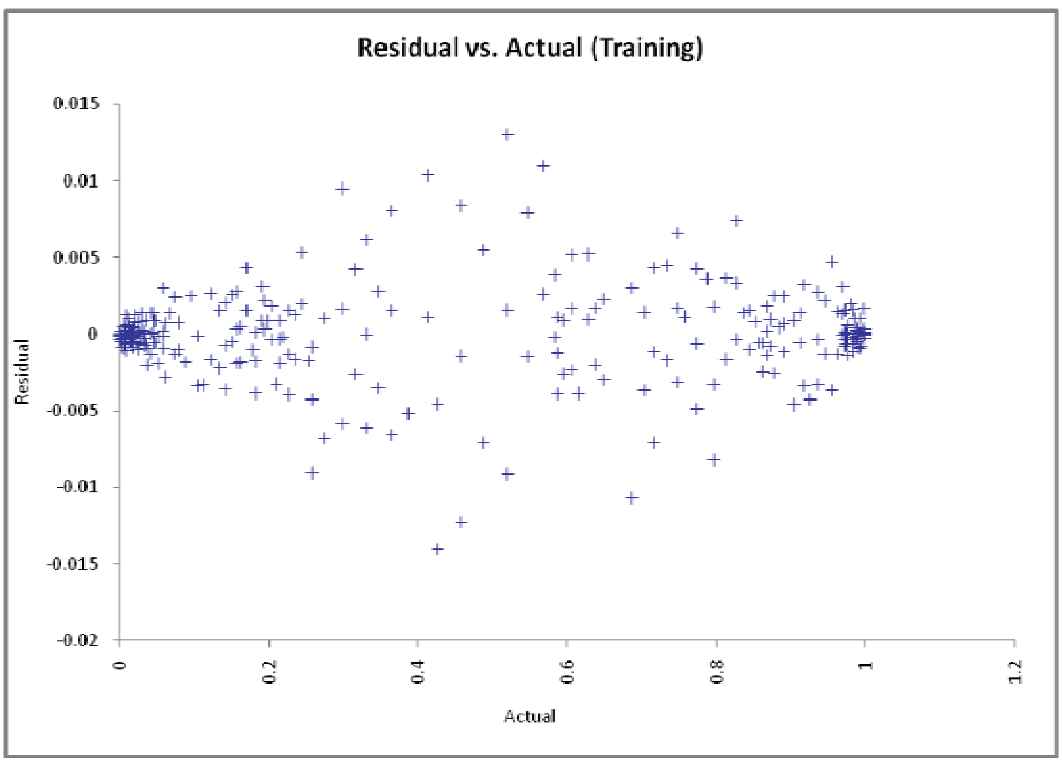


Figure 8.12: Residuals Vs. Actual for Extensive Data (Probability, Age, and Slope)

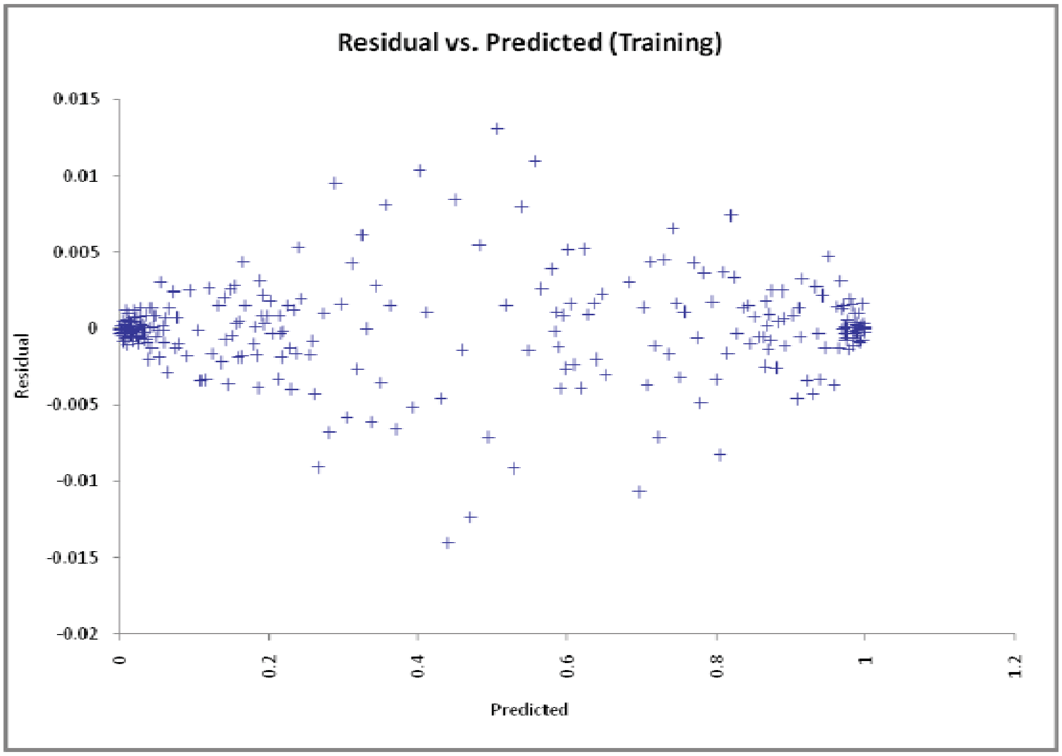


Figure 8.13: Residuals Vs. Predicted for Extensive Data (Probability, Age, and Slope)

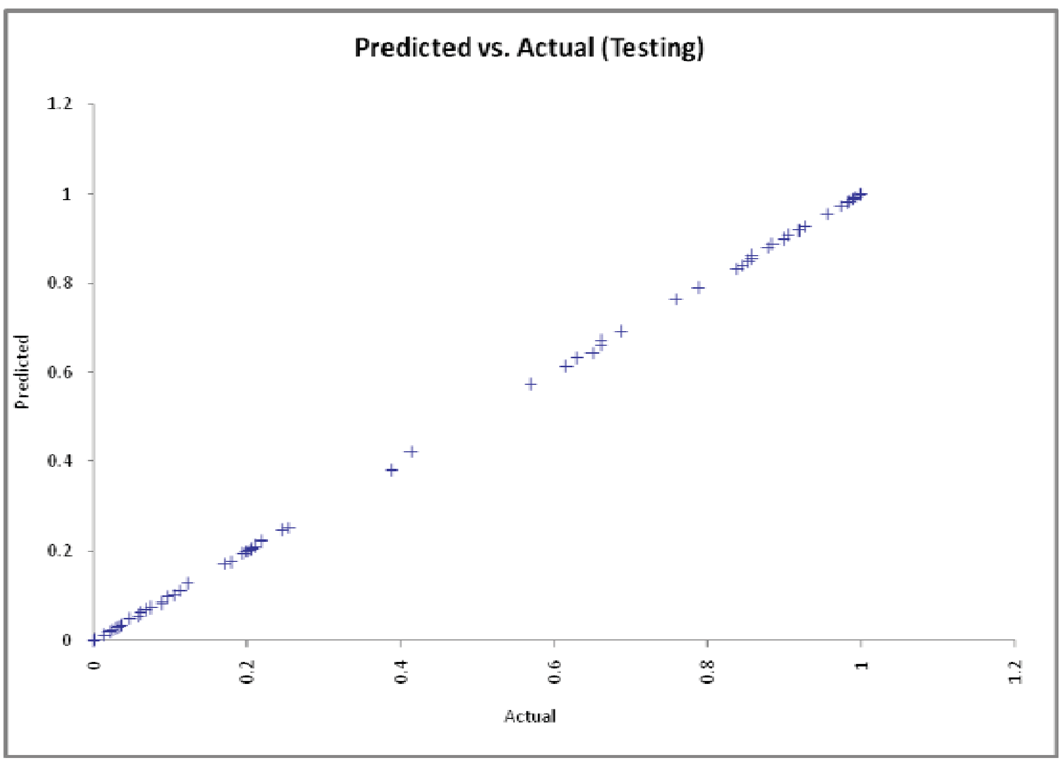


Figure 8.14: Extensive Data Model Validation (Probability, Age, and Slope)

Next, a categorical factor; namely, pipe material was introduced to the model input and the output of the model was measured. Table 8.3 summarizes the results and Figures 8.16 through 8.24 demonstrate the model output, calibration, testing, and validation. This model incorporated 3 numerical variables and one categorical variable as inputs to the model. The model produced only 6.14% and 7.14% of bad predictions during the training and testing phases, respectively. For unknown reasons, some output noise was observed at 40, 73, and 91 years of age.

Configuration	GRNN Numeric Predictor
Independent Category Variables	1 (Material)
Independent Numeric Variables	2 (Slope (%), Age)
Dependent Variable	Numeric Var. (Probability of Failure)
Training	
Number of Cases	114
Number of Trials	58
% Bad Predictions (30% Tolerance)	6.1404%
Root Mean Square Error	1.029
Mean Absolute Error	0.6118
Std. Deviation of Abs. Error	0.8275
Testing	
Number of Cases	28
% Bad Predictions (30% Tolerance)	7.1429%
Root Mean Square Error	4.087
Mean Absolute Error	2.117
Std. Deviation of Abs. Error	3.496

Table 8.3: Summary of NN Testing and Training Results Using Three Independent Variables (Age, Material, and Slope) to Predict The Probability of Failure

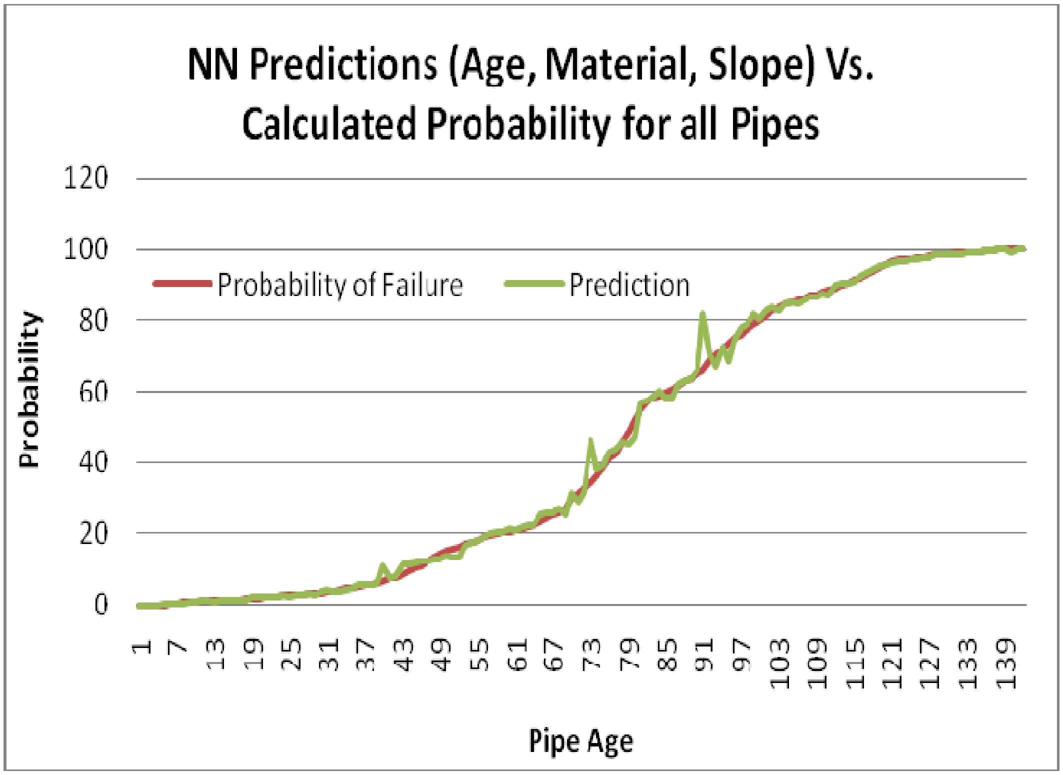


Figure 8.15: NN Prediction Using Extensive Data Points (Probability, Age, Material, and Slope)

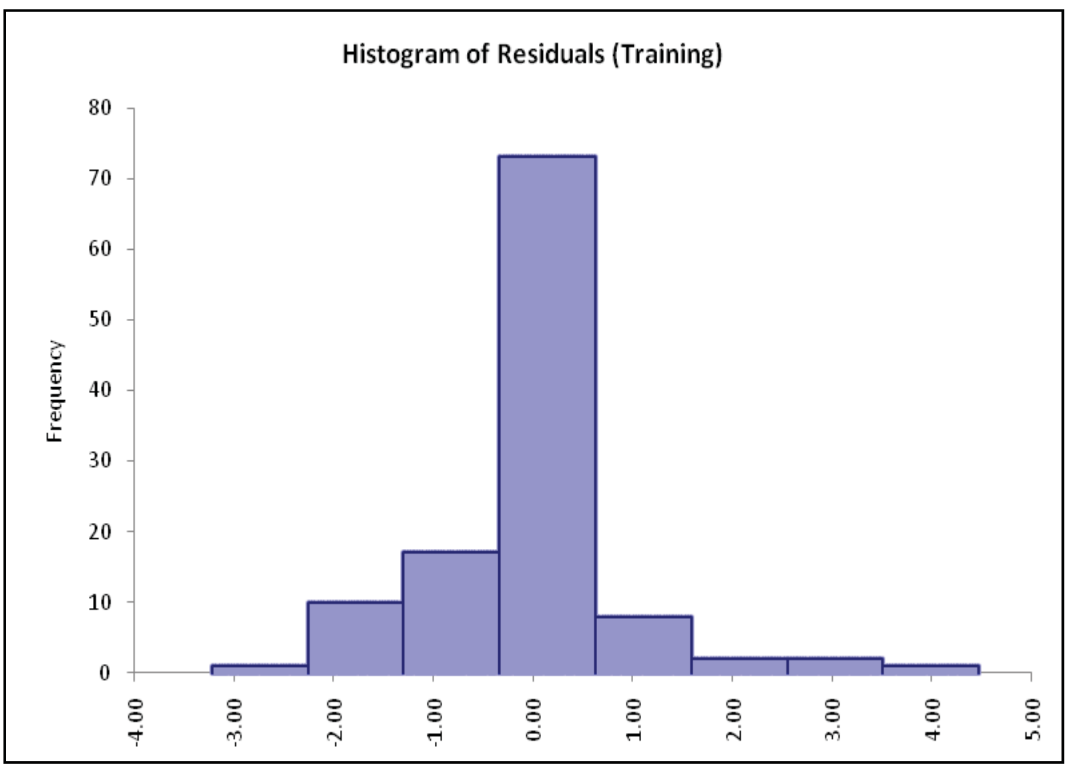


Figure 8.16: Residual Training for Extensive Data (Probability, Age, Material, and Slope)

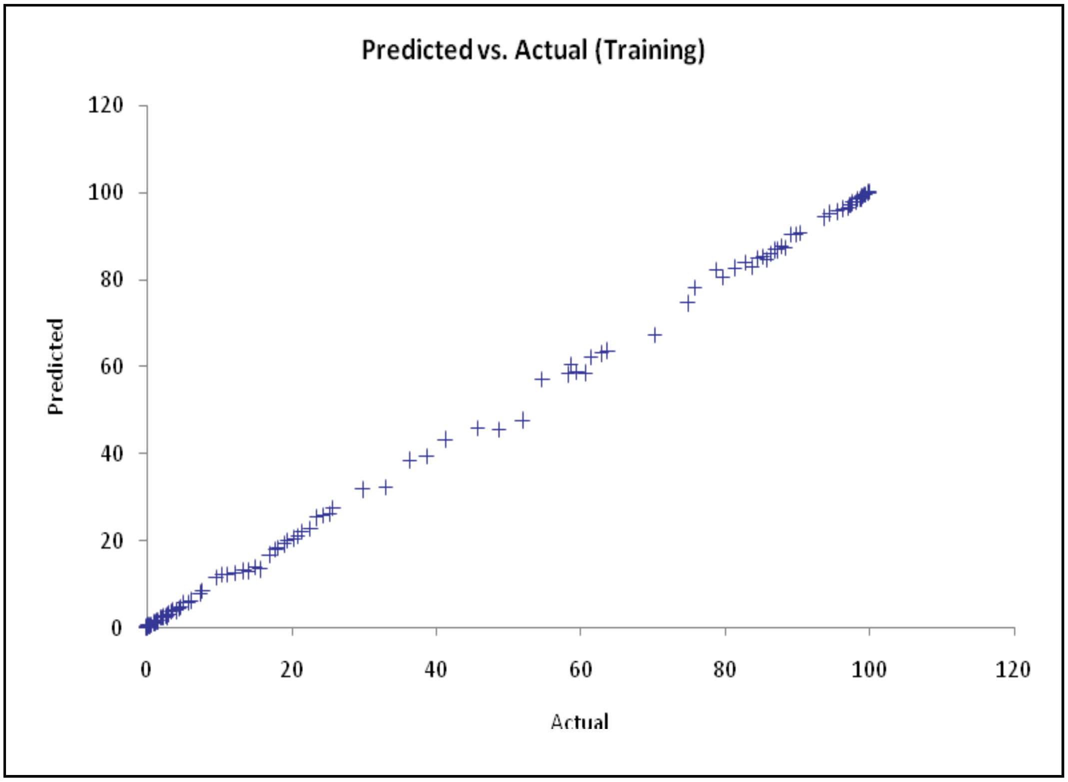


Figure 8.17: Model Calibration Fit for Extensive Data (Probability, Age, Material, and Slope)

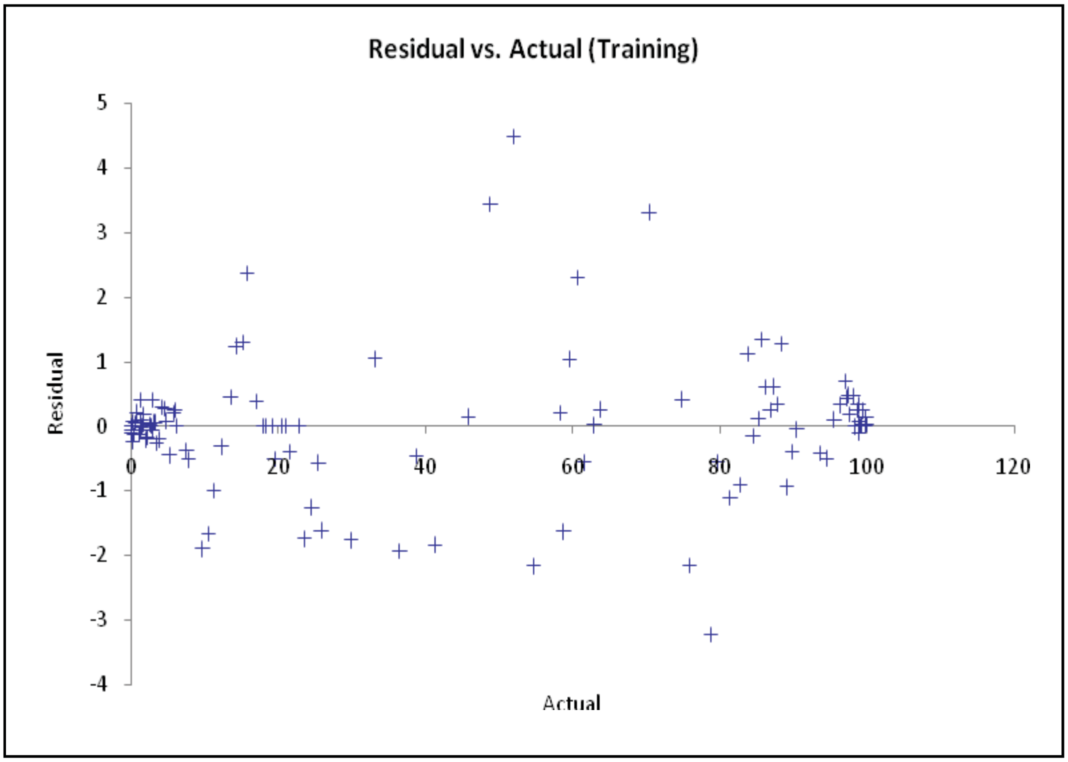


Figure 8.18: Model Calibration Accuracy (Probability, Age, Material, and Slope)

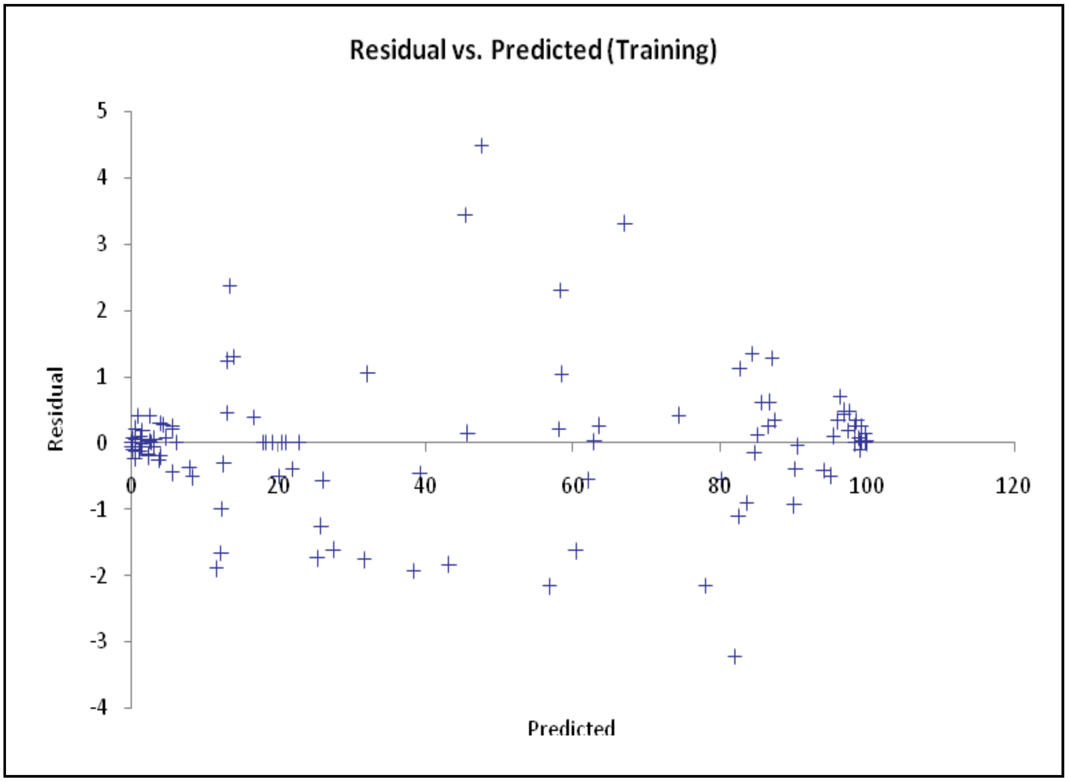


Figure 8.19: Model Calibration Testing (Probability, Age, Material, and Slope)

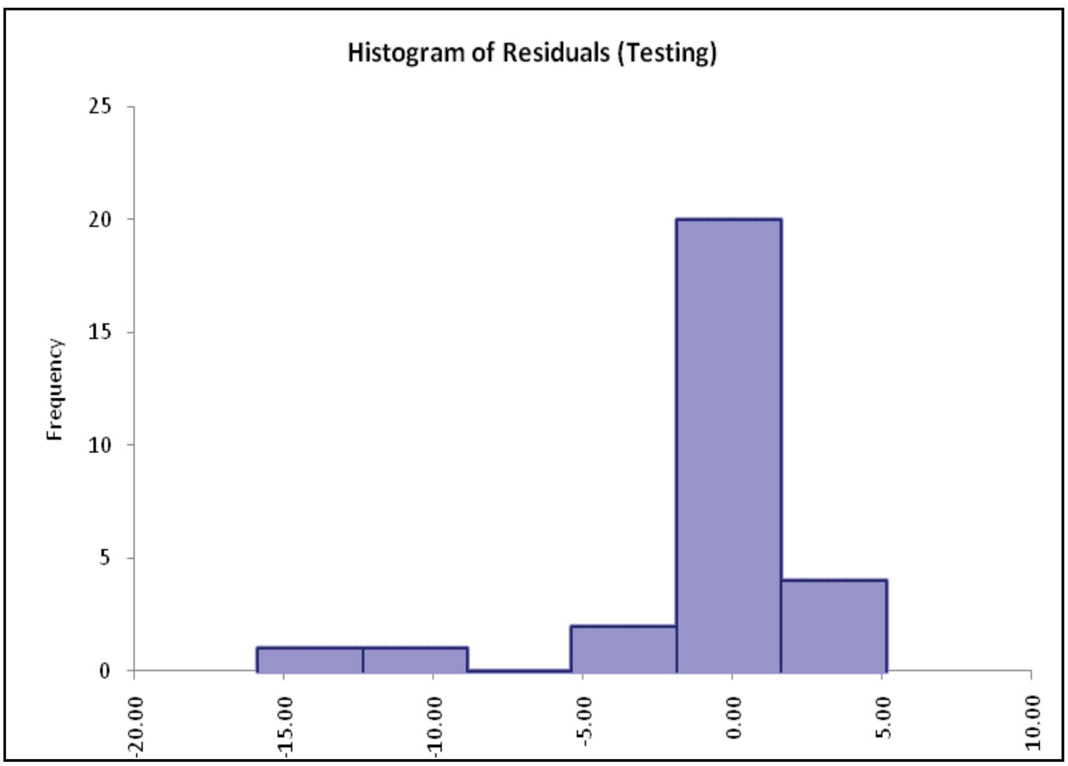


Figure 8.20: Residual Testing for Extensive Data (Probability, Age, Material, and Slope)

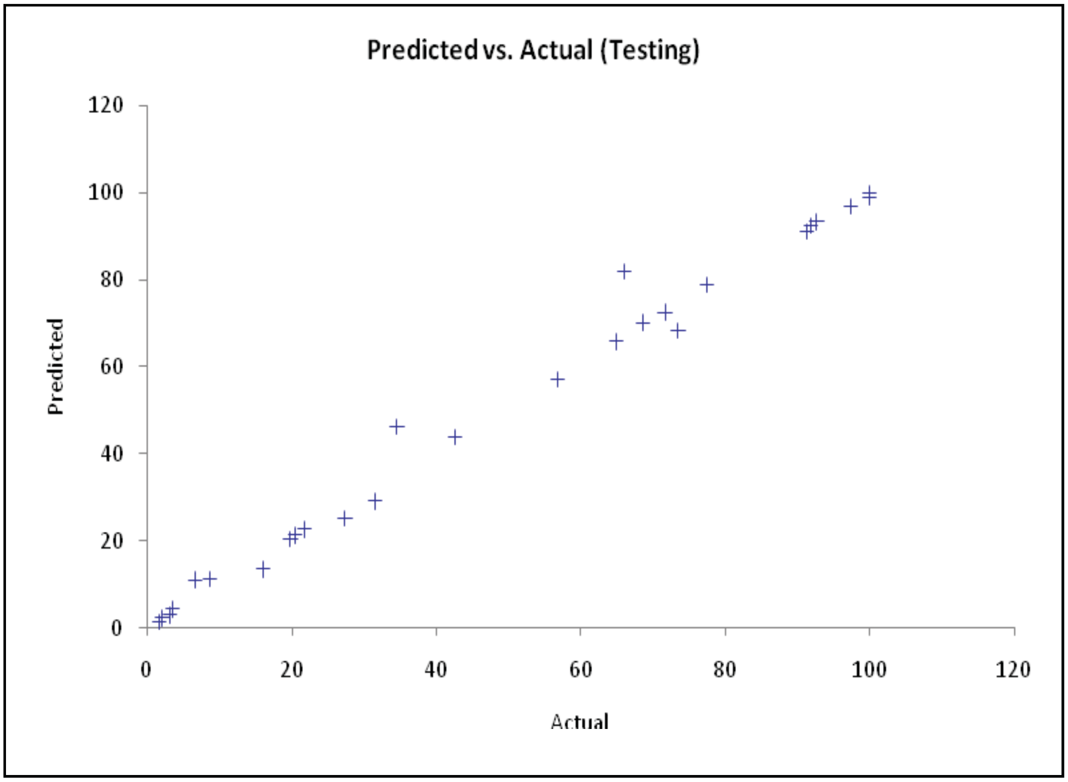


Figure 8.21: Model Validation (Probability, Age, Material, and Slope)

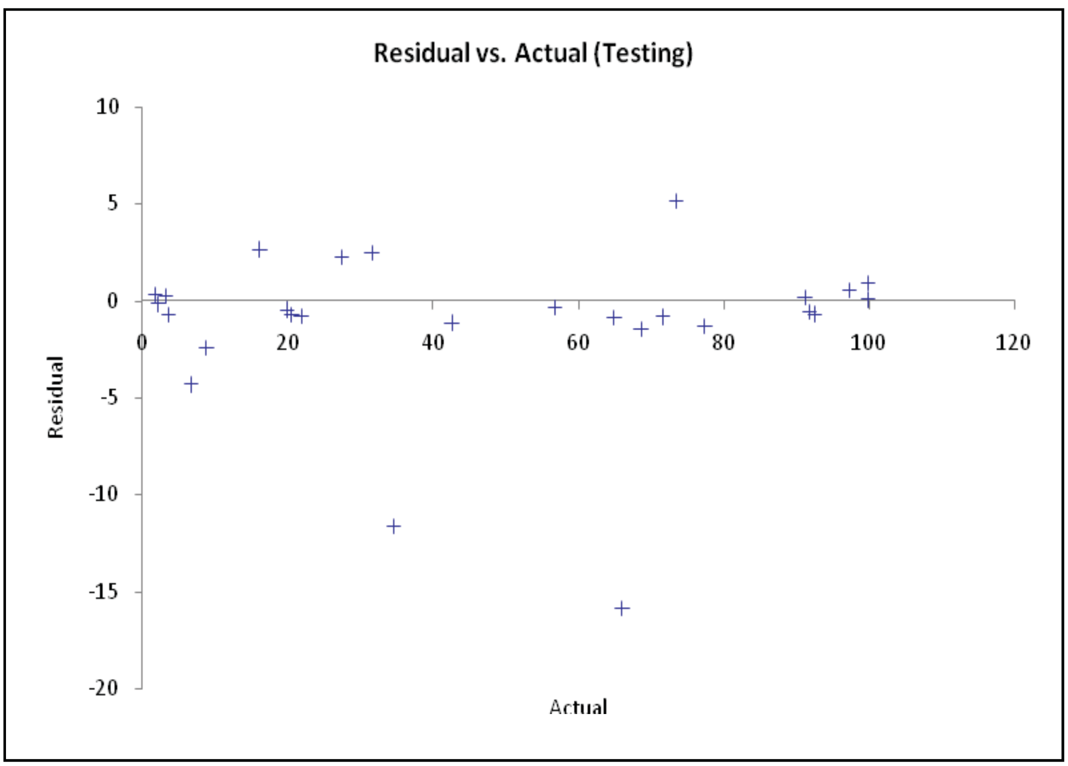


Figure 8.22: Model Input Testing (Probability, Age, Material, and Slope)

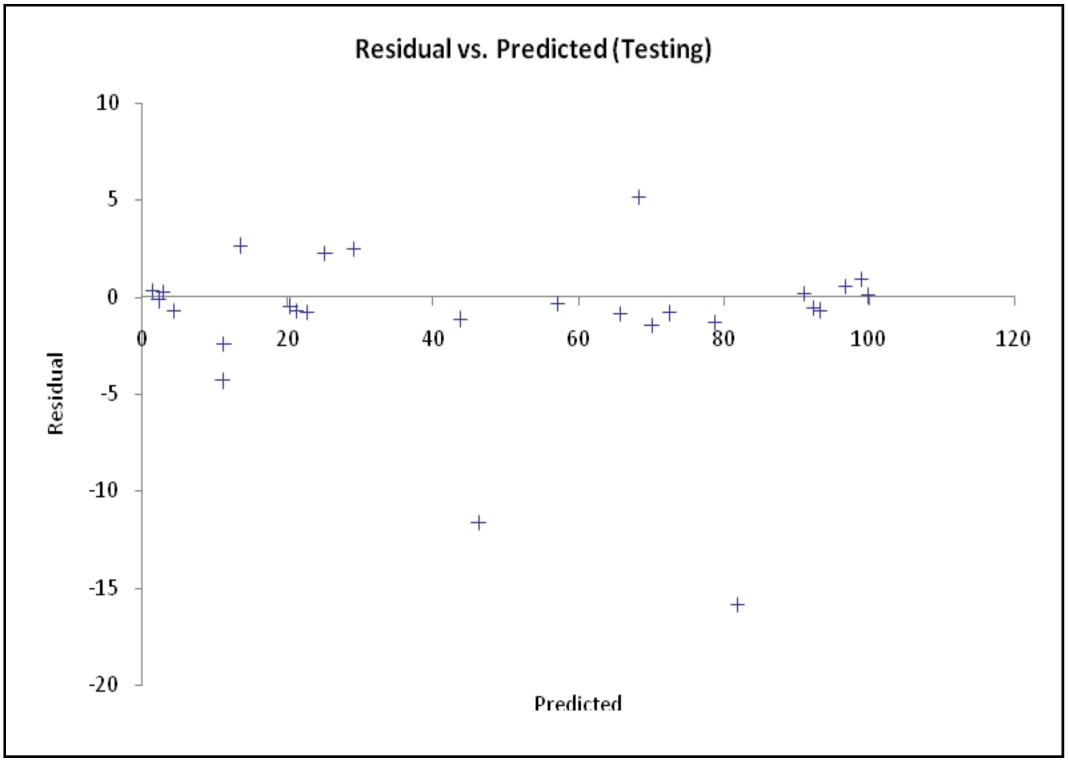


Figure 8.23: Model Prediction Accuracy (Probability, Age, Material, and Slope)

The last model incorporated two categorical (material and soil) and four numerical factors (pipe age, slope, size, and depth) as inputs to the GRNNDM. This model produced the most accurate results among the NN models generated under this study. This model had 1.7% of bad predictions during the training and none during the testing phase. Figures 8.25 through 8.33 show the model output for the detrioration of all sewers as a function of their age as well as the model training, calibration, testing, and validation. Although all NN models under this study produced acceptable results within the set parameters of the model, the results obtained from the last model (Figure 5.25) confirm the observation in the literature that PNN models require extensive data to produce accurate results. The training of the network and testing time for this fairly large model took only few seconds to run. A summary of the model configuration and training and testing results can be found below in table 8.4.

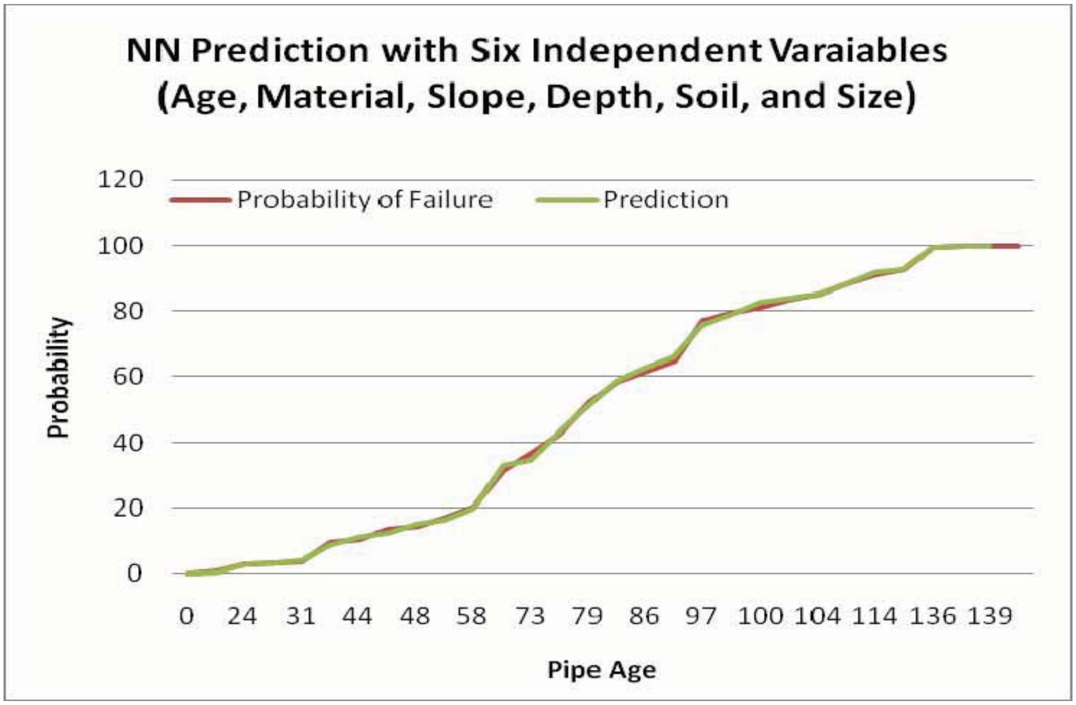


Figure 8.24: GRRN Prediction (age, material, slope, depth, soil, and size)

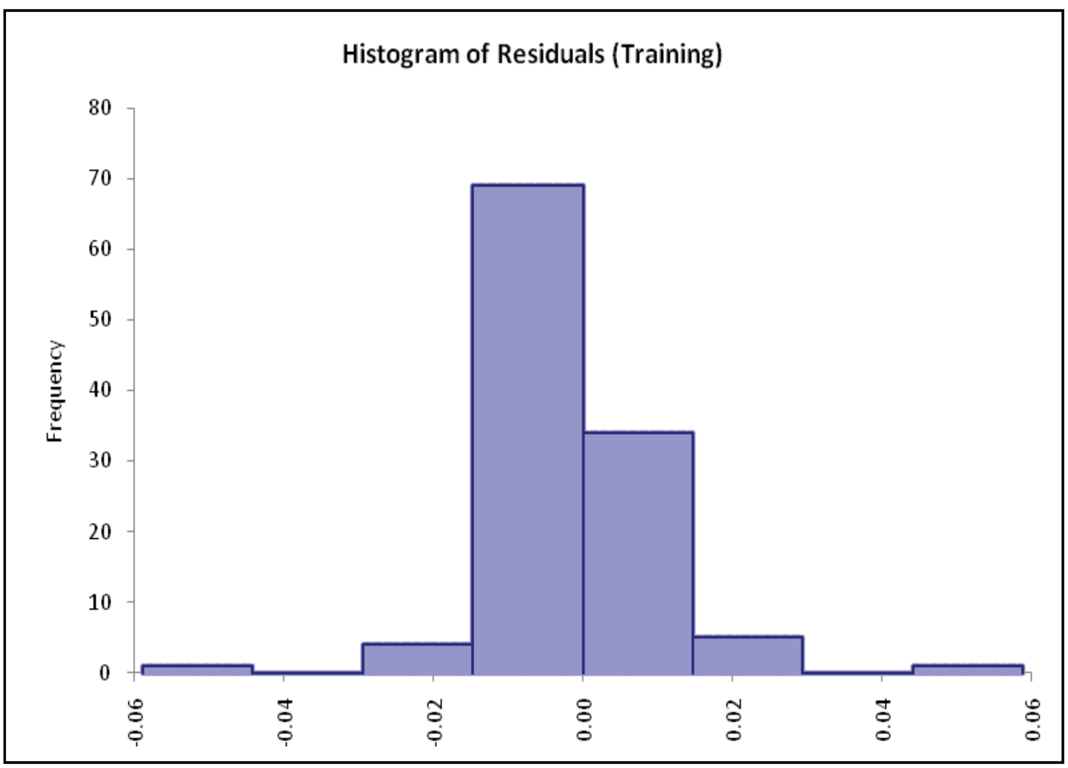


Figure 8.25: Residual Training for Six Inputs (age, material, slope, depth, soil, and size)

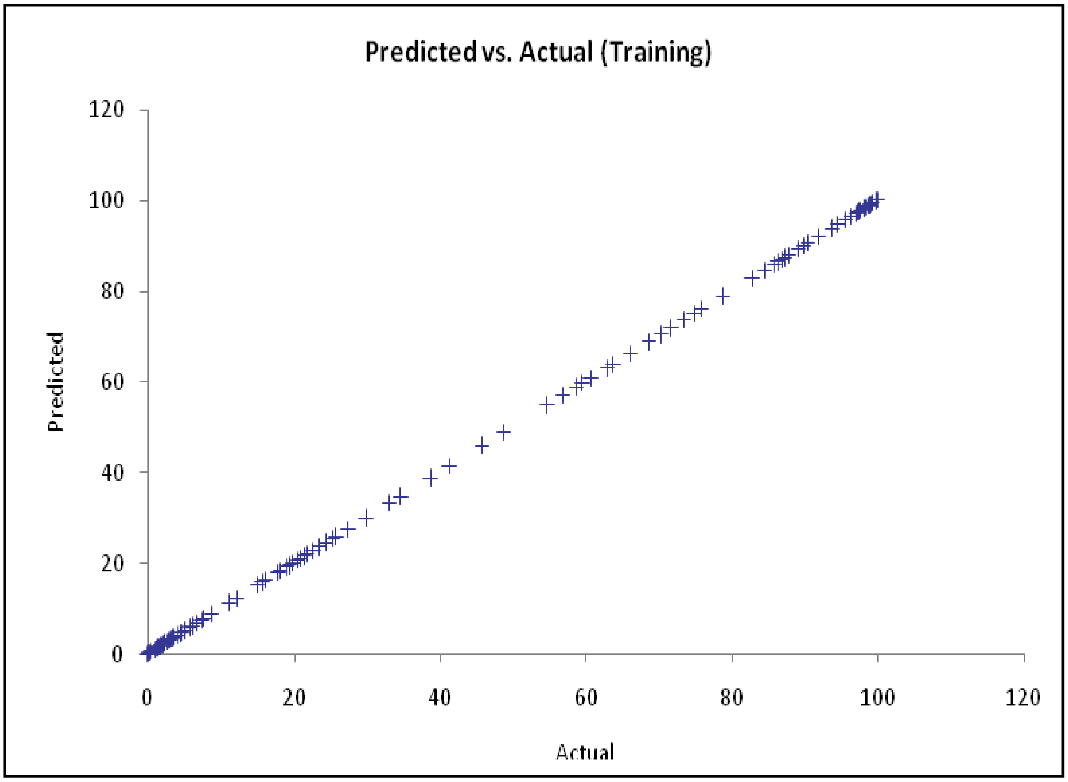


Figure 8.26: Six Inputs Model Calibration (age, material, slope, depth, soil, and size)

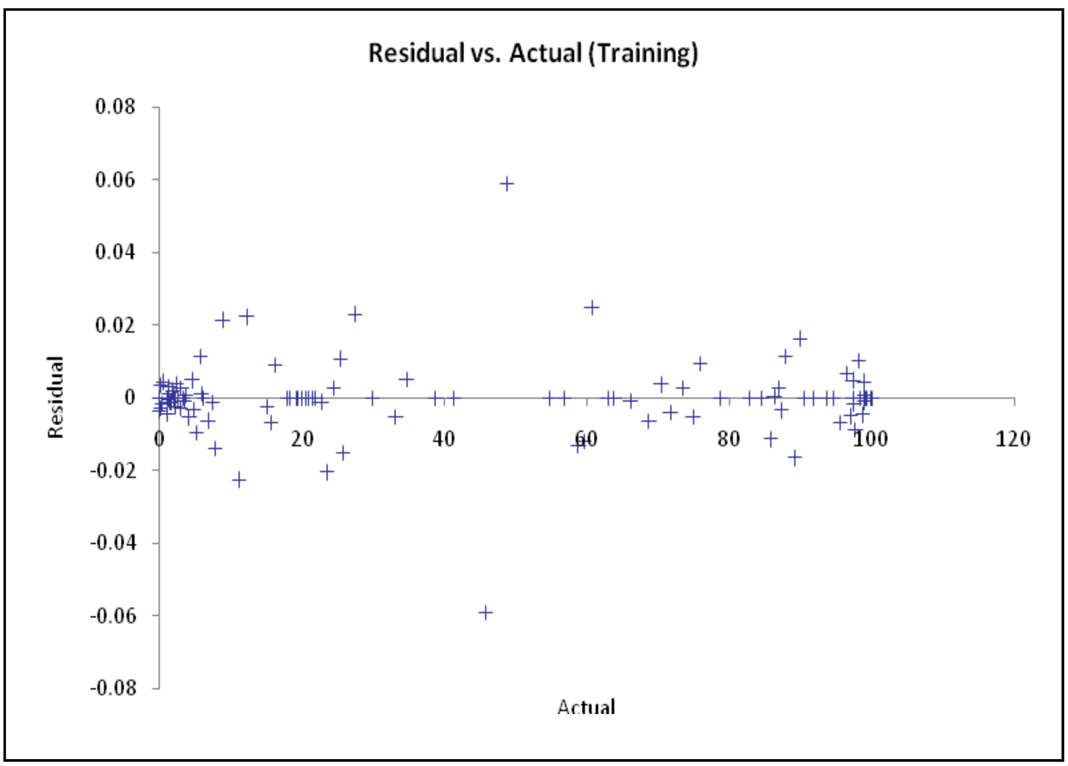


Figure 8.27: Model Calibration Accuracy (age, material, slope, depth, soil, and size)

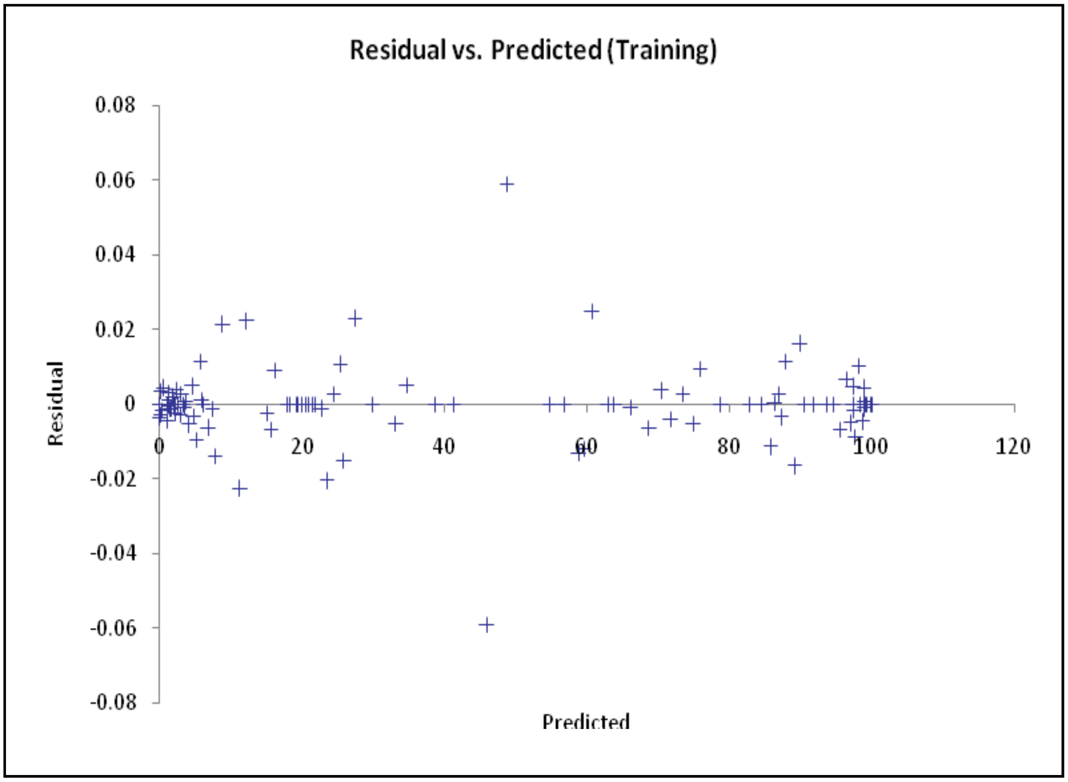


Figure 8.28: Model Output Accuracy (age, material, slope, depth, soil, and size)

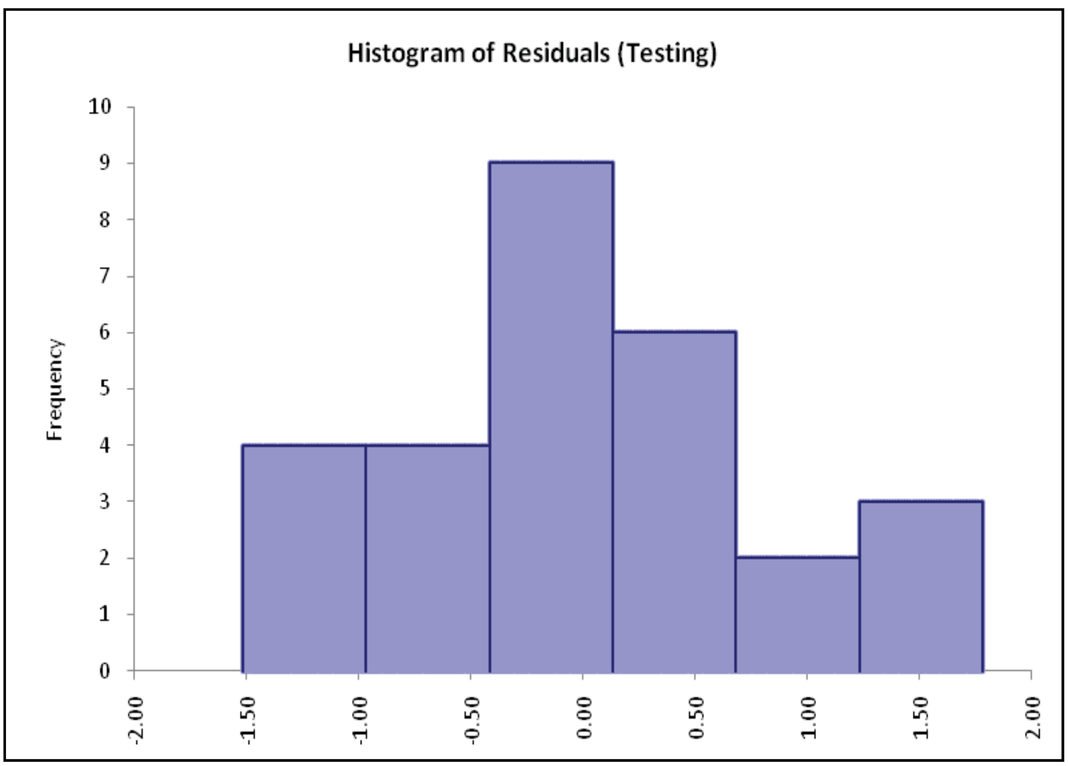


Figure 8.29: Residual Testing for Six Inputs (age, material, slope, depth, soil, and size)

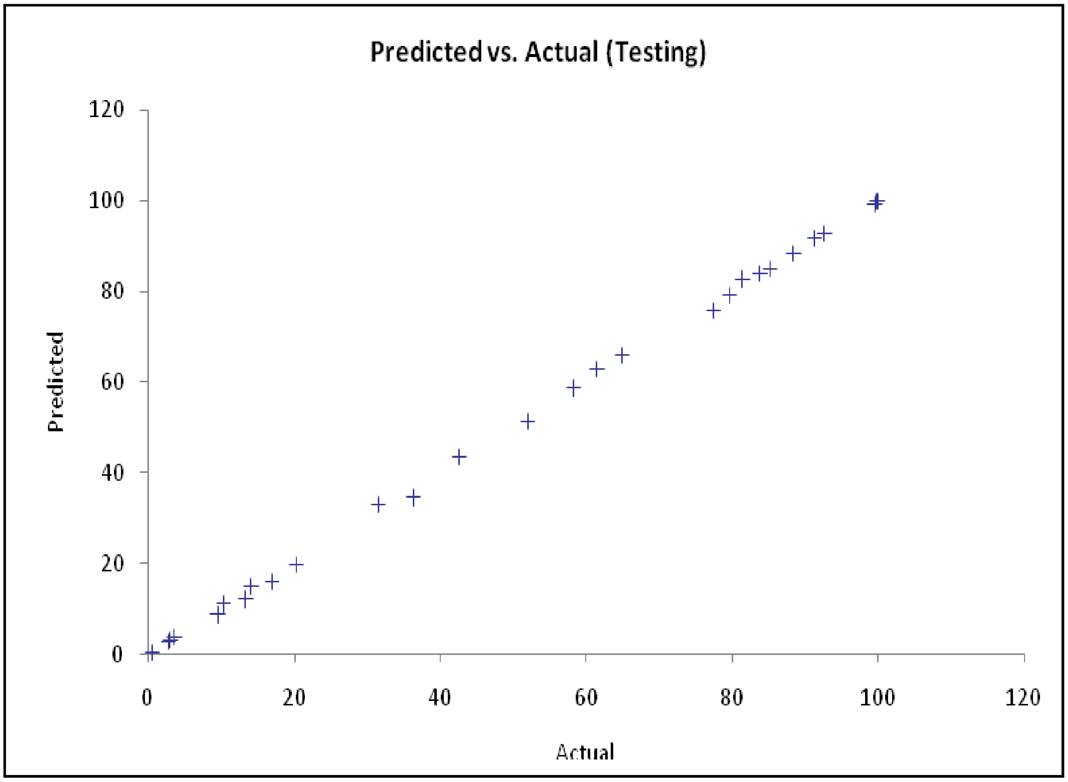


Figure 8.30: Six Inputs Model Validation (age, material, slope, depth, soil, and size)

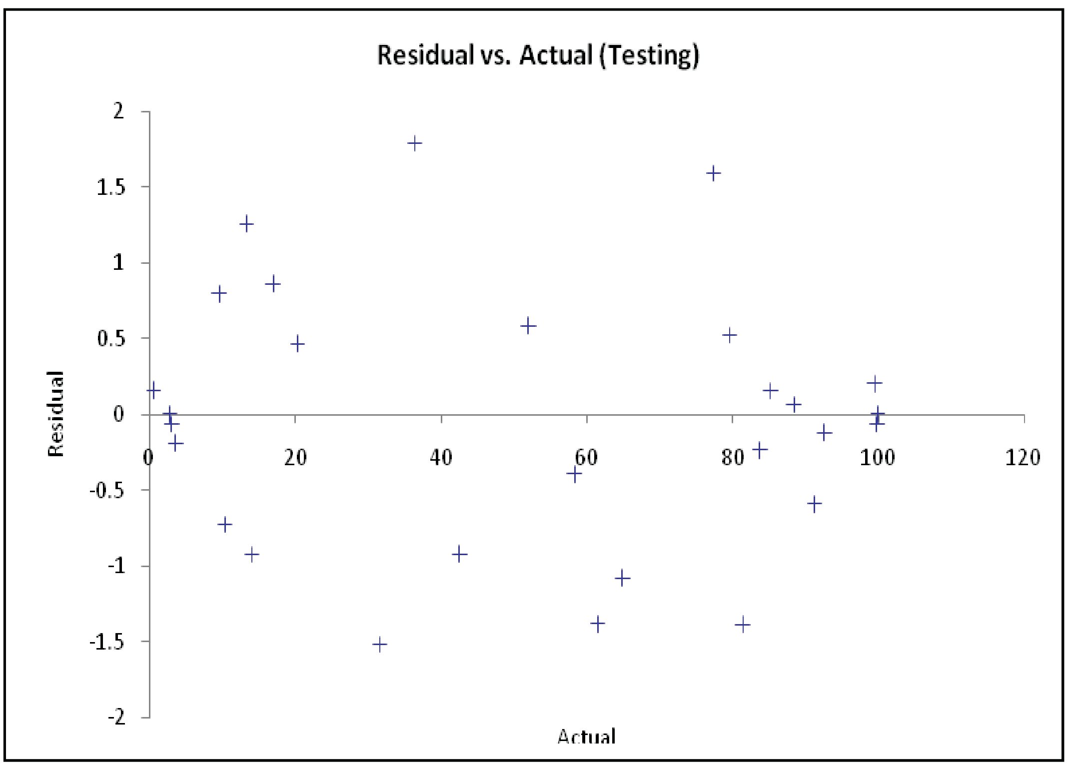


Figure 8.31: Model Residual Vs Actual (age, material, slope, depth, soil, and size)

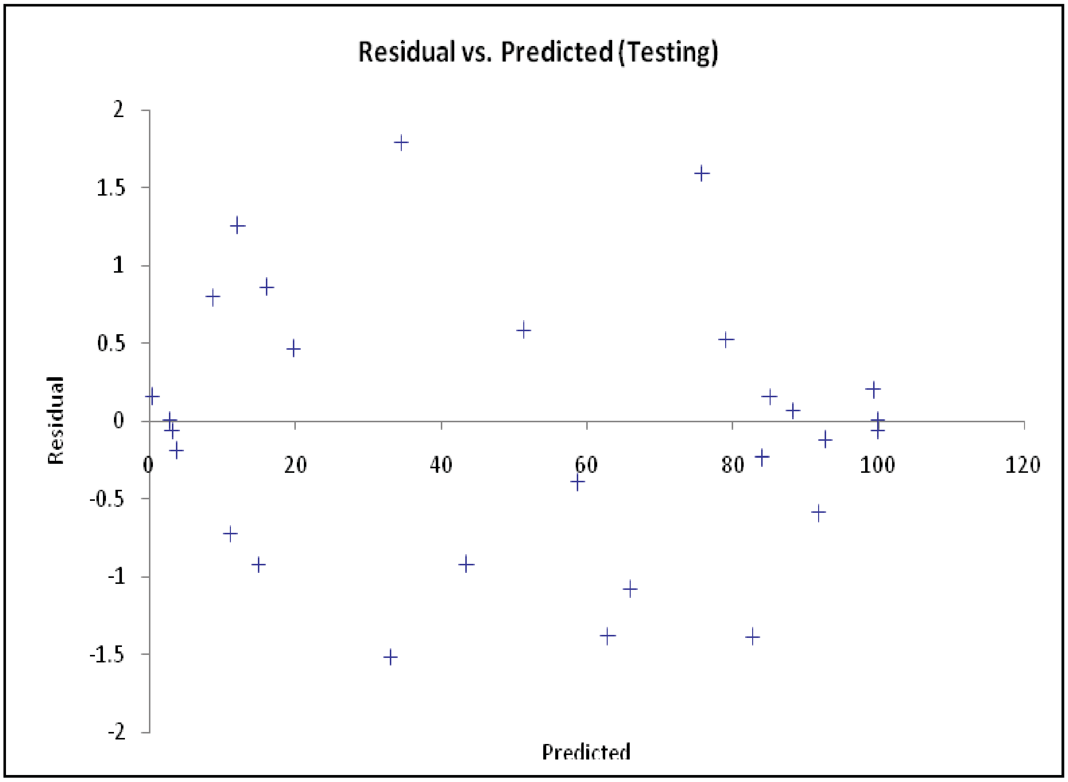


Figure 8.32: Model Prediction Accuracy (age, material, slope, depth, soil, and size)

Configuration	GRNN Numeric Predictor
Independent Category Variables	2 (Soil Type, Material)
Independent Numeric Variables	4 (Size, inches, Depth, ft, Slope (%), Age)
Dependent Variable	Numeric Var. (Probability of Failure)
Training	
Number of Cases	114
Number of Trials	67
% Bad Predictions (30% Tolerance)	1.7544%
Root Mean Square Error	0.01060
Mean Absolute Error	0.005125
Std. Deviation of Abs. Error	0.009280
Testing	
Number of Cases	28
% Bad Predictions (30% Tolerance)	0.0000%
Root Mean Square Error	0.8392
Mean Absolute Error	0.6436
Std. Deviation of Abs. Error	0.5386

Table 8.4: Summary of NN Testing and Training Results Using Six Independent Variables (Age, Material,Slope, Depth, Size, and Soil Type) to Predict The Probability of Failure

8.4 SUMMARY

Neural Networks provide very powerful tools to aid in the prediction of sewer deterioration and failure. Four models were developed under this research using limited and extensive datasets, both numerical and categorical, as input to the model. The limited data model failed to predict the hyperbolic form of the deterioration curve that is typically reported using other methods. Additionally, the limitation of data availability inhibited the model's accuracy and resulted in 25% of bad predictions in its output. As the number of input factor increased, the output accuracy of the models improved and the percentage of bad predictions decreased. Bad predictions were lowered from 25% in the first model where only pipe age and slope were considered to 7.14% where pipe age, slope, and material were considered; and ultimately to 0% when six factors were introduced as input to the model, namely: pipe age, slope, size, depth, material, and type of soil.

The results obtained in this chapter confirm previous observations that PNN models require extensive data; however, they do not require much time for training and predictions. The run time for the training and prediction phases presented in this chapter was only few seconds each for each model. PNN provide an impressive speed when compared to traditional models that could take days to complete the training and predictions of equally complex mathematical interrelationships. The results obtained under this research make a compelling case for the recommendation that wastewater utilities should start using PNN, as one of the plethora of methods presented herein, to predict the failure of sewers irrespective to CCTV condition ratings methods currently being implemented by many utilities in the US and across the world.

Chapter 9

CONCLUSIONS

9.1 CRITICALITY ASSESSMENT

This research examined the factors impacting the consequences of gravity sewers failure. A matrix of influencing factors was compiled using expert opinion. The factors were assigned numerical values on a sliding scale based on hydraulic, structural, and geo-spatial criteria and their relative weight of importance was determined based on an iterative process of model construction and results validation. The GIS-based tool developed at MSDGC was accurate in highlighting the critical arteries of the collection system; most notably, the Mill Creek interceptors. Currently the tool assesses only the criticality score, or the consequences of failure. Business risk exposure associated with asset failure can be calculated by incorporating numerical values for the probability of failure into GIS and a new layer could be added scoring the multiplication of the two components of risk. Once accomplished, CAGIS will produce maps highlighting the overall risk and the wastewater utility will be able to prioritize the capital and O&M spending based on the minimization of risk. This should be accomplished by normalizing the risk factors to the dollars spent and the LCC associated with capital renewal with the highest risk score should receive the highest priority of capital spending. Similarly, vertical assets, or assets that housed and maintained in wastewater treatment plant, have been separately evaluated for criticality. The criteria matrix affecting the criticality scores for vertical assets was different from those developed for sewers. Scores for both classes of assets need to be normalized to the same range of scores. Subsequently the overall BRE scores should be calculated and normalized to the dollars needed to eliminate such risk. This will allow wastewater utilities to implement a risk-based approach to Capital Improvement Plans and to prioritize capital spending based on their risk exposure associated with asset failure.

Other GIS asset management tools were developed for Seattle Public Utilities and the Sanitation District of Los Angeles County, in the U.S.; the City of Sydney, Australia; and the City of Edmonton, Canada; however, their applications do not lend to the prediction of both the deterioration and criticality of all assets, both linear and nonlinear. The GIS asset management tools provided in this research, when fully implemented by MSDGC, will be the first of its kind as a comprehensive asset management platform to predict the overall risk associated with both linear and non-linear assets.

9.2 PROBABILTY OF FAILURE AND DETERIORATION

This research provided methodologies and results to develop deterministic, probabilistic, and artificial intelligence models to predict the deterioration of sewers. Deterministic models were developed for all material types of pipes except for PVC and HDPE pipes due to the lack of sufficient data related to their failure history; however, the general model for all pipes can be used. A similar problem was encountered with segmented block and brick sewers. It is recommended that more attributes of the sewers being repaired to be collected and recorded to aid in the development of future deterioration models. Polynomial regression analysis, although simple and can be performed in Excel spreadsheets, provide powerful and meaningful results that will aid asset managers in wastewater utilities in assessing risk associated with linear assets.

Although other researchers have developed deterioration models for infrastructure before, this research does not rely on condition assessment methodologies that are based on CCTV. Posterior distribution functions were obtained by fitting historical repair data to develop probabilistic models for sewers deterioration. The use of GRNN to model the deterioration of sewers was also done for the first time even though other researchers have used NN to develop a Markovian chain deterioration models for stormwater sewers. Not all attribute that are commonly reported in the literature as contributing factors to deterioration of sewers were available for this research study. For example, the effects of wastewater characteristics, velocity within the pipe, groundwater elevation, among other factors on deterioration were not investigated. The deterioration models are merely tools to assess the probability of failure and should not be interpreted as if they favoured one type of pipe material over another. The data that were used to develop the models represents the condition of sewers within the City of Cincinnati and Hamilton County and the models should be updated periodically as the condition of the infrastructure changes with aging. It should be noted that updating the deterioration models annually could be easily accomplished without spending scarce resources on CCTV and operators training to assess the condition of the entire asset inventory. Various probabilistic deterioration models were developed using historical repair data for the asset inventory that was studied under this research. Two distinct probabilistic methods were used to generate the models. Data fitting was used utilizing known probability distribution functions to estimate the distribution functions parameters and fitting probability curves through the historical repair data. Best distribution fits were determined and a mathematical equation describing the model was developed. The second probabilistic method investigated was the Monte Carlo Simulation method. Simulation results produced high resolution curves due to the high number of iterations, one million, which served as an input to the model. Monte Carlo simulation model for PVC and Ductile Iron sewers was far more accurate and reliable than the ones produced through data fitting due to the limited availability of repair data on those two types of material. A similar conclusion can be made for models that were produced for segmented blocks and brick sewers. While the data fitting models produced good results, the simulation models produced better tools under conditions where limited or no availability of data were present. GRRN models proved to be powerful tools for the predictions of sewers; however, they require lots of data as input. The GRNN models had the advantage of sifting through vast information at an impressive speed and required almost no time for training to produce accurate predictions. Their use, however, is not recommended under limited availability of data.

9.3 OPERATION AND MAINTENANCE CONSIDERATIONS

The deterioration models developed in this dissertation should be utilized to formulate O&M strategies for the sewers infrastructure. Several strategies can be developed. Figure 9.1 shows the general deterioration models for all pipes used as a run-to-failure approach where the sewer is replaced at the end of its useful life. This approach could be used on sewers which are identified by the GIS criticality tools as receiving a low criticality score. The second model for O&M is shown in Figure 9.2. This model incorporates rehabilitation and replacement in conjunction with an acceptable level of service. In this example, a level of service of at least 20% of remaining service life should be maintained although the utility accepts the risk of operating under this LOS for periods of time to extend the life cycle of the asset. In the third model which is shown in Figure 9.3, the utility assumes strict responsibility to meet the LOS required by customers and regulators incorporating a combination of rehabilitation and replacement. In Figures 9.2 and 9.3 it is assumed that the rehabilitation of a sewer line will extend its useful life by 20 years. Needless to say the models in 9.1, 9.2, and 9.3 represent low, medium, and high in terms of capital needs for the utility and level of service provided.

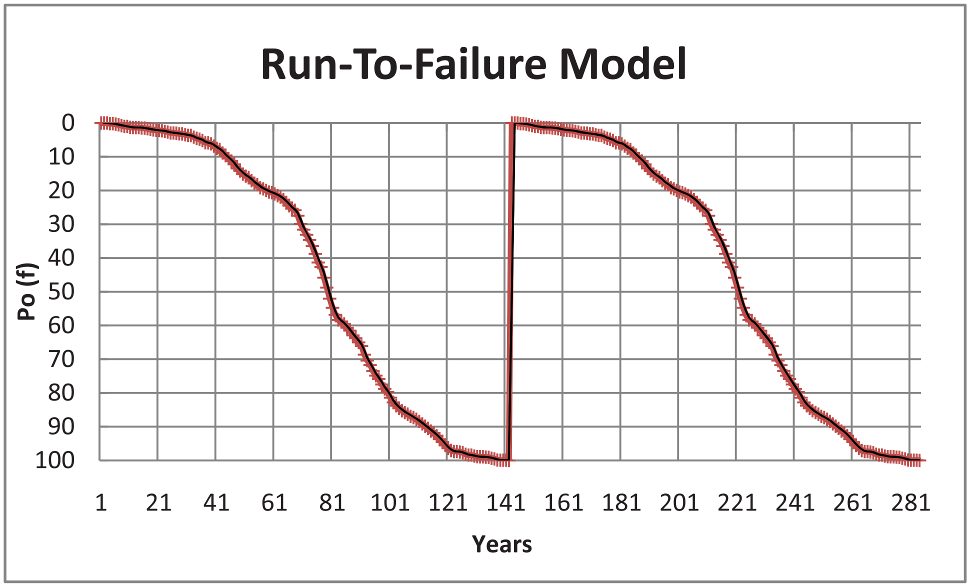


Figure 9.1: Sewer Replacement with no Maintainence

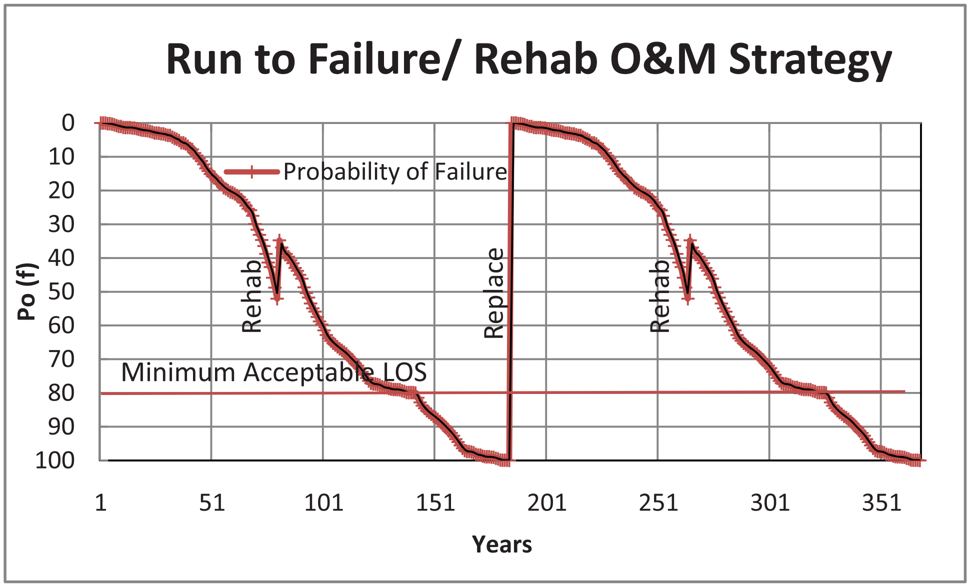


Figure 9.2: Rehabilitation and Replacement Regardless of Acceptable LOS

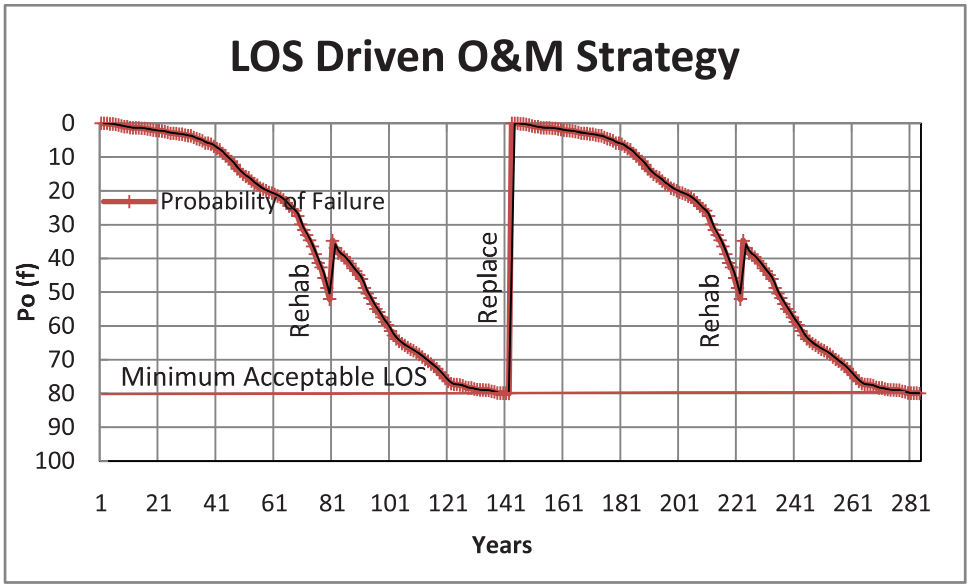


Figure 9.3: Rehabilitation and Replacement of Sewers According to Acceptable LOS

9.4 CAPITAL IMPROVEMENT PLAN CONSIDERATIONS

Currently most wastewater utilities in the U.S. finance their capital improvement plans partially or completely through bond issue (GAO, 2004). Figure 9.4 below shows the cumulative revenues and spending at MSDGC between 2004 and 2011. The figure demonstrates that current spending levels are unsustainable on the long run without substantial rate increases in the double digits, cost avoidance, and/or cost reductions. MSDGC capital spending is comprised of an asset management plan in the range of $55 million annually and approximately $110 million a year for a period of twenty years due to a federally mandated consent decree to address defects in the network during wet weather flow. Since the wet weather plan is already defined by approximately 320 projects that are approved by the federal EPA, at least on a conceptual level, those projects do not compete for funding with the asset management projects. This research recommends a risk based approach to the implementation of all capital improvement projects.

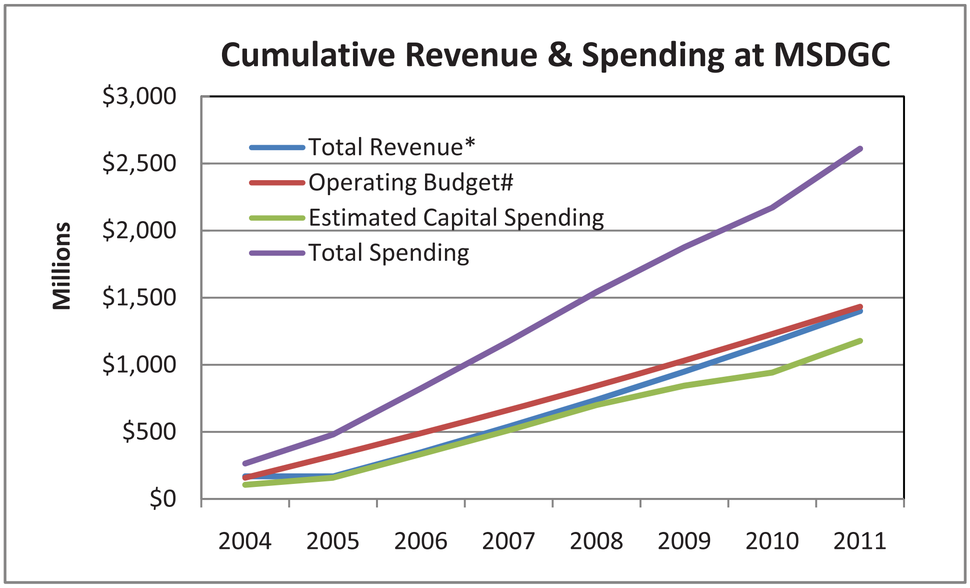


Figure 9.4: Cumulative Revenue and Spending From 2004 to 2011
* Revenues for 2010 and 2011 are estimate at an annual rate increase of 5%
\# Operating budgets for 2010 and 2011 are estimated at 3% increase annually

Appendix F of this dissertation shows the list of projects in the 2007 CIP at MSDGC. The projects were evaluated and prioritized by the planner or the champion who nominated the project for implementation using pre-established criteria in a spreadsheet format. Under this research, the recommended approach of using risk in a systematic manner across all assets to prioritize spending would have yielded different results, arguably cost savings to the utility. All capital projects should be evaluated for their LCC using the BRE scores as the benefits in the analysis. In essence, the BRE score would be normalized by the costs needed over the life of the asset to determine the CIP project's priority. This approach was applied to the project list for the 2007 CIP and the results are tabulated in Appendix G. It is worth noting that some projects that did not receive high priority under the current methods employed by MSDGC received a high risk score; thus priority, and vice versa. For example if the funding availability was reduced from $55 to $50 million during 2007, few critical projects that received funding would not have passed the risk test in Appendix G.

9.5 RECOMMENDATIONS FOR FUTURE WORK

The data collected for this research were obtained from MSDGC; therefore, the results obtained herein should be interpreted with caution especially for other systems. The characteristics of the infrastructure that was studied could widely differ from other systems. For example, a nearby wastewater utility in Clermont County, Ohio maintained a water distribution network where the average age of a pipe in the system was only 24 years whereas the average age of sewer pipe at MSDGC was 79 years. The results should be corroborated by evaluating other cities and municipalities. As mentioned previously, risk assessment for sewers should follow a probabilistic model to predict the failure; therefore, efforts to assess the condition of sewers via CCTV to predict its failure should be abandoned. CCTV use for condition assessment should be selective to the highly critical part of the infrastructure. The data used to develop the deterioration models under this study lacked the availability of data on some of the widely reported contributing factors. For example, only six factors (pipe age, size, material, slope, depth, and soil condition) were used to evaluate the deterioration models using NN. Other contributing attributes should be recorded when conducting repair so that their influence on the deterioration rate of sewers could be investigated in the future.

GIS should be exploited for the development of a comprehensive asset management decision support system incorporating risk assessment methodologies described in this dissertation as well as a module to conduct LCC or TBL analysis to prioritize funding strategies for future CIPs. Wastewater utilities should implement risk based approaches to optimize their capital spending and operation and maintenance costs.

This research made significant contributions as the being first to develop deterioration models by utilizing twelve years worth of historical data instead of inspection data. Additionally, this research is the first to use GRNN to provide numeric predictors for the probability of failure of gravity sewers. Additional research is needed, using the same methodologies, to examine the deterioration of utilities' sewers. A complete assessment of the BRE associated with all of MSDGC assets needs to be completed to provide the overall risk exposure assuming certain risk appetite curves. Further research to validate the benefits of using the risk based methodologies obtained under this research by implementing similar funding strategies recommendations for both O&M and capital spending at MSDGC and measuring the economic implications should be pursued.

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APPENDIX A: GLOSSARY

Artificial Neural Network (ANN): Also called "neural network" (NN), is a form of mathematical models that aims at simulating the structure and/or function of biological interconnected neural networks

Asset: A component of a facility with an independent physical function, condition, and age.

Asset Category: A classification of assets within an organization such as pumps, linear, and nonlinear assets.

Asset Hierarchy: A framework for segmenting an asset base into appropriate classifications. The asset hierarchy can be based on the function of assets or its type.

Asset Inventory/ Register: A list of assets identifying each asset with a unique identifier number detailing important information such as installation date, cost, and condition.

Asset Management: A process for minimizing Life Cycle Costs associated with an asset while delivering a desired level of customer service.

Asset Management Plan (AMO): AMP is a plan developed for the management of one or more infrastructure class of asset with a view to operating, maintaining and renewing the assets within the class in the most cost effective manner possible, whilst providing a desired level of service

Asset Status: Describes the asset status as far as whether it is active, abandoned, or a future investment.

Asset Type: Describes the functional use of the asset.

Capital Improvement Program (CIP) Plan: A plan that details projects to be completed in the future, typically, on a 5-year revolving basis.

Computerized Maintenance Management System: A computer system that schedules, tracks and monitors maintenance activities and provides cost, component item, tooling, personnel and other reporting data and history.

Condition Based Maintenance: A technique that involves monitoring the condition of an asset and using that information to predict its failure.

Condition: The deterioration level of an asset when compared to its new condition.

Consequence of Failure: The economic, social, and environmental impact of failure of an asset.

Expected Useful Life: The time calculated between installation and until the asset is decommissioned.

Failure Mode: Description of the way in which failure occurs.

Geographical Information System: An information system that integrates stores, edits, analyzes, shares, and displays geographic information. GIS applications are tools that allow users to create interactive queries (user created searches), analyze spatial information, edit data, maps, and present the results of all these operations.

Infrastructure: Long life assets that consists of an entire system or network which provide the foundation to support public services and enhance the economy.

Infrastructure Asset Management: The discipline or field providing guidelines for the managing of infrastructure assets.

Level of Service (LOS): Benchmarks describing performance or quality of service to be expected from proper management of assets.

Life Cycle Costing (LCC): A method of assessing the capital investment and O&M costs of an asset over the span of its useful life.

Maintenance: Activities performed on assets to ensure that it is able to deliver a desired LOS until it is scheduled to be renewed, replaced or disposed of.

Asset Network: Network of assets that are interconnected and rely on each other to provide a service.

Probability of Failure: The chance that an asset will fail to perform its intended function.

Rehabilitation: Work carried out to rebuild or replace parts or components of an asset, to restore it to a required functional condition and extend its useful life.

Reliability Centered Maintenance: Known as RCM, is an approach focused on identifying and establishing the operational, maintenance, and capital improvement policies that will manage the risks of equipment failure most effectively.

Remaining Useful Life: The estimated length of time remaining before the asset needs to be replaced.

Renewal: Renewal is the replacement or refurbishment of an existing asset.

Replacement Cost: The cost of replacing the asset with a substantially identical new one in present value.

Residual Value: The estimated value obtained from the disposal of the asset, after deducting the estimated disposal costs and depreciation.

Risk: Known or unknown events that may have adverse consequences.

Risk Assessment: A process to assess the risks associated with a hazard.

Risk Management Plan: A document prepared to foresee risks, to estimate the effectiveness, and to create response plans to mitigate them.

Sewer: A pipeline or other construction, usually buried, designed to convey wastewater.

Manhole: An access point with a removable cover to allow for inspection of sewers.

Stormwater: A term used to describe water that originates during rain events.

Strategic Asset Management Plans (SAMP): A plan that documents service standards, operations, maintenance and renewal strategies for achieving these standards.

Useful Life: The estimated length of time during which the asset is able to deliver a specific LOS.

Wastewater: Wastewater is spent or used water from residential, business or industrial sources.

APPENDIX B: Comparison of Extensive Data Neural Network Predictions (Probability, Age, and Slope as Model Inputs) and Data Fitting Probabilistic Models Results

Pipe Age	Input Data	Normal Distribution	Weibull Distribution	Logistic Distribution	Neural Network Prediction
0.08016	0	0.000992643	0.001905361	0.003931361	5.8284E-08
0.480962	0	0.001046622	0.002009205	0.004042146	3.19795E-07
0.881764	0	0.001103281	0.002117607	0.00415604	1.65535E-06
1.282565	0	0.001162738	0.002230722	0.004273129	7.82455E-06
1.683367	0	0.001225117	0.002348703	0.004393502	3.25368E-05
2.084168	0	0.001290544	0.002471712	0.004517251	0.000115311
2.48497	0	0.001359152	0.002599911	0.004644469	0.000337707
2.885772	0	0.001431078	0.002733466	0.004775253	0.000775312
3.286573	0.0019815	0.001506462	0.002872549	0.004909701	0.001329178
3.687375	0.0019815	0.001585452	0.003017332	0.005047916	0.001778033
4.088176	0.0019815	0.0016682	0.003167993	0.005190001	0.002102061
4.488978	0.0019815	0.001754863	0.003324715	0.005336064	0.002447134
4.88978	0.0019815	0.001845604	0.003487681	0.005486215	0.00292619
5.290581	0.0033025	0.00194059	0.003657082	0.005640567	0.003521562
5.691383	0.0033025	0.002039997	0.00383311	0.005799237	0.004143799
6.092184	0.005284	0.002144003	0.004015962	0.005962343	0.00476289
6.492986	0.005284	0.002252796	0.004205838	0.006130008	0.005417647
6.893788	0.005284	0.002366565	0.004402944	0.006302359	0.006157219
7.294589	0.0072655	0.002485511	0.004607489	0.006479523	0.006993264
7.695391	0.0072655	0.002609838	0.004819684	0.006661634	0.007870428
8.096192	0.0099075	0.002739756	0.005039747	0.006848829	0.008683412
8.496994	0.0099075	0.002875484	0.005267899	0.007041246	0.009351188
8.897796	0.0099075	0.003017246	0.005504364	0.00723903	0.00988883
9.298597	0.0099075	0.003165273	0.005749373	0.007442328	0.010394602
9.699399	0.0099075	0.003319805	0.006003158	0.007651291	0.010951072
10.1002	0.0125495	0.003481088	0.006265957	0.007866074	0.011543636
10.501	0.0125495	0.003649373	0.006538012	0.008086838	0.01208573
10.9018	0.0125495	0.003824922	0.006819569	0.008313746	0.012508573
11.30261	0.01321	0.004008003	0.007110878	0.008546966	0.012805377
11.70341	0.01321	0.004198891	0.007412194	0.00878667	0.013004983
12.10421	0.01321	0.004397871	0.007723776	0.009033036	0.013137764
12.50501	0.01321	0.004605233	0.008045888	0.009286245	0.013237502
12.90581	0.01321	0.004821278	0.008378796	0.009546483	0.013351786
13.30661	0.01321	0.005046312	0.008722774	0.009813942	0.013525118
13.70741	0.01321	0.005280653	0.009078098	0.010088817	0.013776268
14.10822	0.014531	0.005524624	0.009445047	0.010371311	0.014090302
14.50902	0.014531	0.005778557	0.009823909	0.01066163	0.014435967

Pipe Age	Input Data	Normal Distribution	Weibull Distribution	Logistic Distribution	Neural Network Prediction
14.90982	0.014531	0.006042795	0.010214972	0.010959985	0.014799089
15.31062	0.0151915	0.006317687	0.010618531	0.011266595	0.015192305
15.71142	0.0151915	0.006603592	0.011034885	0.011581682	0.015633538
16.11222	0.0165125	0.006900877	0.011464335	0.011905474	0.016131741
16.51303	0.0165125	0.007209918	0.011907191	0.012238207	0.016694983
16.91383	0.0165125	0.007531101	0.012363763	0.01258012	0.017328167
17.31463	0.0184941	0.00786482	0.012834368	0.012931461	0.018005742
17.71543	0.0184941	0.008211479	0.013319328	0.013292482	0.018663976
18.11623	0.0204756	0.008571489	0.013818966	0.013663443	0.019244906
18.51703	0.0204756	0.008945272	0.014333614	0.014044609	0.019756902
18.91784	0.0204756	0.009333259	0.014863605	0.014436252	0.020307668
19.31864	0.0211361	0.009735889	0.015409278	0.014838653	0.020982828
19.71944	0.0211361	0.010153612	0.015970975	0.015252096	0.021547309
20.12024	0.0217966	0.010586886	0.016549045	0.015676876	0.021841934
20.52104	0.0217966	0.011036179	0.017143838	0.016113293	0.022027542
20.92184	0.0217966	0.011501966	0.017755711	0.016561654	0.022243213
21.32265	0.0224571	0.011984734	0.018385024	0.017022275	0.022556957
21.72345	0.0224571	0.012484978	0.019032142	0.017495479	0.02301694
22.12425	0.0244386	0.013003201	0.019697433	0.017981598	0.023671223
22.52505	0.0244386	0.013539918	0.020381271	0.018480969	0.024516934
22.92585	0.0244386	0.014095649	0.021084033	0.01899394	0.025434554
23.32665	0.0264201	0.014670925	0.021806099	0.019520867	0.026287921
23.72745	0.0264201	0.015266288	0.022547857	0.020062112	0.027041096
24.12826	0.0290621	0.015882284	0.023309695	0.020618049	0.027709031
24.52906	0.0290621	0.01651947	0.024092007	0.021189058	0.028305129
24.92986	0.0290621	0.017178414	0.02489519	0.021775529	0.02884744
25.33066	0.0290621	0.017859687	0.025719645	0.022377862	0.029349011
25.73146	0.0290621	0.018563873	0.026565779	0.022996464	0.029777706
26.13226	0.0303831	0.019291561	0.027433998	0.023631753	0.030095606
26.53307	0.0303831	0.020043349	0.028324717	0.024284156	0.030341117
26.93387	0.0303831	0.020819842	0.029238352	0.024954109	0.030630785
27.33467	0.0317041	0.021621654	0.030175321	0.02564206	0.031092332
27.73547	0.0317041	0.022449405	0.031136049	0.026348463	0.031683062
28.13627	0.0323646	0.023303721	0.032120962	0.027073787	0.032192752
28.53707	0.0323646	0.024185237	0.033130489	0.027818507	0.032604369
28.93788	0.0323646	0.025094594	0.034165064	0.02858311	0.033086657
29.33868	0.0343461	0.026032436	0.035225122	0.029368094	0.033760946
29.73948	0.0343461	0.026999418	0.036311103	0.030173966	0.034587874
30.14028	0.0363276	0.027996197	0.037423449	0.031001245	0.035434008

Pipe Age	Input Data	Normal Distribution	Weibull Distribution	Logistic Distribution	Neural Network Prediction
30.54108	0.0363276	0.029023436	0.038562603	0.031850461	0.036234262
30.94188	0.0363276	0.030081803	0.039729015	0.032722154	0.037033757
31.34269	0.0369881	0.031171972	0.040923132	0.033616876	0.037926111
31.74349	0.0369881	0.03229462	0.042145408	0.034535188	0.038983036
32.14429	0.0416116	0.033450426	0.043396296	0.035477665	0.040208714
32.54509	0.0416116	0.034640076	0.044676253	0.036444891	0.041544171
32.94589	0.0416116	0.035864257	0.045985739	0.037437464	0.042908046
33.34669	0.0455746	0.037123658	0.047325211	0.03845599	0.044226992
33.74749	0.0455746	0.038418971	0.048695134	0.039501089	0.045467391
34.1483	0.0475561	0.039750891	0.05009597	0.040573392	0.046698442
34.5491	0.0475561	0.041120111	0.051528183	0.04167354	0.048101617
34.9499	0.0475561	0.042527327	0.05299224	0.042802189	0.049795793
35.3507	0.0515192	0.043973235	0.054488607	0.043960002	0.051639886
35.7515	0.0515192	0.04545853	0.056017752	0.045147658	0.053426795
36.1523	0.0581242	0.046983907	0.057580144	0.046365844	0.055119439
36.55311	0.0581242	0.048550058	0.05917625	0.04761526	0.056673143
36.95391	0.0581242	0.050157674	0.060806539	0.048896618	0.057926529
37.35471	0.0587847	0.051807445	0.062471481	0.05021064	0.058857905
37.75551	0.0587847	0.053500056	0.064171543	0.051558061	0.059695363
38.15631	0.0614267	0.055236187	0.065907193	0.052939624	0.060745923
38.55711	0.0614267	0.057016517	0.0676789	0.054356087	0.062240608
38.95792	0.0614267	0.058841718	0.069487129	0.055808215	0.064238192
39.35872	0.0680317	0.060712456	0.071332346	0.057296787	0.066679412
39.75952	0.0680317	0.062629393	0.073215014	0.058822589	0.069454227
40.16032	0.0746367	0.06459318	0.075135596	0.060386421	0.072212678
40.56112	0.0746367	0.066604466	0.077094552	0.06198909	0.074416297
40.96192	0.0746367	0.068663887	0.07909234	0.063631413	0.075930394
41.36273	0.0779392	0.070772072	0.081129415	0.065314218	0.07719765
41.76353	0.0779392	0.072929641	0.083206231	0.06703834	0.078965887
42.16433	0.0885073	0.075137203	0.085323237	0.068804625	0.082003962
42.56513	0.0885073	0.077395356	0.08748088	0.070613924	0.086199631
42.96593	0.0885073	0.079704686	0.089679603	0.072467098	0.090318188
43.36673	0.0964333	0.082065767	0.091919844	0.074365015	0.093926599
43.76754	0.0964333	0.084479161	0.094202038	0.07630855	0.097654001
44.16834	0.1050198	0.086945414	0.096526616	0.078298582	0.101587211
44.56914	0.1050198	0.089465058	0.098894002	0.080335997	0.105140612
44.96994	0.1050198	0.092038612	0.101304617	0.082421688	0.108390023
45.37074	0.1122853	0.094666577	0.103758875	0.084556549	0.111851986
45.77154	0.1122853	0.097349437	0.106257184	0.086741479	0.115603943

Pipe Age	Input Data	Normal Distribution	Weibull Distribution	Logistic Distribution	Neural Network Prediction
46.17234	0.1221929	0.100087659	0.108799948	0.08897738	0.119533003
46.57315	0.1221929	0.102881693	0.11138756	0.091265156	0.123838419
46.97395	0.1221929	0.105731969	0.114020411	0.09360571	0.128605462
47.37475	0.1347424	0.108638898	0.116698881	0.095999949	0.13320246
47.77555	0.1347424	0.11160287	0.119423345	0.098448775	0.136951999
48.17635	0.1420079	0.114624256	0.122194166	0.100953092	0.139956343
48.57715	0.1420079	0.117703403	0.125011704	0.103513798	0.142727082
48.97796	0.1420079	0.120840637	0.127876305	0.10613179	0.14562643
49.37876	0.151255	0.124036262	0.130788309	0.108807958	0.148691
49.77956	0.151255	0.127290556	0.133748044	0.111543187	0.151708018
50.18036	0.1571995	0.130603774	0.13675583	0.114338352	0.154443306
50.58116	0.1571995	0.133976147	0.139811976	0.117194322	0.156854511
50.98196	0.1571995	0.137407879	0.142916779	0.120111954	0.159100674
51.38277	0.161823	0.140899149	0.146070525	0.123092095	0.161355188
51.78357	0.161823	0.144450109	0.149273489	0.126135578	0.163662846
52.18437	0.1704095	0.148060882	0.152525934	0.12924322	0.166060055
52.58517	0.1704095	0.151731568	0.155828109	0.132415825	0.168861742
52.98597	0.1704095	0.155462232	0.159180251	0.135654177	0.17257556
53.38677	0.178996	0.159252915	0.162582584	0.138959041	0.176764106
53.78758	0.178996	0.163103628	0.166035317	0.142331161	0.180018486
54.18838	0.1822985	0.16701435	0.169538644	0.145771258	0.182185465
54.58918	0.1822985	0.170985032	0.173092747	0.14928003	0.184056004
54.98998	0.1822985	0.175015592	0.17669779	0.152858146	0.186133916
55.39078	0.1915456	0.179105918	0.180353923	0.156506249	0.188424172
55.79158	0.1915456	0.183255868	0.184061278	0.16022495	0.190661868
56.19238	0.1948481	0.187465266	0.187819973	0.164014828	0.192665633
56.59319	0.1948481	0.191733904	0.191630107	0.16787643	0.194526594
56.99399	0.1948481	0.196061543	0.195491762	0.171810265	0.196490633
57.39479	0.1994716	0.200447909	0.199405002	0.175816805	0.198638115
57.79559	0.1994716	0.204892696	0.203369874	0.179896481	0.200687201
58.19639	0.2040951	0.209395566	0.207386404	0.184049682	0.20227798
58.59719	0.2040951	0.213956146	0.2114546	0.188276754	0.20338331
58.998	0.2040951	0.218574029	0.215574451	0.192577996	0.204418675
59.3988	0.2060766	0.223248776	0.219745925	0.196953659	0.206196739
59.7996	0.2060766	0.227979913	0.223968969	0.201403944	0.209047922
60.2004	0.2100396	0.232766933	0.22824351	0.205928999	0.211665195
60.6012	0.2100396	0.237609293	0.232569452	0.21052892	0.213303106
61.002	0.2153236	0.24250642	0.236946681	0.215203744	0.214449964
61.40281	0.2153236	0.247457703	0.241375057	0.219953452	0.215611345

Pipe Age	Input Data	Normal Distribution	Weibull Distribution	Logistic Distribution	Neural Network Prediction
61.80361	0.2153236	0.2524625	0.245854419	0.224777965	0.217170723
62.20441	0.2192867	0.257520134	0.250384582	0.229677142	0.219470266
62.60521	0.2192867	0.262629895	0.254965339	0.234650778	0.22250498
63.00601	0.2272127	0.26779104	0.25959646	0.239698604	0.225676279
63.40681	0.2272127	0.273002792	0.264277688	0.244820283	0.22849979
63.80762	0.2272127	0.278264343	0.269008743	0.250015412	0.231138516
64.20842	0.2351387	0.283574849	0.273789322	0.255283516	0.233888759
64.60922	0.2351387	0.288933438	0.278619095	0.26062405	0.236772556
65.01002	0.2450462	0.294339204	0.283497706	0.266036397	0.239733298
65.41082	0.2450462	0.299791208	0.288424774	0.271519865	0.243059115
65.81162	0.2450462	0.305288483	0.293399894	0.277073691	0.247318252
66.21242	0.2542933	0.310830029	0.298422631	0.282697033	0.252105981
66.61323	0.2542933	0.316414817	0.303492525	0.288388975	0.256013218
67.01403	0.2582563	0.322041788	0.308609091	0.294148526	0.259078998
67.41483	0.2582563	0.327709855	0.313771815	0.299974614	0.262504623
67.81563	0.2582563	0.333417902	0.318980155	0.305866093	0.267289945
68.21643	0.2747688	0.339164784	0.324233544	0.311821739	0.273775733
68.61723	0.2747688	0.344949331	0.329531385	0.31784025	0.281538096
69.01804	0.2992074	0.350770345	0.334873055	0.323920248	0.289701885
69.41884	0.2992074	0.356626602	0.340257902	0.330060277	0.297574905
69.81964	0.2992074	0.362516855	0.345685247	0.336258805	0.305004226
70.22044	0.3163804	0.368439832	0.351154381	0.342514227	0.312133769
70.62124	0.3163804	0.374394237	0.356664569	0.348824862	0.318987693
71.02204	0.331572	0.380378751	0.362215046	0.355188954	0.325451297
71.42285	0.331572	0.386392036	0.36780502	0.361604679	0.331575738
71.82365	0.331572	0.39243273	0.37343367	0.36807014	0.337665739
72.22445	0.3467635	0.398499452	0.379100148	0.374583373	0.343950709
72.62525	0.3467635	0.404590805	0.384803575	0.381142346	0.350299603
73.02605	0.3645971	0.410705371	0.390543046	0.387744964	0.356517417
73.42685	0.3645971	0.416841715	0.396317629	0.394389069	0.363051806
73.82766	0.3645971	0.422998387	0.402126361	0.401072443	0.371166574
74.22846	0.3877147	0.429173924	0.407968255	0.407792811	0.381585094
74.62926	0.3877147	0.435366845	0.413842293	0.414547845	0.392882083
75.03006	0.4134742	0.441575659	0.419747432	0.421335166	0.403141226
75.43086	0.4134742	0.447798863	0.425682602	0.428152344	0.412391455
75.83166	0.4134742	0.454034943	0.431646704	0.434996907	0.421683731
76.23246	0.4266843	0.460282376	0.437638615	0.441866341	0.431243434
76.63327	0.4266843	0.466539629	0.443657185	0.448758095	0.440648503
77.03407	0.4583884	0.472805163	0.449701237	0.455669582	0.449977601

Pipe Age	Input Data	Normal Distribution	Weibull Distribution	Logistic Distribution	Neural Network Prediction
77.43487	0.4583884	0.479077434	0.455769572	0.462598186	0.459804529
77.83567	0.4583884	0.48535489	0.461860963	0.469541265	0.470660097
78.23647	0.488111	0.491635978	0.467974159	0.476496154	0.482632545
78.63727	0.488111	0.49791914	0.474107887	0.483460171	0.495183751
79.03808	0.5204756	0.504202819	0.480260849	0.490430618	0.507456766
79.43888	0.5204756	0.510485455	0.486431724	0.497404788	0.518915603
79.83968	0.5204756	0.516765491	0.492619171	0.504379967	0.529581252
80.24048	0.5475561	0.523041369	0.498821824	0.511353443	0.539618912
80.64128	0.5475561	0.529311538	0.505038299	0.518322501	0.549002271
81.04208	0.5686922	0.535574449	0.511267191	0.525284439	0.557752562
81.44289	0.5686922	0.541828557	0.517507075	0.532236561	0.566099215
81.84369	0.5686922	0.548072327	0.523756508	0.539176189	0.573847098
82.24449	0.5838838	0.554304229	0.53001403	0.546100664	0.580005146
82.64529	0.5838838	0.560522742	0.536278162	0.553007349	0.584073076
83.04609	0.5878468	0.566726357	0.542547411	0.559893637	0.586755442
83.44689	0.5878468	0.572913573	0.548820266	0.566756949	0.589076354
83.8477	0.5878468	0.579082904	0.555095205	0.573594742	0.591717625
84.2485	0.5957728	0.585232875	0.56137069	0.580404514	0.594883354
84.6493	0.5957728	0.591362025	0.567645172	0.587183802	0.598367607
85.0501	0.6070013	0.597468911	0.573917091	0.593930191	0.601853787
85.4509	0.6070013	0.603552104	0.580184876	0.600641313	0.605351167
85.8517	0.6070013	0.609610193	0.586446946	0.607314853	0.609343337
86.25251	0.6155878	0.615641784	0.592701715	0.61394855	0.614208326
86.65331	0.6155878	0.621645504	0.598947586	0.620540203	0.619443563
87.05411	0.6294584	0.627619999	0.605182959	0.62708767	0.624245163
87.45491	0.6294584	0.633563937	0.61140623	0.633588869	0.62850596
87.85571	0.6294584	0.639476006	0.617615788	0.640041788	0.632510748
88.25651	0.6380449	0.645354921	0.623810024	0.646444479	0.636359881
88.65731	0.6380449	0.651199415	0.629987326	0.652795064	0.640052365
89.05812	0.6499339	0.657008249	0.636146082	0.659091735	0.643705876
89.45892	0.6499339	0.662780209	0.642284682	0.665332756	0.647663201
89.85972	0.6499339	0.668514106	0.648401521	0.671516466	0.652945337
90.26052	0.6611625	0.674208778	0.654494994	0.677641276	0.661283635
90.66132	0.6611625	0.679863091	0.660563506	0.683705676	0.672815389
91.06212	0.6869221	0.685475937	0.666605467	0.68970823	0.683904271
91.46293	0.6869221	0.691046239	0.672619295	0.695647578	0.691830516
91.86373	0.6869221	0.696572948	0.678603417	0.701522438	0.697591235
92.26453	0.7040951	0.702055045	0.684556274	0.707331607	0.70268588
92.66533	0.7040951	0.707491541	0.690476316	0.713073956	0.707748764

Pipe Age	Input Data	Normal Distribution	Weibull Distribution	Logistic Distribution	Neural Network Prediction
93.06613	0.7173052	0.712881479	0.696362008	0.718748437	0.712964039
93.46693	0.7173052	0.71822393	0.702211832	0.724354075	0.718462267
93.86774	0.7173052	0.723518	0.708024283	0.729889975	0.724379716
94.26854	0.7351387	0.728762827	0.713797876	0.735355314	0.730643257
94.66934	0.7351387	0.733957578	0.719531145	0.740749348	0.7368272
95.07014	0.7490092	0.739101456	0.725222646	0.746071405	0.74242139
95.47094	0.7490092	0.744193695	0.730870953	0.751320885	0.747339553
95.87174	0.7490092	0.749233563	0.736474667	0.756497262	0.752170271
96.27255	0.7589168	0.754220363	0.742032412	0.76160008	0.75779787
96.67335	0.7589168	0.759153427	0.747542839	0.766628951	0.764311181
97.07415	0.7747688	0.764032126	0.753004623	0.771583558	0.770468731
97.47495	0.7747688	0.76885586	0.758416472	0.776463646	0.775361795
97.87575	0.7747688	0.773624067	0.76377712	0.781269029	0.779608195
98.27655	0.7879789	0.778336216	0.769085334	0.785999581	0.784332803
98.67735	0.7879789	0.782991812	0.774339911	0.790655239	0.78986413
99.07816	0.7972259	0.787590391	0.779539684	0.795235997	0.795438053
99.47896	0.7972259	0.792131526	0.784683517	0.799741908	0.800499517
99.87976	0.7972259	0.796614821	0.789770313	0.804173083	0.805445137
100.2806	0.8143989	0.801039916	0.794799008	0.808529682	0.810696981
100.6814	0.8143989	0.805406482	0.799768578	0.812811919	0.816028931
101.0822	0.8282695	0.809714225	0.804678036	0.817020059	0.820863053
101.483	0.8282695	0.813962883	0.809526436	0.821154412	0.824933513
101.8838	0.8282695	0.818152227	0.81431287	0.825215334	0.828586693
102.2846	0.838177	0.82228206	0.819036473	0.829203228	0.832475657
102.6854	0.838177	0.826352218	0.823696421	0.833118534	0.836776137
103.0862	0.8454425	0.830362568	0.828291933	0.836961733	0.840788258
103.487	0.8454425	0.834313009	0.832822271	0.840733345	0.843921362
103.8878	0.8454425	0.83820347	0.837286741	0.844433925	0.846444106
104.2886	0.8527081	0.842033911	0.841684694	0.84806406	0.848980579
104.6894	0.8527081	0.845804324	0.846015526	0.85162437	0.851922803
105.0902	0.8579921	0.849514727	0.850278679	0.855115505	0.85522466
105.491	0.8579921	0.853165171	0.854473639	0.858538141	0.858527281
105.8918	0.8579921	0.856755734	0.858599941	0.861892982	0.861443066
106.2926	0.8632761	0.860286521	0.862657165	0.865180755	0.863808011
106.6934	0.8632761	0.863757667	0.866644938	0.868402209	0.865731445
107.0942	0.8692206	0.867169332	0.870562934	0.871558116	0.867416918
107.495	0.8692206	0.870521704	0.874410876	0.874649264	0.869011541
107.8958	0.8692206	0.873814997	0.878188532	0.877676461	0.870592798
108.2966	0.8731836	0.877049448	0.881895718	0.880640527	0.872215859

Pipe Age	Input Data	Normal Distribution	Weibull Distribution	Logistic Distribution	Neural Network Prediction
108.6974	0.8731836	0.880225322	0.885532296	0.8835423	0.87396181
109.0982	0.8784676	0.883342905	0.889098177	0.886382629	0.875955276
109.499	0.8784676	0.886402509	0.892593318	0.889162375	0.878303536
109.8998	0.8784676	0.889404466	0.896017722	0.891882407	0.88100884
110.3006	0.8844122	0.892349132	0.899371438	0.894543605	0.883953887
110.7014	0.8844122	0.895236885	0.902654562	0.897146853	0.886829216
111.1022	0.8916777	0.898068121	0.905867234	0.899693046	0.889202877
111.503	0.8916777	0.900843258	0.90900964	0.902183078	0.891005967
111.9038	0.8916777	0.903562733	0.912082009	0.90461785	0.892809614
112.3046	0.8989432	0.906227002	0.915084614	0.906998266	0.895579226
112.7054	0.8989432	0.908836537	0.918017772	0.909325229	0.899722257
113.1062	0.9048877	0.911391829	0.920881841	0.911599645	0.903990316
113.507	0.9048877	0.913893384	0.92367722	0.913822417	0.907160856
113.9078	0.9048877	0.916341726	0.92640435	0.91599445	0.909471472
114.3086	0.9128137	0.918737392	0.92906371	0.918116644	0.911446414
114.7094	0.9128137	0.921080934	0.931655818	0.920189897	0.913369301
115.1102	0.9187583	0.923372916	0.93418123	0.922215104	0.915502803
115.511	0.9187583	0.925613918	0.93664054	0.924193153	0.918287763
115.9118	0.9187583	0.92780453	0.939034373	0.926124932	0.922128962
116.3126	0.9266843	0.929945354	0.941363394	0.928011317	0.926667174
116.7134	0.9266843	0.932037002	0.943628296	0.929853182	0.930936953
117.1142	0.9372523	0.934080096	0.945829807	0.931651393	0.934499877
117.515	0.9372523	0.93607527	0.947968685	0.933406808	0.937580199
117.9158	0.9372523	0.938023164	0.950045717	0.935120278	0.940552263
118.3166	0.9458388	0.939924425	0.952061718	0.936792646	0.943670978
118.7174	0.9458388	0.941779711	0.954017529	0.938424744	0.947103488
119.1182	0.9557464	0.943589685	0.955914018	0.940017397	0.951004748
119.519	0.9557464	0.945355013	0.957752076	0.941571422	0.95529144
119.9198	0.9557464	0.947076372	0.959532616	0.943087622	0.959409702
120.3206	0.9643329	0.948754439	0.961256573	0.944566794	0.962860267
120.7214	0.9643329	0.950389898	0.962924901	0.946009722	0.965630727
121.1222	0.9709379	0.951983434	0.964538572	0.947417182	0.967863233
121.523	0.9709379	0.953535738	0.966098576	0.948789938	0.969621569
121.9238	0.9709379	0.955047502	0.967605917	0.950128742	0.970969302
122.3246	0.9735799	0.956519418	0.969061614	0.951434336	0.972015255
122.7255	0.9735799	0.957952182	0.970466697	0.952707453	0.972830089
123.1263	0.9735799	0.959346489	0.971822207	0.953948811	0.973427764
123.5271	0.9735799	0.960703035	0.973129196	0.955159118	0.973881462
123.9279	0.9735799	0.962022515	0.974388723	0.956339073	0.974328839

Pipe Age	Input Data	Normal Distribution	Weibull Distribution	Logistic Distribution	Neural Network Prediction
124.3287	0.9749009	0.963305623	0.975601854	0.95748936	0.97487079
124.7295	0.9749009	0.964553053	0.97676966	0.958610653	0.97553405
125.1303	0.9768824	0.965765496	0.977893215	0.959703614	0.976303708
125.5311	0.9768824	0.96694364	0.978973596	0.960768896	0.977182884
125.9319	0.9768824	0.968088172	0.980011883	0.961807136	0.978229276
126.3327	0.9815059	0.969199776	0.981009154	0.962818962	0.979527881
126.7335	0.9815059	0.97027913	0.981966485	0.963804992	0.981067921
127.1343	0.984148	0.971326911	0.982884952	0.964765829	0.982572648
127.5351	0.984148	0.972343789	0.983765623	0.965702067	0.98365721
127.9359	0.984148	0.973330431	0.984609564	0.966614289	0.984300915
128.3367	0.984148	0.974287499	0.985417834	0.967503065	0.98477002
128.7375	0.984148	0.975215649	0.986191486	0.968368954	0.985252712
129.1383	0.98679	0.976115532	0.986931561	0.969212506	0.98579558
129.5391	0.98679	0.976987791	0.987639094	0.970034258	0.986399875
129.9399	0.98679	0.977833066	0.988315108	0.970834736	0.987088608
130.3407	0.9887715	0.978651987	0.988960614	0.971614457	0.987847187
130.7415	0.9887715	0.97944518	0.989576613	0.972373925	0.988531771
131.1423	0.989432	0.980213262	0.990164092	0.973113636	0.989000736
131.5431	0.989432	0.980956844	0.990724022	0.973834074	0.989264342
131.9439	0.989432	0.981676529	0.991257361	0.974535712	0.98941253
132.3447	0.989432	0.982372912	0.991765053	0.975219014	0.989526724
132.7455	0.989432	0.98304658	0.992248023	0.975884434	0.989665529
133.1463	0.9900925	0.983698112	0.992707182	0.976532417	0.989874343
133.5471	0.9900925	0.98432808	0.993143422	0.977163396	0.990178869
133.9479	0.9900925	0.984937046	0.993557618	0.977777795	0.990568486
134.3487	0.990753	0.985525565	0.993950627	0.978376031	0.991031432
134.7495	0.990753	0.986094181	0.994323286	0.978958508	0.991607559
135.1503	0.993395	0.986643432	0.994676416	0.979525624	0.992366553
135.5511	0.993395	0.987173845	0.995010815	0.980077765	0.9933092
135.9519	0.993395	0.98768594	0.995327263	0.980615312	0.994303308
136.3527	0.9953765	0.988180226	0.995626522	0.981138633	0.995229897
136.7535	0.9953765	0.988657205	0.995909332	0.981648091	0.996114598
137.1543	0.998679	0.989117368	0.996176412	0.982144038	0.997023159
137.5551	0.998679	0.989561198	0.996428462	0.98262682	0.997903142
137.9559	0.998679	0.989989169	0.996666163	0.983096774	0.998583779
138.3567	0.9993395	0.990401744	0.996890173	0.983554227	0.998985025
138.7575	0.9993395	0.99079938	0.997101131	0.983999502	0.999183172
139.1583	0.9993395	0.991182521	0.997299655	0.984432912	0.999280236
139.5591	0.9993395	0.991551606	0.997486345	0.984854763	0.999344621

Pipe Age	Input Data	Normal Distribution	Weibull Distribution	Logistic Distribution	Neural Network Prediction
139.9599	0.9993395	0.99190706	0.997661779	0.985265353	0.999427593
140.3607	0.9993395	0.992249303	0.997826514	0.985664974	0.999563066
140.7615	0.9993395	0.992578744	0.99798109	0.98605391	0.999728577
141.1623	1	0.992895784	0.998126026	0.986432439	0.999863836
141.5631	1	0.993200812	0.998261821	0.986800832	0.999943483
141.9639	1	0.993494212	0.998388957	0.987159351	0.999980407
142.3647	1	0.993776358	0.998507896	0.987508256	0.999994389
142.7655	1	0.994047612	0.998619081	0.987847797	0.999998694
143.1663	1	0.994308331	0.998722938	0.98817822	0.999999755
143.5671	1	0.994558863	0.998819876	0.988499762	0.999999963
143.9679	1	0.994799544	0.998910284	0.988812658	0.999999996
144.3687	1	0.995030706	0.998994537	0.989117135	1
144.7695	1	0.99525267	0.999072992	0.989413413	1
145.1703	1	0.995465749	0.999145989	0.98970171	1
145.5711	1	0.995670247	0.999213854	0.989982235	1
145.9719	1	0.995866462	0.999276897	0.990255194	1
146.3727	1	0.996054683	0.999335412	0.990520787	1
146.7735	1	0.99623519	0.999389682	0.990779208	1
147.1743	1	0.996408256	0.999439971	0.991030648	1
147.5752	1	0.996574148	0.999486534	0.991275292	1
147.976	1	0.996733122	0.999529611	0.99151332	1
148.3768	1	0.996885431	0.999569429	0.991744909	1
148.7776	1	0.997031316	0.999606203	0.991970229	1
149.1784	1	0.997171015	0.999640138	0.992189447	1
149.5792	1	0.997304756	0.999671425	0.992402727	1
149.98	1	0.997432762	0.999700247	0.992610226	1
150.3808	1	0.997555248	0.999726774	0.992812098	1
150.7816	1	0.997672423	0.999751167	0.993008495	1
151.1824	1	0.997784491	0.99977358	0.993199562	1
151.5832	1	0.997891645	0.999794153	0.993385443	1
151.984	1	0.997994078	0.999813021	0.993566275	1
152.3848	1	0.998091972	0.99983031	0.993742196	1
152.7856	1	0.998185506	0.999846138	0.993913335	1
153.1864	1	0.998274851	0.999860615	0.994079822	1
153.5872	1	0.998360174	0.999873844	0.994241781	1
153.988	1	0.998441635	0.999885921	0.994399335	1
154.3888	1	0.998519391	0.999896936	0.994552601	1
154.7896	1	0.998593591	0.999906974	0.994701695	1
155.1904	1	0.99866438	0.999916113	0.99484673	1

Pipe Age	Input Data	Normal Distribution	Weibull Distribution	Logistic Distribution	Neural Network Prediction
155.5912	1	0.998731899	0.999924424	0.994987815	1
155.992	1	0.998796283	0.999931976	0.995125056	1
156.3928	1	0.998857661	0.999938832	0.995258557	1
156.7936	1	0.99891616	0.999945049	0.995388419	1
157.1944	1	0.998971901	0.999950682	0.99551474	1
157.5952	1	0.999025001	0.99995578	0.995637617	1
157.996	1	0.999075572	0.99996039	0.995757141	1
158.3968	1	0.999123722	0.999964554	0.995873404	1
158.7976	1	0.999169558	0.999968312	0.995986494	1
159.1984	1	0.999213177	0.9999717	0.996096497	1
159.5992	1	0.999254679	0.999974751	0.996203497	1
160	1	0.999294155	0.999977496	0.996307574	1

APPENDIX C: Neural Network Predictions with Extensive Data for 4 Input Factors (Probability, Material, Age, and Slope)

Slope (%)	Age	Material	Probability of Failure	NN Prediction	Residual
11.79	0	Unknown	0	0.00	0.00
0.38	1	Unknown	0	0.07	-0.07
0.64	2	Unknown	0	0.11	-0.11
0.64	3	Unknown	0.198150594	0.13	0.07
1.72	4	Unknown	0.198150594	0.44	-0.24
1.72	5	Unknown	0.330250991	0.46	-0.13
1.72	6	Unknown	0.528401585	0.49	0.04
1.72	7	Unknown	0.72655218	0.52	0.21
5.32	8	Unknown	0.990752972	1.11	-0.12
5.32	9	Unknown	0.990752972	1.13	-0.14
4.61	10	Unknown	1.254953765	1.32	-0.07
5.03	11	Unknown	1.321003963	1.23	0.09
1.22	12	Unknown	1.321003963	0.92	0.40
8.04	13	Unknown	1.321003963	1.38	-0.06
4.28	14	Unknown	1.453104359	1.46	-0.01
4.28	15	Unknown	1.519154557	1.48	0.04
4.51	16	Unknown	1.651254954	1.48	0.17
4.28	17	Unknown	1.849405548	1.52	0.33
6.83	18	Unknown	2.047556143	2.26	-0.21
6.83	19	Unknown	2.113606341	2.29	-0.18
7.08	20	Unknown	2.179656539	2.33	-0.15
7.08	21	Unknown	2.245706737	2.37	-0.13
7.08	22	Unknown	2.443857332	2.42	0.03
16.61	23	Unknown	2.642007926	2.64	0.00
6.83	24	Unknown	2.906208719	2.51	0.40
1.38	25	Unknown	2.906208719	2.98	-0.07
1.38	26	Unknown	3.038309115	2.98	0.05
0.48	27	Unknown	3.170409511	3.12	0.05
1.72	28	Unknown	3.236459709	2.98	0.25
4.89	29	Unknown	3.434610304	3.70	-0.27
2.76	30	Unknown	3.632760898	4.37	-0.74
3.98	31	Unknown	3.698811096	3.91	-0.21
5.22	32	Unknown	4.161162483	3.87	0.29
3.38	33	Unknown	4.557463672	4.29	0.27
7.62	34	Unknown	4.755614267	4.68	0.07
9.4	35	Unknown	5.151915456	5.60	-0.45
9.4	36	Unknown	5.812417437	5.62	0.20
9.4	37	Unknown	5.878467635	5.63	0.25

Slope (%)	Age	Material	Probability of Failure	NN Prediction	Residual
15.05	38	Unknown	6.142668428	6.14	0.00
4.25	39	Brick	6.80317041	11.12	-4.32
1.81	40	Brick	7.463672391	7.85	-0.39
1.58	41	Brick	7.793923382	8.32	-0.52
0.76	42	Brick	8.850726552	11.28	-2.43
0.76	43	Brick	9.64332893	11.54	-1.90
4.25	44	Brick	10.50198151	12.17	-1.67
0.63	45	Brick	11.22853369	12.23	-1.00
0.54	46	Brick	12.21928666	12.54	-0.32
0	47	Brick	13.47424042	13.02	0.45
0.54	48	Brick	14.2007926	12.97	1.23
4.15	49	Brick	15.12549538	13.84	1.29
0.7	50	Brick	15.71994716	13.36	2.36
0	51	Brick	16.18229855	13.53	2.65
3.23	52	Brick	17.04095112	16.66	0.38
28.94	53	CIP	17.8996037	17.90	0.00
12.2	54	CIP	18.22985469	18.23	0.00
0	55	CIP	19.15455746	19.15	0.00
0.8	56	Concrete	19.48480845	20.00	-0.51
9.48	57	Concrete	19.94715984	20.41	-0.46
9.48	58	Concrete	20.40951123	20.41	-0.01
0.84	59	Concrete	20.60766182	21.32	-0.71
14.16	60	Concrete	21.00396301	21.00	0.00
3.41	61	Concrete	21.5323646	21.94	-0.40
7.39	62	Concrete	21.92866579	22.71	-0.78
5.95	63	Concrete	22.72126816	22.72	0.00
1.56	64	Concrete	23.51387054	25.26	-1.75
1.69	65	Concrete	24.50462351	25.77	-1.26
2.53	66	Concrete	25.42932629	26.00	-0.57
1.52	67	Concrete	25.82562748	27.44	-1.62
3.33	68	Concrete	27.47688243	25.20	2.28
0.11	69	Concrete	29.92073976	31.69	-1.76
4.88	70	Concrete	31.63804491	29.17	2.47
0	71	Concrete	33.15719947	32.12	1.04
3.6	72	Concrete	34.67635403	46.32	-11.64
1.32	73	Concrete	36.45970938	38.40	-1.94
10.4	74	Concrete	38.77146631	39.24	-0.46
1.92	75	Concrete	41.34742404	43.18	-1.84
1.69	76	Concrete	42.66842801	43.81	-1.14

Slope (%)	Age	Material	Probability of Failure	NN Prediction	Residual
1.92	77	Concrete	45.83883752	45.70	0.14
0.96	78	Concrete	48.81109643	45.39	3.43
1.86	79	Concrete	52.04755614	47.58	4.47
3.38	80	Concrete	54.75561427	56.92	-2.17
3.18	81	Concrete	56.86922061	57.22	-0.35
9.38	82	Concrete	58.38837517	58.19	0.20
4.21	83	Concrete	58.78467635	60.42	-1.63
2.75	84	Concrete	59.57727873	58.55	1.03
2.4	85	Concrete	60.7001321	58.41	2.29
0.21	86	Concrete	61.55878468	62.13	-0.57
3.95	87	Concrete	62.94583884	62.93	0.01
8.36	88	Concrete	63.80449141	63.55	0.26
1	89	Concrete	64.99339498	65.85	-0.85
6.17	90	Concrete	66.11624835	81.99	-15.88
0.68	91	Concrete	68.69220608	70.16	-1.46
4.11	92	Concrete	70.40951123	67.11	3.30
0.21	93	Concrete	71.73051519	72.55	-0.82
3.65	94	Concrete	73.51387054	68.37	5.14
0	95	Concrete	74.9009247	74.49	0.41
2.41	96	Concrete	75.89167768	78.05	-2.16
2.41	97	Concrete	77.47688243	78.81	-1.33
1.44	98	Concrete	78.79788639	82.02	-3.22
2.39	99	Concrete	79.72258917	80.28	-0.56
6.01	100	Concrete	81.43989432	82.55	-1.11
0.81	101	Concrete	82.82694848	83.74	-0.91
6.14	102	Concrete	83.81770145	82.71	1.11
1.47	103	Concrete	84.54425363	84.70	-0.16
1.47	104	Concrete	85.27080581	85.16	0.11
2.52	105	Concrete	85.7992074	84.47	1.33
1.88	106	Concrete	86.32760898	85.73	0.60
0.68	107	Concrete	86.92206077	86.68	0.25
1.37	108	Concrete	87.31836196	86.71	0.61
0.89	109	Concrete	87.84676354	87.52	0.33
1.69	110	Concrete	88.44121532	87.18	1.26
3.79	111	Concrete	89.1677675	90.11	-0.94
3.79	112	Concrete	89.89431968	90.29	-0.40
3.79	113	Concrete	90.48877147	90.54	-0.06
1.14	114	Concrete	91.28137384	91.09	0.19
1.03	115	Concrete	91.87582563	92.43	-0.56

Slope (%)	Age	Material	Probability of Failure	NN Prediction	Residual
1.03	116	Concrete	92.66842801	93.36	-0.69
1.03	117	Concrete	93.72523118	94.14	-0.42
0.52	118	Concrete	94.58388375	95.09	-0.51
0.63	119	Concrete	95.57463672	95.47	0.10
3.27	120	Concrete	96.4332893	96.11	0.32
3.3	121	Concrete	97.09379128	96.40	0.70
2.12	122	Concrete	97.35799207	96.81	0.55
0.91	123	Concrete	97.35799207	96.93	0.43
3.2	124	Concrete	97.49009247	97.01	0.48
0.81	125	Concrete	97.68824306	97.51	0.18
1.08	126	Concrete	98.15059445	97.69	0.46
7.69	127	Concrete	98.41479524	98.42	0.00
7.69	128	Concrete	98.41479524	98.42	-0.01
0.42	129	Concrete	98.67899604	98.43	0.25
0.42	130	Concrete	98.87714663	98.54	0.34
0.42	131	Concrete	98.94319683	98.62	0.32
2.23	132	Concrete	98.94319683	99.05	-0.11
3.93	133	Concrete	99.00924703	98.94	0.07
15.87	134	Concrete	99.07529723	99.08	0.00
5.14	135	Concrete	99.33949802	99.32	0.01
1.44	136	Concrete	99.53764861	99.30	0.24
10	137	Concrete	99.8678996	99.87	0.00
10	138	Concrete	99.9339498	99.87	0.07
0.53	139	Concrete	99.9339498	99.02	0.91
2.66	140	Concrete	99.9339498	99.80	0.14
7.29	141	Concrete	100	99.98	0.02

APPENDIX D: Neural Network Predictions with Extensive Data (Probability, Material, Age, Size, Depth, and Slope as Model Inputs)

Size, inches	Soil Type	Depth, ft	Slope (%)	Age	Material	Probability of Failure	NN Prediction	Residual
12.00	clay	21.00	11.79	0	Unknown	0	0.00	
12.00	clay	8.00	1.72	7	Unknown	0.72655218	0.57	0.16
15.00	clay	12.00	6.83	24	Unknown	2.906208719	2.91	0.00
63.00	sand	8.00	0.48	27	Unknown	3.170409511	3.24	-0.07
8.00	clay	12.00	3.98	31	Unknown	3.698811096	3.89	-0.19
72.00	clay	12.00	0.76	43	Brick	9.64332893	8.85	0.79
12.00	clay	8.00	4.25	44	Brick	10.50198151	11.23	-0.73
12.00	clay	20.00	0	47	Brick	13.47424042	12.22	1.25
12.00	clay	30.00	0.54	48	Brick	14.2007926	15.13	-0.92
12.00	clay	12.00	3.23	52	Brick	17.04095112	16.18	0.86
15.00	clay	8.00	9.48	58	Concrete	20.40951123	19.95	0.46
8.00	clay	8.00	4.88	70	Concrete	31.63804491	33.16	-1.52
8.00	clay	8.00	1.32	73	Concrete	36.45970938	34.68	1.78
8.00	clay	9.00	1.69	76	Concrete	42.66842801	43.59	-0.92
6.00	clay	8.00	1.86	79	Concrete	52.04755614	51.47	0.58
12.00	clay	12.00	9.38	82	Concrete	58.38837517	58.78	-0.40
8.00	sand	8.00	0.21	86	Concrete	61.55878468	62.95	-1.39
8.00	rock	18.00	1	89	Concrete	64.99339498	66.07	-1.08
8.00	clay	12.00	2.41	97	Concrete	77.47688243	75.89	1.58
8.00	clay	15.00	2.39	99	Concrete	79.72258917	79.20	0.52
8.00	clay	12.00	6.01	100	Concrete	81.43989432	82.83	-1.39
8.00	clay	15.00	6.14	102	Concrete	83.81770145	84.06	-0.24
8.00	rock	24.00	1.47	104	Concrete	85.27080581	85.12	0.15
12.00	rock	24.00	1.69	110	Concrete	88.44121532	88.38	0.06
24.00	clay	12.00	1.14	114	Concrete	91.28137384	91.88	-0.59
24.00	clay	8.00	1.03	116	Concrete	92.66842801	92.79	-0.12
8.00	clay	12.00	1.44	136	Concrete	99.53764861	99.34	0.20
8.00	clay	12.00	10	137	Concrete	99.8678996	99.93	-0.06
12.00	sand	12.00	0.53	139	Concrete	99.9339498	99.93	0.00
48.00	clay	12.00	7.29	141	Concrete	100		

APPENDIX E: Neural Network Predictions for Model with Limited Input Data (Probability, Age, Slope)

Pipe Age	Input Probability of Failure	NN Prediction
36.9144	5%	5%
46.1591	10%	13%
52.3965	15%	17%
57.3538	20%	21%
61.6067	25%	25%
65.426	30%	31%
68.9651	35%	37%
72.3233	40%	41%
75.5725	45%	44%
78.7701	50%	49%
81.9678	55%	54%
85.2169	60%	60%
88.5752	65%	64%
92.1143	70%	69%
95.9335	75%	75%
100.1865	80%	80%
105.1437	85%	84%
111.3811	90%	89%
120.6259	95%	94%

APPENDIX F: Capital Improvement Plan Priority Rankings

Project Name	Priority Ranking	Cost
EMERGENCY SEWER REPAIR	590	$ 5,175,000
BARRINGTON HILLS, BARRINGTON HILLS BLK. F, GIL VOLZ, & KIRKRIDGE ACRES P.S. ELIMINATIONS (DESIGN)	570	$ 1,178,700
FOLEY FOREST, DELLWOOD ESTATES & NORTH BAY VILLAGE P.S. ELIMINATIONS (EASEMENTS)	485	$ 51,800
PALISADES #1 & 2 PS ELIMINATIONS	430	$ 1,095,200
NATIONAL DISTILLERIES REPLACEMENT SEWER	415	$ 304,100
GLENWOOD AVE. SEWER REPLACEMENT	405	$ 911,300
FIRST ST. SEWER REPLACEMENT (DESIGN)	385	$ 28,700
FIRST ST. SEWER REPLACEMENT	385	$ 109,000
WULFF RUN SEWER REPLACEMENT	380	$ 275,400
HIGH MEADOWS P.S. ELIMINATION (DESIGN)	375	$ 179,200
LOSANTIVILLE AVE & SCHUBERT AVE SEWER REPLACEMENT	360	$ 692,300
COLETTE LN. REPLACEMENT SEWER (DESIGN)	360	$ 19,800
FORESTOAK CT SEWER REPLACEMENT (EASEMENTS)	350	$ 45,000
PLACID MEADOWS P.S. ELIMINATION (DESIGN)	345	$ 186,700
PLEASANT RUN CENTRAL FORCE MAIN (DESIGN)	335	$ 656,800
DELLWAY ST. SEWER REPLACEMENT (EASEMENT)	330	$ 75,000
MT. WASHINGTON P.S. UPGRADE (DESIGN)	330	$ 195,400
BENDER RD. AERIAL SEWER CROSSING REPLACEMENT	285	$ 86,600
BENDER RD. AERIAL SEWER CROSSING REPLACEMENT	285	$ 705,400
VIRGINIA CT. & BRIDGETOWN RD. SEWER REPLACEMENT	280	$ 707,000
HARRISON & RACE SEWER REPLACEMENT	280	$ 150,400
RUTLEDGE AVE AREA SEWER REPLACEMENT	280	$ 741,100
HILLSIDE AVE. TO RIVER RD.R/W SEWER REPAIR (DESIGN)	280	$ 46,000
MONTGOMERY RD & LESTER AVE SEWER REPLACEMENT	270	$ 2,299,900
CLOUGH RD. SEWER ABANDONMENT & LATERAL RELOCATION (DESIGN)	270	$ 43,000
OAKLAWN DR. SEWER REPLACEMENT (DESIGN)	265	$ 47,800
HARVEY AVENUE SEWER REPLACEMENT	260	$ 493,700
KEMPER LANE SEWER REPAIR	260	$ 548,200
COLERIDGE AVE. R/W SEWER REPLACEMENT (DESIGN)	260	$ 82,800
SCHOOL SECTION SEWER REPLACEMENT (DESIGN)	260	$ 247,100
670 ROCKDALE AVE. SEWER REPLACEMENT (DESIGN)	260	$ 52,900
670 ROCKDALE AVE. SEWER REPLACEMENT	260	$ 484,200
GRAYDON AVE. MAINLINE & LATERAL REPAIR (DESIGN)	260	$ 16,200
GRAYDON AVE. MAINLINE & LATERAL REPAIR	260	$ 132,100
CENTRAL PARKWAY AT HOPPLE ST. REPLACEMENT SEWER (DESIGN)	260	$ 104,500
WOODBURN AVE. SEWER REPLACEMENT (DESIGN)	260	$ 200,700
BELDARE AVE./HALE AVE. TAP REPAIRS (DESIGN)	260	$ 10,100
BELDARE AVE./HALE AVE. TAP REPAIRS	260	$ 123,500
CHARLEMAR DR. SEWER REPLACEMENT (DESIGN)	250	$ 118,600
BURNET AVE. & NORTHERN AVE. SEWER REPLACEMENT	240	$ 431,300
BATHGATE ST. & WHITTIER ST. MAINLINE AND LATERAL REPAIR (DESIGN)	240	$ 17,500
BATHGATE ST. & WHITTIER ST. MAINLINE AND LATERAL REPAIR	240	$ 163,900
BLAIR AVE. & ERKENBRECHER AVE. MAINLINE & LATERAL REPAIR (DESIGN)	240	$ 23,800
BLAIR AVE. & ERKENBRECHER AVE. MAINLINE & LATERAL REPAIR	240	$ 287,200
GLENWOOD AVE. AT WASHINGTON AVE. SEWER REPLACEMENT	240	$ 16,700

Project Name	Priority Ranking	Cost
RAVINE ST. SEWER REPLACEMENT (DESIGN)	240	$ 38,000
RAVINE ST. SEWER REPLACEMENT	240	$ 239,800
ADAMS RD. & HASTINGS AVE. ALLEYWAY MAINLINE & LATERAL SEWER REPAIR (DESIGN)	220	$ 16,300
ADAMS RD. & HASTINGS AVE. ALLEYWAY MAINLINE & LATERAL SEWER REPAIR	220	$ 134,400
WESTKNOLLS LN. SEWER RELOCATION (DESIGN)	220	$ 69,100
EDEN AVE. & FOREST AVE. MAINLINE AND LATERAL REPAIR (DESIGN)	220	$ 23,800
EDEN AVE. & FOREST AVE. MAINLINE AND LATERAL REPAIR	220	$ 285,700
1110 W. GALBRAITH RD. SEWER LATERAL REPAIR (DESIGN)	220	$ 15,100
1110 W. GALBRAITH RD. SEWER LATERAL REPAIR	220	$ 52,600
FELICITY DR. SEWER REPAIR (DESIGN)	200	$ 23,400
SHOTCRETE	210	$ 517,500
LOCKLAND RD SEWER REPLACEMENT (DESIGN)	120	$ 46,900
LOCKLAND RD SEWER REPLACEMENT	120	$ 249,500
HAGEMAN ST. P.S. UPGRADE (DESIGN)	115	$ 76,600
MILLBROOK 2 P.S. UPGRADE (DESIGN)	115	$ 209,400
MISC HVAC REPAIR	110	$ 1,000,000
BARRINGTON HILLS AND BARRINGTON HILL BLOCK F PUMP STATION EMERGENCY	45	$ 230,000
HAGEMAN PUMP STATION EMERGENCY REPAIR	45	$ 80,000
LASALLE PUMP STATION EMERGENCY REPAIRS	45	$ 200,000
MARVIEW TERRACE PUMP STATION EMERGENCY REPAIR	45	$ 50,000
MSD GARAGE INFRASTRUCTURE REPAIR	45	$ 460,000
SERVICE BUILDING INFRASTRUCTURE	45	$ 225,000
PAINT SHOP BUILDING	45	$ 38,000
MISC HVAC REPAIR	45	$ 100,000
MILL CREEK WWTP ON-SITE SODIUM HYPOCHLORITE FACILITY	105	$ 2,000,000
POLK RUN WWTP INFLUENT SCREEN REPLACEMENT (DESIGN)	90	$ 6,000
POLK RUN WWTP INFLUENT SCREEN REPLACEMENT	90	$ 213,000
MILL CREEK WWTP AERATION TANKS DIFFUSERS REPLACEMENT	90	$ 8,000,000
LITTLE MIAMI WWTP PRIMARY & SECONDARY TANK RECHAINING	85	$ 100,000
LITTLE MIAMI WWTP PRIMARY & SECONDARY TANK RECHAINING	85	$ 6,500,000
WWT TELEMETRY REPLACEMENT	75	$ 5,500,000
MUDDY CREEK WWTP FACILITY PLAN (STUDY)	45	$ 351,600
MSD ADMINISTRATION BUILDING REHAB PHASE 3	45	$ 6,151,000
MILL CREEK WWTP POWER BLDG ASBESTOS REMOVAL	40	$ 521,800
POLK RUN WWTP HEADWORKS ODOR CONTROL (DESIGN)	30	$ 40,100
MILL CREEK WWTP FACILITY PLAN (STUDY)	40	$ 334,300
KROHN CONSERVATORY SEWER RELOCATION	496	$ 561,000
1852 COLUMBIA PKWY SEWER SEPARATION (DESIGN)	191	$ 486,800
CSO 191 PRODUCTION DR. GRATING MODIFICATIONS (DESIGN)	45	$ 49,100
CSO 191 PRODUCTION DR. GRATING MODIFICATIONS	45	$ 122,500
CSO 37 MAPLE ST. DIV. DAM IMPROVEMENTS (DESIGN)	45	$ 26,000
CSO 37 MAPLE ST. DIV. DAM IMPROVEMENTS	45	$ 168,500
CSO 39 64TH ST. DIV. DAM IMPROVEMENTS (DESIGN & ESMTS.)	45	$ 17,300
CSO 39 64TH ST. DIV. DAM IMPROVEMENTS	45	$ 87,100
Total		$ 55,178,800

APPENDIX G: CIP Prioritization Based on Business Risk Exposure

Project Name	BRE	Cost	BRE/ $	Cumulative $
MSD ADMINISTRATION BUILDING REHAB PHASE 3	45	$ 6,151,000	136688.89	$ 6,151,000
MILL CREEK WWTP AERATION TANKS DIFFUSERS REPLACEMENT (DESIGN)	90	$ 8,000,000	88888.889	$ 14,151,000
LITTLE MIAMI WWTP PRIMARY & SECONDARY TANK RECHAINING	85	$ 6,500,000	76470.588	$ 20,651,000
WWT TELEMETRY REPLACEMENT	75	$ 5,500,000	73333.333	$ 26,151,000
MILL CREEK WWTP ON-SITE SODIUM HYPOCHLORITE FACILITY	105	$ 2,000,000	19047.619	$ 28,151,000
MILL CREEK WWTP POWER BLDG ASBESTOS REMOVAL	40	$ 521,800	13045	$ 28,672,800
MSD GARAGE INFRASTRUCTURE REPAIR	45	$ 460,000	10222.222	$ 29,132,800
MISC HVAC REPAIR	110	$ 1,000,000	9090.9091	$ 30,132,800
EMERGENCY SEWER REPAIR	590	$ 5,175,000	8771.1864	$ 35,307,800
MONTGOMERY RD & LESTER AVE SEWER REPLACEMENT	270	$ 2,299,900	8518.1481	$ 37,607,700
MILL CREEK WWTP FACILITY PLAN (STUDY)	40	$ 334,300	8357.5	$ 37,942,000
MUDDY CREEK WWTP FACILITY PLAN (STUDY)	45	$ 351,600	7813.3333	$ 38,293,600
BARRINGTON HILLS AND BARRINGTON HILL BLOCK F PUMP STATION EMERGENCY	45	$ 230,000	5111.1111	$ 38,523,600
SERVICE BUILDING INFRASTRUCTURE	45	$ 225,000	5000	$ 38,748,600
LASALLE PUMP STATION EMERGENCY REPAIRS	45	$ 200,000	4444.4444	$ 38,948,600
CSO 37 MAPLE ST. DIV. DAM IMPROVEMENTS	45	$ 168,500	3744.4444	$ 39,117,100
CSO 191 PRODUCTION DR. GRATING MODIFICATIONS	45	$ 122,500	2722.2222	$ 39,239,600
RUTLEDGE AVE AREA SEWER REPLACEMENT	280	$ 741,100	2646.7857	$ 39,980,700
1852 COLUMBIA PKWY SEWER SEPARATION (DESIGN)	191	$ 486,800	2548.6911	$ 40,467,500
PALISADES #1 & 2 PS ELIMINATIONS	430	$ 1,095,200	2546.9767	$ 41,562,700
VIRGINIA CT. & BRIDGETOWN RD. SEWER REPLACEMENT	280	$ 707,000	2525	$ 42,269,700
BENDER RD. AERIAL SEWER CROSSING REPLACEMENT	285	$ 705,400	2475.0877	$ 42,975,100
SHOTCRETE	210	$ 517,500	2464.2857	$ 43,492,600
POLK RUN WWTP INFLUENT SCREEN REPLACEMENT	90	$ 213,000	2366.6667	$ 43,705,600
GLENWOOD AVE. SEWER REPLACEMENT	405	$ 911,300	2250.1235	$ 44,616,900
MISC HVAC REPAIR	45	$ 100,000	2222.2222	$ 44,716,900
KEMPER LANE SEWER REPAIR	260	$ 548,200	2108.4615	$ 45,265,100
LOCKLAND RD SEWER REPLACEMENT	120	$ 249,500	2079.1667	$ 45,514,600
BARRINGTON HILLS, BARRINGTON HILLS BLK. F, GIL VOLZ, & KIRKRIDGE ACRES P.S. ELIMINATIONS (DESIGN)	570	$ 1,178,700	2067.8947	$ 46,693,300
PLEASANT RUN CENTRAL FORCE MAIN (DESIGN)	335	$ 656,800	1960.597	$ 47,350,100
CSO 39 64TH ST. DIV. DAM IMPROVEMENTS	45	$ 87,100	1935.5556	$ 47,437,200
LOSANTIVILLE AVE & SCHUBERT AVE SEWER REPLACEMENT	360	$ 692,300	1923.0556	$ 48,129,500
HARVEY AVENUE SEWER REPLACEMENT	260	$ 493,700	1898.8462	$ 48,623,200
670 ROCKDALE AVE. SEWER REPLACEMENT	260	$ 484,200	1862.3077	$ 49,107,400
MILLBROOK 2 P.S. UPGRADE (DESIGN)	115	$ 209,400	1820.8696	$ 49,316,800
BURNET AVE. & NORTHERN AVE. SEWER REPLACEMENT	240	$ 431,300	1797.0833	$ 49,748,100
HAGEMAN PUMP STATION EMERGENCY REPAIR	45	$ 80,000	1777.7778	$ 49,828,100
POLK RUN WWTP HEADWORKS ODOR CONTROL (DESIGN)	30	$ 40,100	1336.6667	$ 49,868,200
EDEN AVE. & FOREST AVE. MAINLINE AND LATERAL	220	$ 285,700	1298.6364	$ 50,153,900

Project Name	BRE	Cost	BRE/ $	Cumulative $
REPAIR				
BLAIR AVE. & ERKENBRECHER AVE. MAINLINE & LATERAL REPAIR	240	$ 287,200	1196.6667	$ 50,441,100
LITTLE MIAMI WWTP PRIMARY & SECONDARY TANK RECHAINING (DESIGN)	85	$ 100,000	1176.4706	$ 50,541,100
KROHN CONSERVATORY SEWER RELOCATION	496	$ 561,000	1131.0484	$ 51,102,100
MARVIEW TERRACE PUMP STATION EMERGENCY REPAIR	45	$ 50,000	1111.1111	$ 51,152,100
CSO 191 PRODUCTION DR. GRATING MODIFICATIONS (DESIGN)	45	$ 49,100	1091.1111	$ 51,201,200
RAVINE ST. SEWER REPLACEMENT	240	$ 239,800	999.16667	$ 51,441,000
SCHOOL SECTION SEWER REPLACEMENT (DESIGN)	260	$ 247,100	950.38462	$ 51,688,100
PAINT SHOP BUILDING	45	$ 38,000	844.44444	$ 51,726,100
WOODBURN AVE. SEWER REPLACEMENT (DESIGN)	260	$ 200,700	771.92308	$ 51,926,800
NATIONAL DISTILLERIES REPLACEMENT SEWER	415	$ 304,100	732.77108	$ 52,230,900
WULFF RUN SEWER REPLACEMENT	380	$ 275,400	724.73684	$ 52,506,300
BATHGATE ST. & WHITTIER ST. MAINLINE AND LATERAL REPAIR	240	$ 163,900	682.91667	$ 52,670,200
HAGEMAN ST. P.S. UPGRADE (DESIGN)	115	$ 76,600	666.08696	$ 52,746,800
ADAMS RD. & HASTINGS AVE. ALLEYWAY MAINLINE & LATERAL SEWER REPAIR	220	$ 134,400	610.90909	$ 52,881,200
MT. WASHINGTON P.S. UPGRADE (DESIGN)	330	$ 195,400	592.12121	$ 53,076,600
CSO 37 MAPLE ST. DIV. DAM IMPROVEMENTS (DESIGN)	45	$ 26,000	577.77778	$ 53,102,600
PLACID MEADOWS P.S. ELIMINATION (DESIGN)	345	$ 186,700	541.15942	$ 53,289,300
HARRISON & RACE SEWER REPLACEMENT	280	$ 150,400	537.14286	$ 53,439,700
GRAYDON AVE. MAINLINE & LATERAL REPAIR	260	$ 132,100	508.07692	$ 53,571,800
HIGH MEADOWS P.S. ELIMINATION (DESIGN)	375	$ 179,200	477.86667	$ 53,751,000
BELDARE AVE./HALE AVE. TAP REPAIRS	260	$ 123,500	475	$ 53,874,500
CHARLEMAR DR. SEWER REPLACEMENT (DESIGN)	250	$ 118,600	474.4	$ 53,993,100
CENTRAL PARKWAY AT HOPPLE ST. REPLACEMENT SEWER (DESIGN)	260	$ 104,500	401.92308	$ 54,097,600
LOCKLAND RD SEWER REPLACEMENT (DESIGN)	120	$ 46,900	390.83333	$ 54,144,500
CSO 39 64TH ST. DIV. DAM IMPROVEMENTS (DESIGN & ESMTS.)	45	$ 17,300	384.44444	$ 54,161,800
COLERIDGE AVE. R/W SEWER REPLACEMENT (DESIGN)	260	$ 82,800	318.46154	$ 54,244,600
WESTKNOLLS LN. SEWER RELOCATION (DESIGN)	220	$ 69,100	314.09091	$ 54,313,700
BENDER RD. AERIAL SEWER CROSSING REPLACEMENT (ADD'L. DESIGN & ESMT. FUNDING)	285	$ 86,600	303.85965	$ 54,400,300
FIRST ST. SEWER REPLACEMENT	385	$ 109,000	283.11688	$ 54,509,300
1110 W. GALBRAITH RD. SEWER LATERAL REPAIR	220	$ 52,600	239.09091	$ 54,561,900
DELLWAY ST. SEWER REPLACEMENT (EASEMENT)	330	$ 75,000	227.27273	$ 54,636,900
670 ROCKDALE AVE. SEWER REPLACEMENT (DESIGN)	260	$ 52,900	203.46154	$ 54,689,800
OAKLAWN DR. SEWER REPLACEMENT (DESIGN)	265	$ 47,800	180.37736	$ 54,737,600
HILLSIDE AVE. TO RIVER RD.R/W SEWER REPAIR (DESIGN)	280	$ 46,000	164.28571	$ 54,783,600
CLOUGH RD. SEWER ABANDONMENT & LATERAL RELOCATION (DESIGN)	270	$ 43,000	159.25926	$ 54,826,600
RAVINE ST. SEWER REPLACEMENT (DESIGN)	240	$ 38,000	158.33333	$ 54,864,600
FORESTOAK CT SEWER REPLACEMENT (EASEMENTS)	350	$ 45,000	128.57143	$ 54,909,600

Project Name	BRE	Cost	BRE/ $	Cumulative $
FELICITY DR. SEWER REPAIR (DESIGN)	200	$ 23,400	117	$ 54,933,000
EDEN AVE. & FOREST AVE. MAINLINE AND LATERAL REPAIR (DESIGN)	220	$ 23,800	108.18182	$ 54,956,800
FOLEY FOREST, DELLWOOD ESTATES & NORTH BAY VILLAGE P.S. ELIMINATIONS (EASEMENTS)	485	$ 51,800	106.80412	$ 55,008,600
BLAIR AVE. & ERKENBRECHER AVE. MAINLINE & LATERAL REPAIR (DESIGN)	240	$ 23,800	99.166667	$ 55,032,400
FIRST ST. SEWER REPLACEMENT (DESIGN)	385	$ 28,700	74.545455	$ 55,061,100
ADAMS RD. & HASTINGS AVE. ALLEYWAY MAINLINE & LATERAL SEWER REPAIR (DESIGN)	220	$ 16,300	74.090909	$ 55,077,400
BATHGATE ST. & WHITTIER ST. MAINLINE AND LATERAL REPAIR (DESIGN)	240	$ 17,500	72.916667	$ 55,094,900
GLENWOOD AVE. AT WASHINGTON AVE. SEWER REPLACEMENT (DESIGN)	240	$ 16,700	69.583333	$ 55,111,600
1110 W. GALBRAITH RD. SEWER LATERAL REPAIR (DESIGN)	220	$ 15,100	68.636364	$ 55,126,700
POLK RUN WWTP INFLUENT SCREEN REPLACEMENT (DESIGN)	90	$ 6,000	66.666667	$ 55,132,700
GRAYDON AVE. MAINLINE & LATERAL REPAIR (DESIGN)	260	$ 16,200	62.307692	$ 55,148,900
COLETTE LN. REPLACEMENT SEWER (DESIGN)	360	$ 19,800	55	$ 55,168,700
BELDARE AVE./HALE AVE. TAP REPAIRS (DESIGN)	260	$ 10,100	38.846154	$ 55,178,800
Total		$ 55,178,800		