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Wastewater Pipe Condition and Deterioration Modeling for Risk-Based Decision-Making

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WASTEWATER PIPE CONDITION AND DETERIORATION MODELING FOR RISK-BASED DECISION-MAKING

by

Greta J. Vladeanu, B.S., M.S.

A Dissertation Presented in Partial Fulfillment
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ABSTRACT

The dissertation research work described here has four primary objectives: (1) the development of a comprehensive wastewater pipe condition rating model that incorporates a large number of environmental, structural, and hydraulic parameters of the pipe; (2) the development of a wastewater pipe deterioration model used to predict future overall condition states of the pipe, as well as determining the probability of failure at any given age of the pipe; (3) the development of a comprehensive consequence of failure model that assesses the consequence of wastewater pipe failure using economic, social, and environmental cost factors; and (4) the development of a proposed risk-based decision-making framework that combines the probability of failure with the consequence of failure to determine the wastewater pipe's risk of failure for rehabilitation and/or renewal decision-making purposes.

The industry-accepted protocol for condition rating of sewer pipes in the U.S. is the Pipeline Assessment and Certification Program (PACP) developed by the National Association of Sewer Service Companies (NASSCO, 2001). The PACP method relies exclusively on visual inspections performed by means of Closed-Circuit Television (CCTV) where existing structural and operation and maintenance (O&M) defects are observed by certified operators. A limitation of the PACP method is that it does not use pipe characteristics, depth, soil type, surface conditions, pipe criticality and capacity, nor the distribution of structural defects, or history of preventative maintenance to determine

the condition rating of the sewer pipe segment. Therefore, this research work addresses this limitation and develops a condition rating model that incorporates information about pipe characteristics, environmental parameters, as well information about structural and O&M defects, and hydraulic factors. Factors such as pipe material, diameter, shape, pipe material's age, soil type, depth of burial, type of carried waste, seismic zone, loading, groundwater, flow, inflow, and pipe surcharge are used.

As part of an asset management program, the ability to predict future sewer pipe conditions and potential failures is vital for capital improvement planning and budgeting. The deterioration model developed herein is unique in that it uses a Continuous Time Markov Chain method, as opposed to the widely used Discrete Time Markov Chain methods in the literature, to determine probabilities of transitioning from a better to a worse condition at any given age of the pipe.

To obtain a complete risk-based decision-making framework, the probability of failure is combined with the consequence of failure of the pipe to determine its risk of failure. The developed consequence of failure model incorporates a large number of economic, social, and environmental cost factors to determine the consequence of failure of the asset. Among the factors considered in the assessment of the consequence of failure are the pipe age, diameter, length, depth of burial, access to pipe, distance to critical laterals, soil type, seismic zone, distance to critical laterals, average daily traffic, proximity to other infrastructure, distance to bodies of water, and land use. Combined with the probability of failure, it results in the pipe' risk of failure. The obtained information is useful for future capital project planning and improvement budgeting.

APPROVAL FOR SCHOLARLY DISSEMINATION

Author ______________________________

Date ______________________________

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DEDICATION

This work is dedicated to my loving husband, who encouraged and supported me every step of the way during my studies, and my dear mother, father, and brother to whom I am forever grateful for their love and support. You are my rock.

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CHAPTER 1

INTRODUCTION

1.1 Background

Prioritizing pipe rehabilitation, renewal, and replacement projects is a fundamental task of water and wastewater utilities that have to maximize the efficiency of their yearly allocated budgets to provide the required level of service to their customers. To address the need for sewer pipe inspection, maintenance and renewal, a variety of prioritization tools have been developed and are currently being used by utilities to identify pipes that have the highest risk of failure. Determining a pipe's risk of failure involves two main steps: determining its likelihood of failure and determining its consequence of failure. Likelihood of failure involves determining the probability of a pipe to fail at some time in the future. Failure, in the case of a sewer pipe, can be defined as the condition rating of a pipe that is no longer structurally acceptable, the event where a maintenance action takes place, or any other way that suits the needs of the utility. To make these predictions, statistical tools are employed that utilize the existing historical pipe condition inspection data. The consequence of pipe failure, however, is a more complicated component that involves several factors that need in-depth evaluation. Upon a sudden sewer collapse, the consequences related to such an event have an impact on the environment, society and the utility, more specifically the finances of the utility that manages those assets. By determining the risk of failure of all sewer pipes within a system, a ranking of the most critical assets can be done to prioritize inspection and renewal plans.

1.2 Objective

The primary objective of this research is to provide the industry with a comprehensive method to assist in risk-based decision-making for sewer pipe management. This objective is achieved by combining several components into a risk-based decision-making framework. The first component is a comprehensive Pipe Overall Condition Score (POCR) model that is developed with the Analytic Hierarchy Process (AHP) multi-criteria decision-making method using information from televised inspection about the asset's structural, operational, and hydraulic conditions, as well as information about the pipe's internal and external factors. The same AHP method is used to develop a Consequence of Failure of Sewers (COFS) model using the Triple Bottom Line (TBL) method to evaluate economic, social, and environmental impacts of a possible sewer pipe failure. Additionally, a Continuous Time Markov Chain (CTMC) model is developed to forecast future sewer conditions; this information can be used by utilities to budget current and future capital improvement projects efficiently. The methods used in this dissertation can be applied to any sewer inspection data that corresponds to currently approved industry practices within the U.S. The following steps achieve this objective:

- Develop the POCR model by using the AHP method that considers a series of pipe characteristics, external pipe parameters, and structural, operational, and hydraulic conditions of the pipe;

- Based on POCR, develop a CTMC model to predict future sewer pipe conditions based on the current condition score, as well as determine Probability of Failure (PoF) at any age of the pipe material;
- Using the TBL method, determine the COFS score of a given sewer segment;
- Determine Risk of Failure (RoF) of sewer pipes by using the multiplication between the PoF and COFS values;
- Develop a risk-based decision-making framework based on sewer pipe RoF for current and future sewer pipe renewal capital project planning;
- Scenario analysis to test and validate the efficiency of the proposed model against the currently used industry practices for sewer pipe renewal decision-making.

Figure 1.1 summarizes the proposed research work presented in this dissertation.

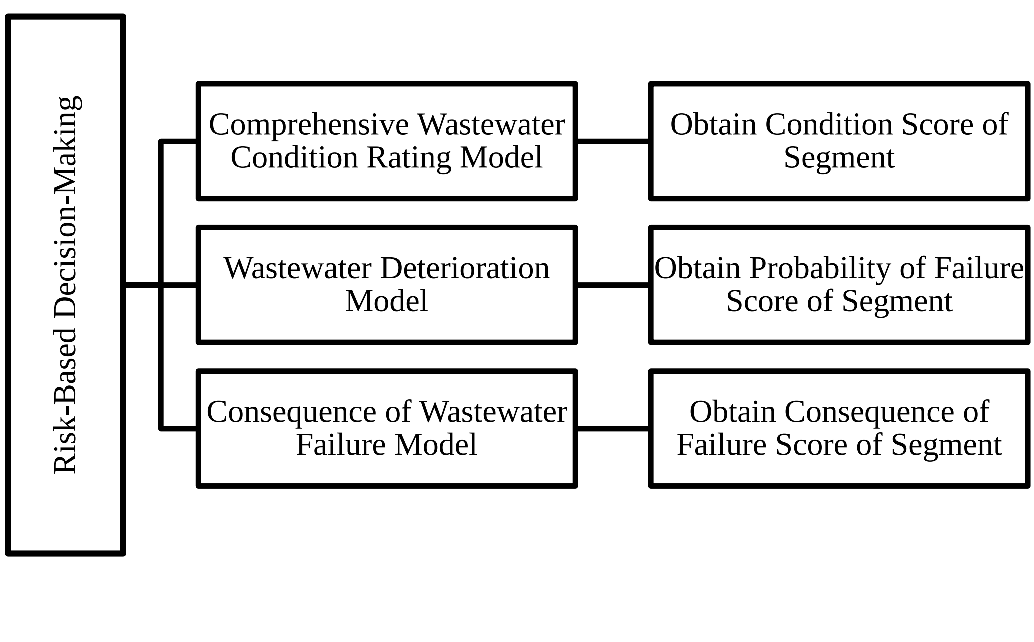

Figure 1.1. Proposed risk-based decision-making framework.

1.3 Dissertation Organization

This dissertation is organized into seven chapters: (1) Introduction; (2) Review of Relevant Literature; (3) Sewer Pipe Overall Condition Rating Model; (4) Sewer Pipe Deterioration Model Using Continuous Time Markov Chain Model; (5) Consequence of Failure of Sewers Model; (6) Scenario Analysis; and (7) Conclusions and Recommendations.

Chapter 2 reviews the relevant literature as it relates to risk-based decision-making for sewer pipe renewal. Specifically, an overview of pipe failure and deterioration models, consequence of failure estimation, risk assessment methods and models, and decision support systems for risk management are reviewed.

Chapter 3 presents the Pipe Overall Condition Rating (POCR) model development using the Analytic Hierarchy Process (AHP) method. A detailed description of the model's factors as well as of the AHP method is provided.

Chapter 4 presents the development of a Continuous Time Markov Chain (CTMC) model that determines sewer pipe Probability of Failure (PoF), as well as the probability of being in one of the conditions determined from the POCR model at a given time.

Chapter 5 describes the development of a Triple Bottom Line (TBL) Consequence of Failure of Sewers (COFS) model, also using the AHP method. A detailed description of the model's factors is provided.

Chapter 6 presents a framework for a risk-based decision-making method by incorporating the PoF and COFS scores determined in the previous chapters. Three different scenario analyses are also presented for yearly replacement schedule of sewers cost estimation.

Chapter 7 presents some concluding remarks of the research presented in this dissertation, as well as future work for improving the reliability and accuracy of the models presented.

1.4 Key Contributions

The main contributions of this work are detailed below:

1. The development of a comprehensive sewer condition rating model that incorporates the U.S. industry accepted condition rating method, the Pipeline Assessment Condition Program (PACP) developed by NASSCO. To the best of the author's knowledge, this is the first attempt at developing such a model.

2. The development of a CTMC sewer deterioration model based. For sewer deterioration modeling, models in the literature are comprised of Discrete Time Markov Chains (DTMC) due to ease of calculation of transition probabilities between conditions. The author proposes a CTMC for calculation of these probabilities. To the best of the author's knowledge, CTMC deterioration models have been developed for modeling bridge deterioration, but not sewer deterioration.

3. The development of a TBL COFS model that incorporates economic, social, and environmental impact factors to determine the COFS score for each analyzed sewer pipe segment. This model too is based on the proposed guideline in the PACP methodology, but several factors are considered in addition to those proposed by the PACP guidelines.

4. The development of a risk-based decision-making framework based on the developed models that can be used by utilities for renewal decision-making and capital improvement project planning.

CHAPTER 2

REVIEW OF RELEVANT LITERATURE

2.1 Decision-Making for Trenchless Rehabilitation

Prioritizing pipe rehabilitation, renewal, and replacement projects is a fundamental task of water and wastewater utilities that have to maximize the efficiency of their yearly allocated budgets to provide the required level of service to their customers. However, with the continuous aging of the water and wastewater infrastructures, and the underfunding of these systems in the US (ASCE, 2017), it is challenging for utilities to keep up with the maintenance and expansion of their water and wastewater assets. To improve and to meet the needs of the continuously growing population, the Environmental Protection Agency (2010) estimated that approximately $271 billion is needed for the wastewater infrastructure over the next 25 years (Sterling *et al.*, 2010; ASCE, 2017).

To address the need for sewer pipe inspection, maintenance and renewal, a variety of prioritization tools have been developed and are currently being used by utilities to identify pipes that have the highest risk of failure. Determining a pipe's risk of failure involves two basic steps: determining its likelihood of failure and determining its consequence of failure. Likelihood of failure involves determining the probability of a pipe to fail at some time in the future. Failure, in the case of a sewer pipe, can be defined as the condition rating of a pipe that is no longer structurally acceptable, the event where a maintenance action takes place, or any other way that suits the needs of the utility. To make these predictions, statistical tools are employed that make use of existing historical pipe condition inspection data. Consequence of pipe failure, however, is a more complicated component that involves several factors that need to be evaluated. Upon a sudden sewer collapse, the consequences related to such an event have an impact on the environment, society and the utility, more specifically the finances of the utility that manages those assets. By determining the risk of failure of all sewer pipes within a system, a ranking of the most critical assets can be done to prioritize inspection and renewal plans.

There are not many tools available for selecting the optimal technology for sewer pipe renewal as they are for critical asset prioritization, as described above. Most of the DSS developed for this purpose are concentrated in three areas: (i) using the expertise of designers and in-house engineers for municipalities and utilities, (ii) using tools developed by consulting firms for municipalities, which are proprietary, in most cases, and (iii) internally developed tools (Matthews, Selvakumar, Sterling & Condit, 2012).

The decision-making process for trenchless sewer pipe rehabilitation involves several complex tasks that cannot be captured by one single model or method. The uncertainties related to random physical, economic, social, environmental, and technological parameters require an extensive decision-making tool that can capture the variability of the system. As a result, comprehensive DSS has been developed with the purpose of capturing the complexity of the process and help water utility managers and stakeholders in their decision-making process of sewer pipe renewal.

A simple overview of the decision-making process for pipe renewal is presented in Figure 2.1. An efficient DSS should yield the optimal solution based on a series of constraints applied to a deterioration model developed based on the input data. The process should flow from inputting the data into the system to determining the most at-risk assets and giving an optimal inspection and renewal schedule for those assets, given a series of constraints.

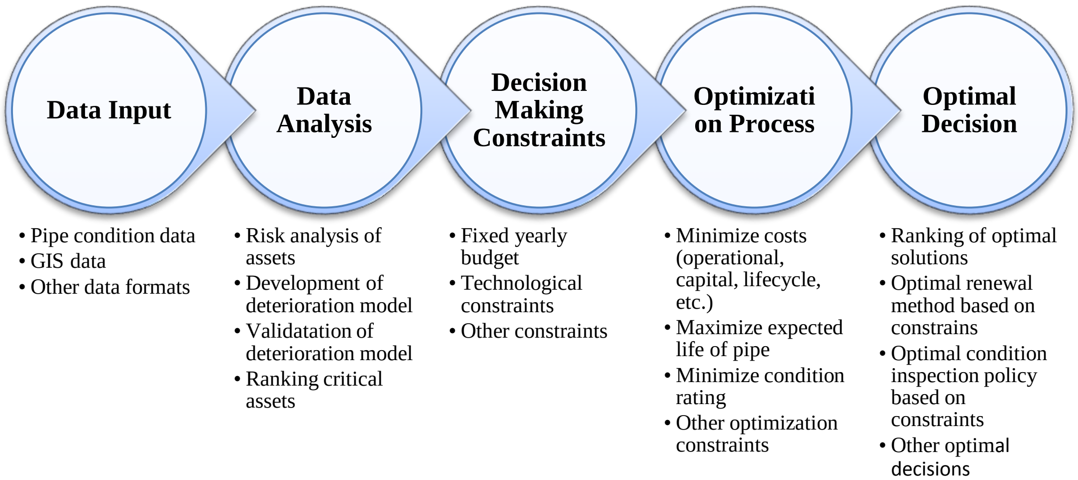

Figure 2.1. Decision-making process for pipe renewal.

2.2 Pipe Failure and Deterioration Modeling

Several studies in the literature exist that critically review the research in the area of pipe failure and deterioration modeling. Some of the most significant reviews are those by Kleiner and Rajani (2001a, 2001b), Liu, Kleiner, Rajani, Wang and Condit (2012), Nishiyama and Filion (2013), and St. Clair and Sinha, (2012). The reviews above focus on statistical deterministic and probabilistic failure models, as well as describing advanced models such as artificial neural networks and heuristic models (St. Clair & Sinha, 2012), and provide a detailed description of the most important models and techniques developed in the past 35 years. The review of Scheidegger, Leitão, and Scholten (2015) discusses these models from a unified perspective and provides model assumptions, clarifications, data assumptions, type of published probabilistic predictions, as well as software implementations of the relevant published works.

Usually, pipe failure (or break) models are used to predict water main failures where inspection data contains historical break events. Deterioration models are useful for large diameter transmission mains and wastewater pipes, where a condition rating system describes the current condition of a pipe. As a result, historical deterioration data is collected over time, which then can be used for developing various deterioration curves and predicting future conditions of the analyzed assets, as well as the probability of failure at a given time in the future. The type of model used strongly depends on the availability of historical failure or deterioration data, and the type of data collected (i.e., either pipe breaks over time or condition deterioration of individual pipe segments over time).

2.1.1 Probability of Pipe Failure

The first component of a risk analysis framework, the likelihood of pipe failure, can be determined by predicting the future condition rating of the asset from historical pipe condition data that is typically obtained by pipe inspection. Numerous studies in the literature use a variety of statistical models and methods to determine the condition rating, and subsequent probability of failure of sewer pipes. Such methods include regression analysis (e.g. Chugtai & Zayed, 2008; Salem, Salman, & Najafi, 2012; Vladeanu & Koo, 2015), Markov Chain models (e.g. Wirahadikusumah, Abraham, & Iseley, 2001; Micevski, Kuczera, & Coombes, 2002; Baik, Jeong, & Abraham, 2006), artificial neural networks (e.g. Najafi & Kulandaivel, 2005), survival functions (e.g. Baur & Herz, 2002), and Bayesian networks (e.g. Anbari, Tabesh, & Roozbahani, 2017). These models use a series of predictive variables, among which the most often used ones are the pipe's age, material, length, depth, diameter, the slope of the pipe and soil type, to determine the condition rating of the pipe. Table 2.1 shows selected studies on sewer deterioration modeling highlighting the factors used for determining the condition rating.

Table 2.1. Studies on sewer deterioration modeling.

Author(s)/Year of Publication	**Parameters Used in Study**	**Method Used**
Wirahadikusumah *et al*. 2001	Cohorts of pipes based on material, groundwater table elevation, soil type, and depth of cover.	Discrete Time Markov Chain (DTMC) Model with Non-Linear Optimization
Micevski *et al.* (2002)	Cohorts of pipes based on material, diameter, soil type, serviceability, and exposure class.	DTMC Model with Metropolis-Hastings Algorithms
Baur & Herz (2002)	Pipe age, material, slope, category of street, sewer function, pipe shape, type of pipe.	Survival Functions
Najafi & Kulandaivel (2005)	Pipe age, diameter, length, material, depth of cover, pipe slope, and type of sewer.	Artificial Neural Networks (ANN)
Baik *et al*. (2006)	Pipe length, diameter, age, material, and slope.	DTMC based on Ordered Probit Method
Chugtai & Zayed (2008)	Pipe age, diameter, length, material, class of material, bedding factors, and category of street.	Multiple Regression
Anbari *et al*. (2017)	Pipe age, material, cover and coating of the sewer, flow velocity diameter, depth of cover, traffic volume, number of connections, groundwater table, type of sewer, number and type of trees.	Bayesian Network

2.1.2 Factors Affecting Sewer Pipe Condition

The mechanism of sewer pipe deterioration never follows a pre-established pattern, and it is affected by various internal and external pipe conditions (Najafi & Kulandaivel, 2005). The most often used factors for determining sewer pipe condition are the pipe's age, material, and diameter (Ennaouri & Fuamba, 2011). However, a variety of other parameters also affect the structural and operational condition of the sewer; these factors have been extensively utilized to determine the current sewer pipe condition, and predict future pipe conditions using deterioration models. As noted by Davies, Clarke, Whiter, & Cunningham (2001) and Davies, Clarke, Whiter, Cunningham, and Leidl (2001), the most often occurring factors that influence sewer pipe deterioration can be grouped into the following categories: (1) construction factors, (2) external parameters, and (3) miscellaneous factors. Construction factors include information about the sewer pipe's diameter, pipe material, depth of burial, pipe bedding, load transfer, pipe joint type and material, sewer pipe connection (e.g., Wirahadikusumah *et al.*, 2001; Ariaratnam, El-Assaly, & Yang, 2001; Gedam, Mangulkar, & Gandhi, 2016; Elsawah, Bakri, & Moselhi, 2016). External parameters are considered for example the surface loading, ground conditions, groundwater level, soil type used for backfill, and root interface (e.g., Yan & Vairavamoorthy, 2003; Chugtai & Zayed, 2008; Elsawah *et al.*, 2016). Finally, other miscellaneous factors are the type of waste carried, pipe's age, sediment level, surcharge and improper maintenance (Ennaouri & Fuamba, 2011).

When physical inspections are performed for parts of, or for the entire sewer network, its current condition is expressed using a condition rating (or grading) system. Many methods have been developed to capture the condition of sewer pipes. Different techniques utilize different input factors to calculate a structural and operational condition grade. The aim of developing such a condition rating system is to have a method that can be easily carried out and implemented quickly and efficiently by utilities. The condition rating system implemented by a municipality is typically expressed on a 1 to 5 scale, with pipes in condition 1 being in the best condition and 5 needing immediate renewal action (e.g. the Water Research Centre, 2004; Wirahadikusumah *et al.*, 2001; McDonald & Zhao, 2001; the PACP method by NASSCO, 2001; Khazraeializadeh, Gay, & Bayat, 2014; Angkasuwansiri & Sinha, 2014).

Based on Rahman and Vanier (2004), defect scores used to establish sewer condition rating are determined by calculating a mean score, peak score, or total score. These scores are calculated based on the deduct values. Deduct values determine how the defect impacts the service life and overall performance of the sewer pipe, and are assigned for each defect according to the protocols used for the condition assessment method. Mean scores represent the average value of the deduct values over the entire length of the pipe segment. Peak scores represent the highest deduct value, and total scores are the sum of all deduct values. These scores are calculated based on Eqs. (2.1), (2.2) and (2.3).

$$Mean\ Score = \frac{\sum(Deduct\ Values)}{Length\ of\ Pipe\ Segment} \tag{2.1}$$

$$Peak\ Score = Maximum\ Deduct\ Value \tag{2.2}$$

$$Total\ Score = \sum(Deduct\ Values) \tag{2.3}$$

Condition assessment guidelines and protocols currently used worldwide include the WRc protocol developed in the UK (Water Research Centre, 2004) that is the basis for several other sewer condition assessment protocols used, such as the National Research Council (NRC) Guidelines for large sewers in Canada (Zhao, McDonald, & Kleiner, 2001).

The PACP method developed by NASSCO is also based on the guidelines by WRc. The following section details the PACP method. For further information on those above and other globally used sewer condition evaluation methodologies, the reader is referred to Rahman and Vanier (2004) and Kley, Kropp, Schmidt, and Caradot (2013).

2.1.3 Sewer Pipe Condition Rating Systems in the U.S.

The standard method to inspect the internal condition of sewer pipes is by video inspection using CCTV. To determine the structural state of a pipe, a relevant, repeatable and validated methodology must be employed (Opila, 2011). By using a condition rating system, the visual inspection data from CCTV inspection is translated into an easily understandable and manageable form, which then can be used for prioritizing rehabilitation needs within the system (Kley *et al.*, 2013). Additionally, by using a standardized condition rating system, the pipe condition data can be benchmarked and used within and across utilities. By using the same condition rating system, deterioration models and DSSs can be developed using the same data options.

2.1.3.1 Pipeline Assessment and Certification Program (PACP)

In the U.S., the accepted industry standard for sewer pipe condition evaluation is the Pipeline Assessment and Certification Program, or PACP, developed by the National Association of Sewer Service Companies, NASSCO (NASSCO, 2001). The PACP condition rating system uses pre-established capital letters as codes to assess the sewer pipe's defects. Each PACP code is also assigned a condition grade based on the severity of the defect. The grading scale used to assess the structural condition of the pipe is 1 to 5, as presented in Table 2.2.

Table 2.2. PACP condition scoring scale (NASSCO, 2001).

Grade	Description
1	Minor defect grade
2	Minor to moderate defect grade
3	Moderate defect grade
4	Significant defect grade
5	Most significant defect grade

An Overall Pipe Rating is computed by adding all condition grades per pipe segment. By dividing the Overall Pipe Rating by the number of defects, the Pipe Rating Index can be calculated, which is a representation of the average severity of defects in the pipe.

Additionally, a Quick Rating index provides a 4-digit code that quantifies the number of occurrences for the two most severe defects within a pipe segment. The first digit represents the highest severity grade occurring along the entire pipe length; the second number is the total number of occurrences of the most severe defect observed along the pipe length. The third and the fourth digits represent the same for the second highest severity defect observed in the pipe. So for example, if there were one defect of condition score 5 and five defects of condition score 4 observed along the pipe, the Quick Rating index would be 5145. Besides PACP, NASSCO also developed MACP and LACP that stand for Manhole Assessment Condition Program and Lateral Assessment Condition Program, respectively.

Probably one of the most critical limitations of the PACP method is the fact that the OR equates two pipes with varying defect grades. For example, a pipe with defects of severities 2 and 3 are assumed to be equal to a pipe with a single defect of severity 5 (i.e., is completely collapsed). Naturally, this result yields a practically unrealistic scenario: a fully collapsed pipe does not have the same condition as a pipe with a longitudinal crack (PACP score of 2) and a longitudinal fracture (PACP score of 3). The QRI, though it gives an overview of the most severe defects occurring on a pipe segment, does not offer the possibility to compare between surveys of different severities (Opila, 2011; Opila & Attoh-Okine, 2011). Besides the limitations mentioned above of the PACP method, the fact that it does not use any internal or external pipe parameters (such as pipe material, burial depth, soil characteristics, and other) makes it unsuitable for pipe renewal decision-making purposes (Thornhill, 2008). As noted by Thornhill (2008), just because severe defects are existing on a sewer pipe segment, it does not mean that the pipe needs immediate replacement. It is entirely possible that a severe defect occurred during pipe installation, and as a result, the defect is still there after decades.

2.1.3.2 SCREAM^{TM}

SCREAM^{TM} is a sewer and manhole condition assessment tool developed by the consulting company CH2MHill. SCREAM stands for Sewer Condition Risk Evaluation Algorithm Model and was developed by Dr. Kathula, at the Trenchless Technology Center at Louisiana Tech University with the purpose of using scientific and mathematical principles to develop a defect rating system and decreasing operator subjectivity (Kathula, 2001). The defect scores are based on scientific research, and it provides a scoring and ranking process together with a coding scale from 1 to 100 (Rowe, 2006). The developed Multiple Attribute Method (MAM) calculates a Sewer Condition Score (SCS) that was further improved to integrate it easily into the mathematical process. As a result, SCREAM^{TM} Unite (or Unite^{TM}) was developed (Rowe, Kathula, Bergin, & Kennedy, 2011). Eq. (2.4) presents the formula to compute the score of a sewer segment.

$$\text{SCREAM}^{TM}\ \text{Unite} = \text{Max}(\text{TS}_n) + [\{100 - \text{Max}(\text{TS}_n)\} \times \sum_{n=1}^{m} \frac{\text{TS}_n}{\text{K}}] \qquad (2.4)$$

where

- TS_n is the total score for an inspection
- $Max(TS_n)$ is the maximum (highest) score of all various inspection scores
- n represents the number of inspection techniques scores used for the aggregation
- K is an integer constant

Both the PACP and the Unite™ scoring approaches are aggregated score methods, meaning that all scores associated with defects on a given asset are combined to obtain an overall score. The PACP uses an intermediate score aggregation method that is relatively easy to use, but it has the disadvantage of diminishing the high and low values of the obtained scores (Rowe *et al.*, 2011). The Unite™ scoring method uses a robust aggregation method in which the high score is used as a starting point to which the aggregated values of the remaining scores are added (Rowe *et al.*, 2011).

The same authors present a comparison between the PACP and the SCREAM™ scoring systems and offer an example application. The results showed that for a Top Down risk approach, the robust aggregation method is more adequate. For a Bottom-Up risk approach, the robust aggregation method is also more representative because it offers a more complex mathematical framework to calculate risk scores that offer a final condition score and priority ranking of the assets. However, the scoring method developed by CH2MHill is a proprietary standard method that is not freely available, thus making it difficult to use.

2.3 Consequences of Sewer Pipe Failure

The second component of a risk assessment process involves determining the consequence of sewer pipe failure. Not many works in the literature thoroughly document the process of estimating the consequences of pipe failure. The lack of documentation can be attributed to the fact that estimating both direct and indirect costs associated with a pipe's failure involves high uncertainty and subjectivity. Additionally, while direct economic costs borne by the utility can be computed in monetary terms, indirect impacts are quite challenging to quantify regarding cost (for example, hours of traffic delay). Rather than coming up with a total cost of the CoF, utilities developed various metrics and CoF indices that reflect the criticality of a potential pipe failure (Salman & Salem, 2011).

As presented in the Water Research Foundation report on the consequences of failure for buried assets (Raucher *et al.*, 2017), current practices focus on assessing mostly the direct economic costs of asset failure which might be one of the main causes of the underfunding of buried assets. The report stresses the importance of assessing the consequence of failure not only from an economic perspective, but from a social and environmental aspect as well, called the Triple Bottom Line (TBL). A TBL approach accounts for a large number of impact factors resulted from a possible failure such as (1) economic costs borne by the utility, (2) social impacts borne by the customers and the affected community due to travel delays, rerouting, service outages, property damages (Raucher *et al.*, 2017), and (3) environmental impacts that might arise due to percent land lost upon an unforeseen sewer failure, contamination of groundwater and wildlife habitats, and other environmental impacts.

Research works assessing the CoF of sewers use information such as the pipe diameter, depth of burial, and adjacency to railways, water bodies, interstates, state routes, U.S. roads, etc. (Anderson & Hyer, 2014) to determine the CoF score for further use in risk-based decision-making. In their work, McDonald and Zhao (2001) assessed the impact level of large diameter sewer pipes by analyzing the location, type of soil, burial depth, pipe diameter, seismic zone, and pipe use. Each of the six factors was evaluated as having a low, moderate, or high impact. The weighted average of impact ratings was computed for each pipe segment, and prioritization of renewal was obtained by combining the segment's impact rating with its condition rating. Similar factors were used by Halfawy, Dridi, and Baker (2008) to determine the consequence of sewer pipe failure (i.e., pipe diameter, depth, soil type, sewer type, as well as land use, traffic volume, proximity to other critical assets, social and economic impact, road classification, seismic zone, and functionality). The risk of failure was then obtained by multiplication of the consequence of failure (or risk factor) and the failure index.

The Wanganui District in New Zealand considered the size and depth of the pipes, adjacency to slopes, soil type, location under heavy trafficked area or railway tracks, the crossing of natural gas pipelines, adjacency to high pedestrian areas and water courses, and the service of critical customers (Toy, 2008). For the risk assessment, four criticality grades were selected and assigned to assets based on the criticality criteria listed previously, and decisions were made based on the overall criticality of each asset, using multi-criteria analysis. The benefit of this kind of approach is that various levels of asset criticality can be set, and improved decisions can be taken for maintenance and rehabilitation and or/repair (Toy, 2008).

There are not many studies in the literature that document TBL consequences of failure because it is difficult for utilities to quantify the impact of pipe failure that are outside the agency, such as social or environmental impacts (Raucher *et al.*, 2017). Works on water main break TBL consequences include those of Raucher *et al.* (2014), Gaewski and Blaha (2007), Grigg (2007), Damodaran *et al.* (2005) and Cromwell, Reynolds, and Young (2002). While the report by Raucher *et al.* (2017) focused on water main consequence of failure, the same method of assessing sewer pipe consequences of failure can be implemented. It was shown that the TBL costs can be up to four times the direct economic cost borne by the utility (Gaewski & Blaha, 2007; Raucher *et al.*, 2017). Another important conclusion of these works is that the location of the pipe and its proximity to important receptors is the most significant predictive factor in estimating a potential high consequence of failure (Raucher *et al.*, 2017). Additionally, key findings include the fact that traffic disruption, property damages and service interruptions to high-value customers increase the consequences of failure (Raucher *et al.*, 2017).

Anbari *et al.* (2017) used a weighted average method to determine consequence of sewer pipe failure that were then combined with probabilities of failure resulted from Bayesian inference to determine risk of sewer pipes as part of Tehran's sewer system in Iran. The consequence of failure was assessed based on economic, social, and environmental impacts, and a total consequence of failure score was assigned to the analyzed sewers. Factors considered by the authors in assessing the consequence of failure include the pipe diameter, distance from groundwater level, distance from water well, wastewater quality, proximity to river or lake, type of road, proximity to public places, number, and importance of lateral connections. The risk of failure was determined using fuzzy logic by combining the probability and consequence of failure of the pipes.

However, assessing the consequence of sewer pipe failure using the TBL approach is a rather challenging task due to the multiple and complex aspects related to determining the consequences on economic, social, and environmental levels. The difficulty lies in quantifying these consequences due to the differing measurement scales of these impacts. For example, economic impact is typically measured in monetary units, while social and environmental impact, although measurable in monetary units, they can also be quantified using various indices and/or metrics, such as for example hours of traffic delay due to repairs, percent of lost land, or percent of groundwater contaminated.

For sewer pipe consequence of failure, the TBL is also the method proposed by NASSCO in the PACP program to quantify the CoF of sewers. As part of the risk-based decision-making framework, the PACP methodology provides a general guideline on determining the CoF of a sewer pipe. To determine a sewer segment's TBL CoF, a series of factors are considered under economic, social, and environmental criteria: pipe diameter, depth of burial, location of the pipe, relative network position of the pipe, proximity to environmentally sensitive features, type of customers served, and pipe accessibility. Each of the factors is given a weight based on its contribution to economic, social, and environmental impacts of failure. An overall CoF score of the analyzed segment is calculated as a weighted average of all individual factors. However, this method is presented only as a general guideline for CoF score calculation, and utilities are advised to either expand on or remove factors from the assessment, based on their particular situation.

2.4 Risk Assessment of Pipe Failure

Risk involves a certain degree of uncertainty and can be thought of as a random variable that might follow a stochastic process, or not (Friedl & Fuchs-Hanusch, 2011). Utilities cannot completely eliminate risks and uncertainties within their systems as it would lead to high costs from an engineering perspective. As a result, all risk management approaches undertaken by water and wastewater utilities involve the minimization of pipe failures and their associated costs. Several methods have been developed and successfully used by utilities to quantify and assess the risk of a pipe failure. Below, the most widely used methods are summarized.

2.1.4 Risk of Failure

Probably the easiest and most widely used method to quantify risk of a pipe failure is expressed as the multiplication between the probability of the occurrence of an event and the consequence of that event occurring (e.g. Hess, 2015; Pietig, 2015; Mann & Frey, 2011; Liberator, 2008). Eq. (2.5) presents the formula.

$$\text{Risk of Failure} = \text{Probability of Failure} \times \text{Consequence of Failure} \tag{2.5}$$

In this case, both the probability and consequence of failure must have values on a numerical scale.

This method provides a quick overview of the most vulnerable assets within a system; however, due to the uncertainties of the many factors that can affect the probability and consequence of failure of both water and sewer pipes, the accuracy of the multiplication prediction might not be desirable. Additionally, a disadvantage of this method is the fact that it cannot differentiate between pipe segments with high probability of failure and low consequence of failure and those with low probability of failure and high consequence of failure. Given this situation, the overall risk value for both of these pipes would be similar, but there might be different actions needed to be performed by the utility for the two cases (Salman, 2010).

2.1.5 Risk Matrix

Risk matrices are typically square matrices, where the columns represent the consequence of failure and the rows represent the probability of failure (or condition) on the same scale. A risk matrix can be used to determine the risk associated with a combination of probability and consequence of failure. If compared to the previously described method, the use of risk matrices has the advantage of allowing to identify among pipes that have a low probability of failure and high consequence of failure and those that have a high probability of failure and low consequence of failure. A typical risk matrix (scale 1-5) is presented in Table 2.3.

Table 2.3. General risk matrix.

	Consequence of Failure (CoF)				
Probability of Failure (PoF)	**1 (Low)**	**2 (Fair)**	**3 (Moderate)**	**4 (Medium High)**	**5 (High)**
1 (Low)	Low	Low	Fair	Fair	Fair
2 (Fair)	Low	Fair	Fair	Moderate	Moderate
3 (Moderate)	Fair	Fair	Moderate	Moderate	Moderate
4 (Medium High)	Fair	Moderate	Moderate	Moderate	High
5 (High)	Fair	Moderate	Moderate	High	High

One notable disadvantage of this method is the fact that the PoF must be expressed on an ordinal scale (1 to 5). As a result, re-coding the numerical values of PoF and CoF into ordinal values might result in losing information, because pipes with different values of PoF and CoF might be assigned to the same risk group, depending on the pre-established cut-off values for each ordinal value (Salman, 2010). Additionally, selecting the cut-off value for each ordinal value is problematic, because it involves subjectivity and depends on how one perceives a “moderate probability of failure” or a “high consequence of failure”. More so, pipes that have similar PoF and CoF values can be assigned to different ordinal values as a result of the selected cut-off values. This might result in a differing risk value associated with those pipes. A recent example of using risk matrices is the work of Elsawah *et al.* (2016), who used this method to determine the criticality index of water and sewer segments based on 13 economic, social and environmental factors for an integrated DSS for planning rehabilitation of water and sewer pipes sharing the same corridor.

2.1.6 Fuzzy Set Theory

A fuzzy inference system uses fuzzy set theory to compute the output based on an input. To avoid the issues related to using a risk matrix, fuzzy inference uses “if-then” rules to allow subject matter experts to make decisions based on their expertise. For example, if the probability of failure is “medium-high” and consequence of failure is “high”, then the overall risk of failure is “high”. Fuzzy logic takes linguistic terms (such as “high probability of failure” or “low consequence of failure”) and translates them into precise values to be used for decision-making (Salman, 2010).

Fuzzy logic was first discussed by Zadeh in the 1960s to model the uncertainty of spoken language. Fuzzy methods use the fuzzy set theory to analyze and manage imprecise information. This method is suitable to model deterioration of buried infrastructure which has insufficient data and for which there is an imprecise knowledge of cause and effect (Kleiner, Sadiq, & Rajani, 2006). The variables used in the model are assigned a membership function on a continuous interval [0,1] and interpreting these variables involves expert judgment, i.e. subjectivity (Liu et al, 2012). As a result, this method is well suited to model deterioration of buried infrastructure, because experts and practitioners with experience have a good overview and understanding of the deterioration process. Therefore, this subjectivity is well captured with the fuzzy method (Liu *et al.*, 2012).

Work in this area includes Kleiner *et al.* (2006), who modeled the deterioration of large diameter water mains using fuzzy-based non-homogeneous Markov process to obtain the probability of failure throughout the life of an asset. Ammar, Moselhi, and Zayed (2012) used a fuzzy based lifecycle cost model in a DSS that ranks rehabilitation methods and accounts for the life-cycle cost of each competing scenario along with the uncertainty. By using this method, the model can consider data that is vague as it relates to human subjectivity and qualitative assessment. Fares and Zayed (2010) evaluated the risk of failure using a hierarchical fuzzy expert system. The risk was calculated using the multiplication method. Atef, Osman, and Moselhi (2012) incorporated fuzzy set theory into two evolutionary genetic algorithms to select the optimal inspection policy given a fixed budget. All these models were developed for aiding decision-making as they relate to water main deterioration. Adapting these works to sewers, however, should not make a difference in the validity of these models.

2.5 Decision Support Systems for Risk Management

Once the sewer deterioration model is selected, developed, and validated, the next step is typically the creation of a DSS to automatize all, or a part of, the process. The development of a DSS is achieved by incorporating the pipe failure/deterioration model with optimization of decisions based on the priority to rehabilitate, repair, or replace the analyzed assets. DSSs are used by water utility managers and other stakeholders to support them in their decision-making process to prioritize rehabilitation, repair, and replacement of their water and wastewater infrastructure. There are five components in a DSS: a database management system, a model management system, knowledge engine, a user interface, and users (Marakas, 2003). According to Zhang, Zargar, Achari, Islam, and Sadiq (2013), the data management system is used for data collection, storage, and analysis. The model management system can incorporate physical, mechanical, data-driven, artificial intelligence or hybrid models that allow various modeling possibilities within the DSS. The knowledge engine contains an inference system that generates an output based on a series on input parameters. The most common technique used in a DSS is a multi-criteria decision analysis tool that can select the optimal alternative among several options, given a series of constraints. A geographical information system (GIS) should be used to facilitate a user-friendly environment, as well as database and model management. A more in-depth description of the architecture of a DSS as well as of its primary components can be found in Zhang *et al.* (2013).

The decisions are made based on pre-determined constraints, such as minimizing the costs involved in the process, maximizing the expected life of the asset while minimizing the average condition rating of the system (e.g. Altarabsheh, Kandil, & Ventresca, 2016; Ward & Savic, 2012, 2014; Allouche, Ariaratnam, & AbouRizk, 2000). For this, optimization algorithms are incorporated into the DSS to search and find the optimal solution for any number of constraints (see Figure 2.1).

For buried infrastructure management, DSSs are commonly used to prioritize the most critical assets (e.g., Park & Loganathan, 2002; Kleiner & Rajani, 2004; Berardi, Giustolisi, Kapelan, & Savic, 2008). Furthermore, DSSs are also used to optimize condition assessment actions (e.g., Kleiner, 2001; Dridi, Mailhot, Parizeau, & Villeneuve, 2005; Altarabseh *et al.*, 2016) and select the optimal trenchless rehabilitation, repair or replacement technology for an efficient decision-making process (e.g. Kleiner & Rajani, 2010; Deb, Pratap, Agarwal, & Meyarivan, 2002; Herz & Kropp, 2002). A comprehensive review of DSSs for risk management can be found for example in Matthews *et al.* (2012) and Vladeanu & Matthews (2018a).

2.6 Summary

There have been a variety of models, methods, and tools developed both in the academic literature and wastewater industry to determine sewer pipe condition rating for renewal decision-making, the consequence of failure scores, and the likelihood of failure for risk assessment. The work presented in this dissertation provides a novel and comprehensive risk-based decision-making framework that incorporates a series of parameters related to pipe internal and external factors, as well as information about economic, social, and environmental impact factors to determine its risk of failure. This information can be used to develop capital improvement plans for upcoming renewal projects more efficiently and cost-effectively for proactive asset management.

CHAPTER 3

PIPE CONDITION RATING MODEL

3.1 Background

In the U.S., the industry-accepted protocol for condition rating of sewer pipes is the Pipeline Assessment and Certification Program (PACP) developed by the National Association of Sewer Service Companies (NASSCO, 2001). Since the initial development of the method, several updated versions exist, the most current one is PACP version 7.0 from 2015. Some utilities develop their own, in-house defect rating methods, but typically these are also some variations of the PACP method (Angkasuwansiri & Sinha, 2014). The PACP method relies exclusively on visual inspections performed using Closed-Circuit Television (CCTV) where certified operators observe existing structural and operation and maintenance (O&M) defects. As noted by Thornhill (2008), a limitation of the PACP method is that it does not use pipe characteristics, depth, soil type, surface conditions, pipe criticality, and capacity, nor the distribution of structural defects, or history of preventative maintenance to determine the condition rating of the sewer pipe segment.

Taking into consideration both visual inspection data and exterior parameters that affect sewer pipe condition assures that the condition of the sewer is evaluated more accurately and comprehensively. Geographically changing parameters, such as soil characteristics, groundwater table elevation, surface conditions, and other specificities impact on a varying scale the condition rating assigned to sewer pipes (Ahmadi *et al.*, 2014). Therefore, it is essential to consider both the visually observable defects and the surrounding environment's impact on those defects as well when determining a condition score for the sewer pipe.

This chapter aims to develop a comprehensive sewer condition rating model that incorporates the already well-established PACP defect rating methodology, and that also considers additional pipe internal and external parameters and factors. Multi-criteria decision-making is used to develop a Pipe Overall Condition Rating (POCR) model that assesses the overall condition of the sewer pipe on a scale of 1 through 5. The novelty of this study consists of including PACP structural and O&M defects, as well as sewer pipe internal and external factors to determine the overall condition of the sewer pipe. The goal is to offer a more comprehensive method to determine the condition of a sewer pipe, given the existing CCTV inspection data, as well as physical, operational, and environmental factors that affect the overall condition of the pipe.

3.2 Pipe Overall Condition Rating (POCR) Model

As mentioned above, the goal of this chapter is to present a sewer pipe condition rating model that incorporates pipe characteristics, external pipe conditions, and other factors that affect sewer pipe condition, as well as PACP coded defects that exist on the segment. Operational and hydraulic factors are also included in the model. The goal is to determine one single defect grade that reflects the overall condition of the sewer pipe. For this, the proposed method uses multi-criteria decision-making technique that utilizes expert input to address complex decisions related to determining the condition of the sewer pipes. The Analytic Hierarchy Process (AHP) is used to break down the complex decision-making process into smaller decision blocks. Figure 3.1 presents the proposed model.

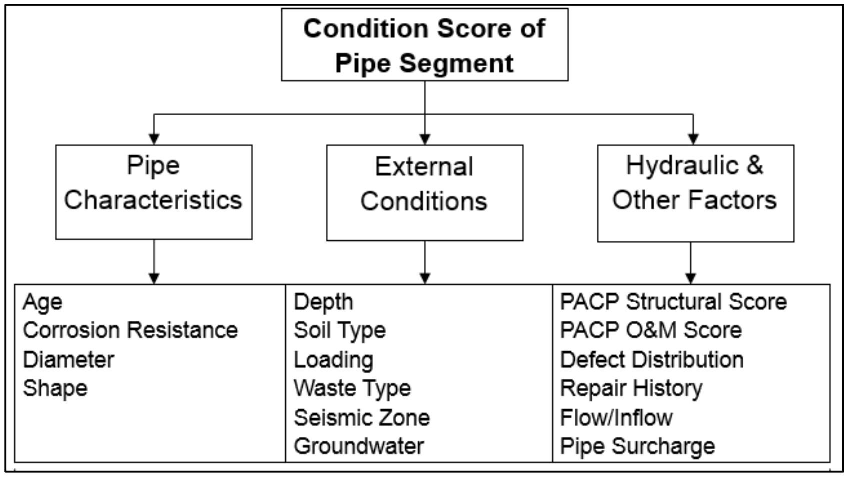

Figure 3.1. Pipe Overall Condition Rating (POCR) model.

The proposed model is the initial step in the framework of the overall risk-based decision-making system that is incorporating the PACP condition rating scores as well. The obtained individual condition grades from subsequent inspection data will be used to develop a Continuous Time Markov Chain (CTMC) wastewater deterioration model that, combined with a comprehensive consequence of failure model, can be used for risk-based decision-making. These will be presented in Chapters 4 and 5, respectively. The following section describes the AHP method, followed by the methodology to determine the POCR score of the pipe, incorporating all factors as presented in Figure 3.1.

3.3 Analytic Hierarchy Process

The Analytic Hierarchy Process (AHP) is a formal decision-making framework that presents the elements of a problem in a hierarchical order. As a result, decision-makers are guided through smaller decision blocks that compose the central problem. Pairwise comparisons are made between decision elements that express relative importance of the given element in the hierarchy (Saaty, 1980).

The following steps are needed to construct the AHP problem: structuring the problem, constructing the model (the hierarchy), preparing the pairwise comparison matrices, and determining the importance weights of all factors. According to Saaty (1980), the upper level of the hierarchy is the decision problem while the lowest level is the alternative to be evaluated. Expert judgment is utilized for obtaining the relative importance weights of the factors relative to the evaluation criteria. Typically, the following question is asked: What is the relative importance of the first factor compared to the second factor concerned with influencing the criterion? The answers are given on a 1-9 scale, as described in Table 3.1.

Table 3.1. Rating scale of AHP pairwise comparison.

Intensity of Importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective.
2	Weak	Represents compromise between importance 1 and 3.
3	Moderate importance	Experience and judgment slightly favor one (row component) over the other (column component).
4	Moderate plus	Represents compromise between importance 3 and 5.
5	Strong importance	Experience and judgment strongly favor one (row component) over the other (column component).
6	Strong plus	Represents compromise between importance 5 and 7.
7	Very strong or demonstrated importance	An activity is favored very strongly over another and its dominance is demonstrated in practice.
8	Very, very strong	Represents compromise between importance 7 and 9.
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation.

The steps involved in the AHP are detailed in the following paragraphs based on the methodology described by Saaty (1980).

Step 1. The problem is broken down into a hierarchy of goal, criteria (or factors), sub-criteria (or sub-factors), and alternatives. This is the most critical step in the AHP process because it establishes the hierarchical relationship between criteria and factors. Table 3.2 presents the description of criteria and factors of the POCR model, while Table 3.3 describes in detail the rating assigned to each of the factors.

Table 3.2. Description of condition rating criteria and factors.

Criteria	Factor	Description and Importance
Pipe Characteristics	Pipe Age	The time (in years), between pipe installation and inspection year. Aged pipes have higher probability for collapsing.
	Pipe Material	Plastic/glass reinforced plastic, clay, non-reinforced concrete/asbestos cement, reinforced concrete and metallic pipes. Differing pipe materials have different failure patterns, as well as differing corrosion resistance.
	Pipe Diameter	Nominal pipe diameter. Smaller diameter pipes are more likely to suffer beam failure.
	Pipe Length	Length of pipe segment. Bending stresses affect longer pipes.
	Geometrical Shape	Circular, semi-elliptic, ovoid, horseshoe, arched. Geometrical shape of the pipe’s cross-section.
External Conditions	Burial Depth	Higher depths overburden the pipe, while lower depths increase the surface live load. Moderate depths are optimal.
	Soil Type	Low, low to moderate, moderate, moderate-to-high, and high corrosiveness.
	Traffic Load	Low, low-to-moderate, moderate, moderate-to-high, and high traffic.
	Waste Carried	Low, low-to-moderate, moderate, moderate-to-high, and high corrosiveness.
	Seismic Zone	Zone 1, Zone 2, Zone 3, Zone 4, and Zone 5**
	Groundwater Level	Low, low-to-moderate, moderate, moderate-to-high, and high.
Hydraulic and Other Factors	Structural Defect Score	As derived from PACP codes: 1, 2, 3, 4, or 5.
	O&M Defect Score	As derived from PACP codes: 1, 2, 3, 4, or 5.
	Distribution of Structural Defects	Less than 1 ft. apart, between 1 and 2 ft., between 2 and 3 ft., between 3 and 4 ft., more than 4 ft. deep.

Criteria	Factor	Description and Importance
	Flow	Sufficient, moderately sufficient, moderately insufficient (?) and insufficient.
	Inflow	No, minor, moderate, significant, and extremely significant inflow.
	Pipe Surcharge	Full pipe, height difference between water depth and pipe burial < 5 ft. and ≥ 5 ft.
	History of Maintenance	No significant maintenance, minor maintenance events/year, moderate maintenance events/year, significant maintenance events/year, extremely abrasive maintenance events/year.

***** Based on 2017 USGS Seismic Maps (U.S. Geological Survey, 2017)
Seismic Zone 1: ND, MN, WI, MI, IA, NE, FL, South LA, TX, Northeast MT, West KS, OK (except Central)
Seismic Zone 2: West NY and PA, OH, WV,VA, East NC, MD, DC, South GA, South AL, South MS, North LA, Southwest AR, Central OK, East KS, North IL, North IN, North KY, North and West MO, North TX, East CO, East NM, South SD, North NE, ME, North NH, North VT
Seismic Zone 3: Parts of East SC, AR and MO, Parts of South IL, Parts of West KY and TN, North of VT, Central WA, Large part of OR and NV, Central AK, Central CA, Parts of NM, AZ, Co and TN, MA, CT, RI, East NY, North NJ, East PA
Seismic Zone 4: Parts of West WA, OR, CA, NV, WY, and MT, Parts of East SC, AR and MO, Parts of South IL, Parts of West KY and TN, Parts of MT, West WY, East ID, Central UT
Seismic Zone 5: West and East CA, West NV, West WA, West OR, HI, South AK

Table 3.3. Rating of condition of sewer pipe factors.

Criteria	Factor	Attribute	Rating
Pipe Characteristics	Pipe Age [years]	< 10	1
		≥ 10 yrs and < 25 yrs	2
		≥ 25 yrs and < 40 yrs	3
		≥ 40 yrs and < 50 yrs	4
		≥ 50 yrs	5
	Pipe Material	Plastic/GRP	1
		Clay	2
		NRCP/AC	3
		RCP	4
		Metallic	5
	Pipe Diameter [inches]	< 6"	1
		≥ 6" and < 12"	2
		≥ 12" and < 18"	3
		≥ 18" and < 30"	4
		≥ 30"	5
	Pipe Length [feet]	< 20’	1
		≥ 20’ and < 40’	2
		≥ 40’ and < 60’	3
		≥ 60’ and < 80’	4
		≥ 80’	5

Criteria	Factor	Attribute	Rating
	Geometrical Shape	Circular	1
		Oval	2
		Horseshoe	3
		Semi-elliptic	4
		Arch	5
External Conditions	Burial Depth [feet]	≤ 4'	1
		≥ 4' and <10'	2
		≥ 10' and <18'	3
		≥ 18' and <24'	4
		≥ 24'	5
	Soil Type	Granular soil (crushed stone, gravel)	1
		Coarse grained soils (gravel-sand mixtures)	2
		Silty gravels, clayey gravels	3
		Fine grained soils (very fine sands and silts)	4
		Inorganic silts and inorganic clays	5
	Traffic Load	No traffic to very light traffic	1
		Light traffic	2
		Medium traffic	3
		Moderate to heavy traffic	4
		Heavy traffic	5
External Conditions	Waste Carried	Mildly corrosive	1
		Mildly to Moderately Corrosive	2
		Moderately corrosive	3
		Moderately to Highly Corrosive	4
		Highly Corrosive	5
	Seismic Zone	Zone 1	1
		Zone 2	2
		Zone 3	3
		Zone 4	4
		Zone 5	5
	Groundwater Level	Low	1
		Low to moderate	2
		Moderate	3
		Moderate to high	4
		High	5
Hydraulic and Other Factors	Structural Defect Score, O&M Defect Score	1	1
		2	2
		3	3

Criteria	Factor	Attribute	Rating
		4	4
		5	5
	Distribution of Structural Defects [feet]	> 4’	1
		> 3' and ≤ 4'	2
		> 2' and ≤ 3'	3
		≥ 1' and ≤ 2'	4
		< 1'	5
	Flow	Sufficient	1
		Moderately sufficient	2
		Moderately insufficient	3
		Insufficient	4
		Insufficient	5
	Inflow	No inflow	1
		Minor inflow	2
		Moderate inflow	3
		Significant inflow	4
		Extremely significant inflow	5
	Pipe Surcharge	Full pipe	1
		N/A	2
		Height difference between burial and water depth < 5 ft	3
		N/A	4
		Height difference between burial and water depth ≥ 5 ft	5
	Repair History	No significant maintenance events/year	1
		Minor maintenance events/year	2
		Moderate maintenance events/year	3
		Significant maintenance events/year	4
		Extremely abrasive maintenance events/year	5

The structure of an AHP model is an inverted tree where the decision-maker has to compare lower level elements relative to their upper-level contribution (Bhushan & Rai, 2007).

Step 2. Subject matter experts are asked to perform a pairwise comparison of lower level elements relative to their contribution to upper level elements. The comparisons are rated on a 1 to 9 scale (as presented in Table 3.1). Typically, the following question is asked: What is the relative importance of the first factor compared to the second factor with respect to influencing the criterion?

Step 3. A pairwise comparison matrix is used for collecting the data at Step 2. The row components are compared to the column components, and if the criterion in row *i* is more important than the criterion in column *j*, then the value of the matrix element (*i*,*j*) is more than 1. Otherwise, the column component is more important than the row component. The diagonal elements are always 1. The (*j*,*i*) element is the reciprocal value of the (*i*,*j*) matrix element.

Step 4. Relative importance weights of the factors with respect to the criteria are calculated by finding the principal eigenvalue and the normalized right eigenvector of the pairwise comparison matrix.

Step 5. A Consistency Index (CI) is evaluated to test the consistency of the responses by experts. When the CI does not reach the desired level, the comparisons must be re-examined. The CI is calculated as shown in Eq. (3.1).

$$CI = \frac{(\lambda_{max} - n)}{(n-1)} \tag{3.1}$$

where

- λ_{max} is the maximum eigenvalue of the comparison matrix.
- n is the order of the matrix.

A Consistency Ratio (CR) is calculated by dividing CI with the value for the set of judgments corresponding to the order of the matrix, called the Random Consistency Index (RCI), as presented in Eq. (3.2):

$$CR = \frac{CI}{RCI} \tag{3.2}$$

The values of RCI have been pre-determined by Saaty (1980), who calculated these values for large samples of random matrices of varying orders, as shown in Table 3.4. The suggested value of the CR for a consistent AHP is less than 0.1.

Table 3.4. Random Consistency Indeces for matrices of varying order (Saaty, 1980).

n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
RCI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.46	1.49

Step 6. Finally, local ratings are obtained with respect to each criterion for each factor. The sum of local weights within each criterion adds up to 1. The multiplication of the local ratings by the weights of the corresponding criterion yields global ratings. The sum of all global ratings adds to 1.

The questionnaires distributed to subject matter experts for both the POCR and COFS models are found in Appendix A. Before the start of this research study, IRB approval from Louisiana Tech University's Research Office has been obtained. The answers provided by the six subject matter experts are attached on the CD accompanying this dissertation.

3.4 Analytic Hierarchy Process-Based Group Decision-Making

It is common that decision-making is performed not only by one expert but by a group of experts. As a result, there must be a consensus among the answers of these experts, so that the obtained weights of factors are consistent. In this study, answers from six subject matter experts were obtained. The AHP method described previously was applied individually to each expert's comparison matrices. However, after performing the analysis, three of the judgments showed high inconsistencies. As a result, these comparisons were removed from the analysis. The final factor weights were determined by aggregating the individual relative importance weights derived from each expert's answers. For this, importance weights for each of the three experts were determined, based on the consistency of their judgments.

In this work, weights of expert judgments are determined based on the methodology presented by Srdevic, Blagojevic, and Srdevic (2011). The method uses two consistency measures to determine the individual weights of experts: their individual Consistency Ratios (CR) as computed for each comparison matrix, as shown in Eq. (3.2), and the generalized Euclidean Distance (ED). The ED compares each entry of the comparison matrix, a_{ij}, and the related ratios of the obtained weights of factors, w_i/w_j. Consistency of the weights should approximate the comparison matrix entry, i.e. $a_{ij} = w_i/w_j$. ED measures the distance between individual judgment elements in the comparison matrix and the derived weight ratios and is calculated as given in Eq. (3.3):

$$ED = \left[\sum_{i=1}^{n} \sum_{j=1}^{m} \left(a_{ij} - \frac{w_i}{w_j} \right)^2 \right]^{1/2} \tag{3.3}$$

Individual weights for the experts are determined based on the following steps:

Step 1. For all subject matter experts, CR and ED values are computed for each comparison matrix.

Step 2. For each matrix, the sum of CR and ED are obtained.

Step 3. The reciprocals of the sums of CR and ED are computed.

Step 4. Normalization of the reciprocal values of CR and ED, as obtained in Step 3, is performed by dividing individual reciprocal values by the sum of all reciprocal values. This is performed separately for all CR and ED values.

Step 5. The average values of the normalized CR and ED values are calculated for each subject matter expert. The obtained value is the weight of the expert, in accordance with the consistency of the answers of the expert, w_k.

As a result, two consistency measures, namely CR and ED, are incorporated into determining the weight of each decision-maker in the final computation of factor weights. An example of CR and ED calculation for a decision-maker is presented in Appendix B.

3.5 Aggregation of Individual Expert Response

Aggregation of individual judgments (AIJ) and aggregation of individual priorities (AIP) are the two methods proposed in the literature to aggregate the responses and results of multiple decision-makers (Ramanathan & Ganesh, 1994; Forman & Peniwati, 1998). With the AIJ method, individual judgments are aggregated into a new pairwise comparison matrix by means of expert consensus, voting, separation of experts, or by using statistical methods like the weighted geometric mean (Lai *et al.*, 2002). From here, the individual priorities (weights) are determined using the AHP method. Using the AIP method, individual priorities (weights) are first computed, and then aggregated to obtain final priorities (Altuzarra, Moreno Jimenez, & Salvador, 2005). As suggested by Saaty (1980), the weighted geometric mean is an efficient method to aggregate group decision weights. In this work, final group priority vectors are obtained by implementing the AIP method to aggregate the individual priority vectors of experts, using Eq. (3.4):

$$w_i^G = \prod_{k=1}^{K} [w_i(k)]^{w_k} \tag{3.4}$$

where

- K is the number of experts
- w_i (k) is the priority (weight) of the i^{th} alternative for the k^{th} expert
- w_k is the weight of the k^{th} expert
- w_i^G is the value aggregated group priority (weight)

Both w_k and w_i^G must be additively normalized. In this way, the weights of the Pipe Characteristics (w_{PC}), External Conditions (w_{EC}) and Hydraulic and Other Factors (w_{HOF}) criteria are determined, as well as of all the factors under these criteria. These weights are then combined with the factor ratings to obtain the POCR score (see Figure 3.1). Once the aggregated final weights of factors are determined, Eqs. (3.5) through (3.8) are used to calculate the POCR score for all sewer pipe segments:

$$\text{POCR} = w_{PC}\text{PC} + w_{EF}\text{EF} + w_{HOF}\text{HOF} \tag{3.5}$$

$$\text{PC} = \sum_{i=1}^{n} (w_i x R_i) \tag{3.6}$$

$$\text{EC} = \sum_{j=1}^{m} (w_j x R_j) \tag{3.7}$$

$$\text{HOF} = \sum_{k=1}^{o}(w_k x R_k) \tag{3.8}$$

where

- POCR = pipe overall condition rating
- PC = pipe characteristics score
- EC = external conditions score
- HOF = hydraulic and other factors score
- w_{PC} = pipe characteristics criterion weight
- w_{EC} = external conditions criterion weight
- w_{HOF} = hydraulic and other factors criterion weight
- w_i, w_j, w_k = factors weight under the PC, EC, and HOF criteria, respectively
- $R_{i,}$ $R_{j,}$ R_k = i, j, k category factor rating (on a 1 to 5 scale)
- n, m, and o is the number of factors under criteria PC, EC and HOF

3.6 Analytic Hierarchy Process Results

3.6.1 Aggregation of Individual Expert's Judgments

The questionnaires have been filled out by six subject matter experts with extensive experience in wastewater pipe condition assessment and trenchless rehabilitation methods. However, after performing the AHP analysis on the individual responses, it was found that out of the six experts, only three had consistent answers. Therefore, the inconsistent results were not considered in this study.

The comparison matrices from three experts were analyzed. The CR of all their comparison matrices were less than 0.1, meaning that their judgments were consistent. Local relative importance weights of factors affecting sewer pipe condition were obtained and are presented in Table 3.5.

Table 3.5. Relative importance weights and ranking of POCR model factors for all experts.

Criteria Vs Goal	**Expert 1**		**Expert 2**		**Expert 3**	
	weight	**Rank**	**weight**	**Rank**	**weight**	**Rank**
Pipe Characteristics	0.200	3	0.260	2	0.701	1
External Conditions	0.400	1	0.633	1	0.062	3
Other Factors	0.400	2	0.106	3	0.236	2
Pipe Characteristics	**Expert 1**		**Expert 2**		**Expert 3**	
	weight	**Rank**	**weight**	**Rank**	**weight**	**Rank**
Age	0.196	2	0.252	2	0.439	2
Corrosion Resistance	0.647	1	0.555	1	0.439	1
Diameter	0.078	3	0.097	3	0.074	3
Shape	0.078	4	0.097	4	0.049	4
External Factors	**Expert 1**		**Expert 2**		**Expert 3**	
	weight	**Rank**	**weight**	**Rank**	**weight**	**Rank**
Depth	0.039	5	0.038	6	0.379	1
Soil Type	0.078	6	0.425	1	0.173	3
Loading	0.050	4	0.169	3	0.116	4
Waste Type	0.293	3	0.086	5	0.038	6
Seismic Zone	0.254	2	0.196	2	0.062	5
Groundwater	0.286	1	0.086	4	0.233	2
Other Factors	**Expert 1**		**Expert 2**		**Expert 3**	
	weight	**Rank**	**weight**	**Rank**	**weight**	**Rank**
Structural Score	0.374	1	0.317	1	0.381	1
O&M Score	0.030	6	0.053	5	0.162	3
Defect Distribution	0.077	5	0.130	4	0.046	5
Repair History	0.120	4	0.317	2	0.103	4
Flow/Inflow	0.275	2	0.053	6	0.242	2
Pipe Surcharge	0.124	3	0.130	3	0.066	6

The results show that two experts considered External Factors as the most important criterion that affects the sewer pipe's condition, and the opinions are divided related to the other two criteria. There is a unanimous decision about the pipe's corrosion resistance and its structural score being the most important among the Pipe Characteristics factors, and Hydraulic and Other Factors, respectively. The ranking under the External Factors criteria varies by expert. CR and ED values for each matrix for each expert were calculated based on Eqs. (3.2) and (3.3). The results are shown in Table 3.6.

Table 3.6. Consistency Ratios (CR) and Euclidean Distances (ED) of expert judgments for the POCR model.

	Expert 1		**Expert 2**		**Expert 3**	
	CR	**ED**	**CR**	**ED**	**CR**	**ED**
Criteria vs Goal	0.000	6.250	0.033	1.113	0.062	2.491
Pipe Characteristics	0.027	2.116	0.016	0.000	0.015	2.788
External Conditions	0.087	2.233	0.019	1.240	0.036	3.930
Other Factors	0.080	6.447	0.012	2.023	0.023	2.801
Σ	**0.195**	**17.046**	**0.081**	**4.376**	**0.136**	**12.009**

Individual expert judgment weights were obtained based on the CR and ED consistency indicators, as presented in Section 3.5. Table 3.7 summarizes the results.

Table 3.7. Weights of expert judgments based on consistency measures CR and ED for POCR model.

	Expert 1	**Expert 2**	**Expert 3**
1/Σ CR	5.136	12.342	7.367
1/Σ ED	0.059	0.229	0.083
NORMALIZED CR	0.207	0.497	0.297
NORMALIZED ED	0.158	0.617	0.225
Expert's Judgment Weights, w_k	**0.183**	**0.557**	**0.261**

3.6.2 Relative Importance Weights of Factors Affecting Wastewater Pipe Condition

Once the expert's judgment weights have been determined, the relative importance weights of factors affecting the sewer pipe's condition were determined, using Eq. (3.4). The results in Table 3.8 show the criteria weights, factors weights, global weights of factors, and the final ranking of factors, based on the judgment of the three experts. Global weights are obtained by multiplying the individual factor's relative importance weights with the weight of the criterion under which they fall. Note that the sum of global weights adds up to 1.

Table 3.8. Relative importance weights of criteria and factors affecting pipe condition.

Criteria	Factors	Criteria Weight	Relative Importance Weight	Global Weight	Final Ranking
Pipe Characteristics		**0.399**			
	Age		0.284	0.113	3
	Corrosion		0.548	0.219	1
	Diameter		0.089	0.035	10
	Shape		0.079	0.032	12
		∑	**1.0**	**0.399**	
External Conditions		**0.394**			
	Depth		0.085	0.033	11
	Soil Type		0.302	0.119	2
	Loading		0.15	0.059	7
	Waste Type		0.107	0.042	9
	Seismic Zone		0.186	0.074	5
	Groundwater		0.17	0.067	6
		∑	**1.0**	**0.394**	
Hydraulic & Other Factors		**0.207**			
	PACP		0.377	0.078	4
	PACP O&M		0.07	0.015	16
	Defect		0.099	0.02	15
	Repair		0.218	0.045	8
	Flow/Inflow		0.117	0.024	14
	Pipe		0.119	0.025	13
		∑	**1.0**	**0.207**	

3.6.3 Application of the Developed Pipe Overall Condition Rating Model

PACP inspection data was obtained from a municipality from Northwest Louisiana to apply the proposed method. For this study, a total of 154,060 ft. of vitrified clay pipe (VCP) of 8-inch diameter were selected from one sewer basin with a total of 633 segments. The installation year is 1965. The data contained information about pipe location, diameter, segment length, shape, type of waste carried, and cleaning methods (if applicable). Table 3.9 presents characteristics of selected pipe segments.

Table 3.9. Characteristics of selected VCP 8-inch sewer pipe segments.

InspectionID	Sewer_Use	Flow_Control	Age	Shape	Length_Surveyed [ft.]	Pre-Cleaning	Location_Code
925	Sanitary	De-Watered using Jetter	51	Circular	286.8	Jetting	Light Highway
197	Sanitary	Not Controlled	51	Circular	449.6	Jetting	Sidewalk
213	Sanitary	De-Watered using Jetter	51	Circular	527.3	Jetting	Sidewalk
822	Sanitary	Bypassed	51	Circular	123	Jetting	Light Highway
3656	Sanitary	De-Watered using Jetter	51	Circular	146	Jetting	Light Highway
343	Sanitary	Not Controlled	51	Circular	249.9	Jetting	Light Highway
334	Sanitary	Not Controlled	51	Circular	297.7	Jetting	Light Highway

There was missing, or no information related to the depth of burial, soil type, groundwater table, repair history, and pipe surcharge. For these factors, all possible ratings of 1 through 5 were randomly distributed across the 633 pipe segments in equal proportions. Therefore, 20% of all sewers have been randomly assigned the rating 1 for depth of burial, soil type, groundwater table, repair history, and pipe surcharge, then 20% of all sewers have been randomly assigned the rating 2 for these factors, and so on with the remaining ratings of 3, 4, and 5. This practice allowed for an unbiased representation of the factors for which there was no known information for the purposes of the case study presented herein. Obviously, for a real world application of the model, this practice is unacceptable and the utility should take every effort to obtain accurate information about all factors.

PACP structural and O&M scores were determined first from the CCTV inspection database, then a centralized spreadsheet was created with data for each pipe segment containing all factors listed in Table 3.8. Pipe characteristics of selected sewer segments are presented in Table 3.9, external conditions for the same segments are shown in Table 3.10, and Table 3.11 lists hydraulic and other factors for those pipes. The POCR scores were calculated, using Eqs. (3.5) through (3.8) for all individual sewer segments. The obtained POCR scores for selected pipes are presented in Table 3.12.

Table 3.10. External conditions of selected VCP 8-inch sewer pipe segments.

InspectionID	**Depth [ft.]**	**Soil Type**	**Loading**	**Waste Type**	**Seismic Zone**	**Groundwater**
925	≥ 10 and < 18	Inorganic silts and inorganic clays	Medium traffic	Moderately corrosive	Zone 2	Low to moderate
197	≥ 10 and < 18	Fine grained soils (very fine sands and silts)	Moderate to heavy traffic	Moderately corrosive	Zone 2	Moderate
213	≥ 18 and < 24	Inorganic silts and inorganic clays	Light traffic	Moderately corrosive	Zone 2	Low
822	≤ 4	Silty gravels, clayey gravels	Medium traffic	Moderately corrosive	Zone 2	Moderate to high
3656	≥ 10 and < 18	Granular soil (crushed stone, gravel)	Medium traffic	Moderately corrosive	Zone 2	High
343	> 4 and < 10	Granular soil (crushed stone, gravel)	Medium traffic	Moderately corrosive	Zone 2	Moderate to high
334	≥ 24	Coarse grained soils (gravel-sand mixtures)	Medium traffic	Moderately corrosive	Zone 2	Moderate

Table 3.11. Hydraulic and other factors of selected VCP 8-inch sewer pipes.

InspectionID	**Structural Score**	**O&M Score**	**Defect Distribution [ft.]**	**Repair History**	**Flow/Inflow**	**Pipe Surcharge**
925	1	2	> 4	No significant maintenance events/year	Sufficient/No inflow	Full pipe
197	1	1	> 4	No significant maintenance events/year	Sufficient/No inflow	Height difference between burial and water depth ≥ 5 ft.
213	3	1	≥ 1 and ≤ 2	Minor maintenance events/year	Sufficient/No inflow	Height difference between burial and water depth ≥ 5 ft
822	1	1	≥ 1 and ≤ 2	Moderate maintenance events/year	Insufficient/Significant inflow	Height difference between burial and water depth < 5 ft
3656	5	3	> 4	Moderate maintenance events/year	Sufficient/No inflow	Height difference between burial and water depth ≥ 5 ft
343	1	1	< 1	Moderate maintenance events/year	Sufficient/No inflow	Full pipe
334	1	1	> 4	Extremely abrasive maintenance events/year	Sufficient/No inflow	Height difference between burial and water depth < 5 ft

Table 3.12 presents the POCR scores of the selected sewer pipes.

Table 3.12. POCR score of selected sewer pipes.

InspectionID	Pipe Characteristics Score	External Conditions Score	Hydraulic & Other Factors Score	POCR Score
925	2.477	3.198	1.067	2.482
197	2.755	3.241	1.360	2.676
213	2.755	2.954	2.743	2.894
822	2.477	2.828	2.210	2.609
3656	2.477	2.608	3.553	2.844
343	2.755	3.298	3.178	3.135
334	2.755	2.342	1.815	2.428

For the analyzed VCP cohort, the minimum POCR score was 2.03 and the maximum was 3.93. A more detailed analysis is presented in Chapter 6.

3.7 Wastewater Pipe Condition Based on POCR Score

The POCR score of a wastewater pipe is a measure of the overall deteriorated condition of the segment. The score of 5 represents the most severe condition, while a score of 1 shows a pipe in excellent condition. However, reaching a score of 5 involves the fact that the majority of the 16 factors have a rating of 5. As seen from the results in Section 3.6.3, the maximum POCR score of the analyzed pipe cohort was 3.93. If the majority of the 16 factors have intermediate values of 2, 3, and 4, the POCR score will be in this interval, even if some remaining factors have a rating value of 5. Only in extreme values the POCR score will reach the maximum score of 5. Therefore, to categorize each segment into a condition, based on the segment's POCR score, the following method was implemented.

The top-ranked factor based on the AHP analysis is the Corrosion Resistance factor. For this study, the selection criterion is the type of material considered for the project.

Based on the type of material, five cases were analyzed. In each one, all but the Corrosion Resistance factors were given the same rating. First, all factors were set to 1; then all were given a rating of 2, then a rating of 3, 4, and finally all factors' ratings were set to 5. The purpose of this process was to obtain an approximate interval variability of the POCR score, based on the value of the factor ratings. The results are summarized in Table 3.13.

Table 3.13. POCR score by pipe material.

Pipe Material	All 1's	All 2's	All 3's	All 4's	All 5's
Plastic/GRP	1	1.781	2.562	3.343	4.124
Clay	1.219	2	2.781	3.562	4.343
NRCP/AC	1.438	2.219	3	3.781	4.562
RCP	1.657	2.438	3.219	4	4.781
Metallic	1.876	2.657	3.438	4.219	5

Based on the values presented in Table 3.13, the following categories of wastewater pipe conditions were defined: a POCR score of less than or equal to 2.562 is condition 1, a POCR score between the values of 2.562 and 3.343 is condition 2, and all POCR score values that are larger than or equal to 3.343 is condition 3. These critical values were defined based on the POCR values of the least corrosive pipe material and were selected because of the values presented in Table 3.13. A detailed case study is presented in Chapter 6. Figure 3.2 presents the condition categories based on the thresholds of POCR values.

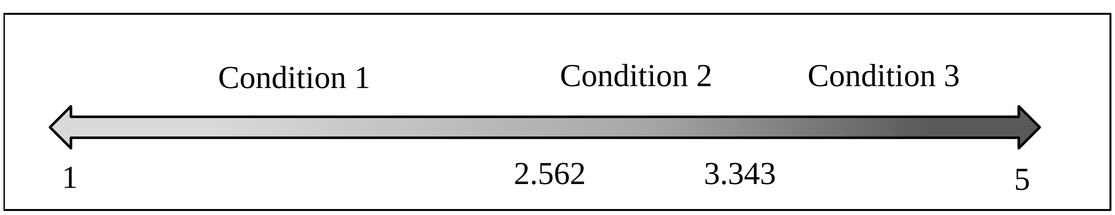

Figure 3.2. Sewer pipe condition based on POCR score.

As a general guideline, pipes in condition 1 do not require any further consideration as these pipes are in good condition. For pipes in condition 2, a re-inspection within one year is recommended to develop an optimal rehabilitation design method according to the overall condition of the pipe. Finally, pipes in condition 3 are in the worst overall condition and require immediate attention.

3.8 Sensitivity Analysis of POCR Model

Sensitivity analysis in this study is implemented to analyze how differing relative importance weights of the criteria, and implicitly of all factors, impact the model's output (Saltelli, Chan, & Scott, 2000). It is essential to analyze the sensitivity of the model output to determine if for a series of different expert answer, and subsequently differing weights, it is still usable. Specifically, the following question is asked: How will the POCR score change if the relative importance weights of the three main criteria are changed? To answer this question, the relative importance weights of the criteria were incrementally changed from their original weights. Super Decisions software was used for performing a portion of the sensitivity analysis (Saaty & William, 2004).

There are three primary methods to perform sensitivity analysis for AHP models: (1) numerical incremental analysis, (2) probabilistic simulations, and (3) mathematical models (Leonelli, 2012). In this dissertation, the numerical incremental analysis was used to perform the sensitivity analysis.

In the numerical incremental analysis, one criterion's weight is changed incrementally at a time, and the new weights of all parameters are calculated. The results of the global weights of all model factors can be graphically presented. These global weights are a linear function of the local weights and factor ratings. Because in this method only one weight, w_i, is changed at a time. The priority P_i of factor A_i is expressed as a function of the changed weight, w_i using Eq. (3.9):

$$P_i = \frac{P_i^{"} - P_i'}{w_i^{"} - w_i'}(w_i - w_i') + P_i' \tag{3.9}$$

where

- $P_i^{"}$ is the priority value for $w_i^{"}$
- P_i' is the priority value for w_i'

Using this method, two iterations are enough to plot a graphical representation of all the factors' weights for the range of 0 to 1 of one of the criteria weights (Leonelli, 2012).

To analyze how sensitive the outcome POCR score is to changing factor weights, the weights of criteria PC, EF, and HOF were progressively changed from their original weights of 0.399, 0.394, and 0.207, respectively, by -50%, -25%, -10%, +10%, +25%, and + 50%. This led to a change of values of the three criteria presented in Table 3.14.

Using the software Super Decisions, at each change of the criteria's weight, all factors' weights are automatically recalculated. Based on the changed weights of the criteria, there are a total of 18 scenarios (6 changed weights for each criterion with the corresponding weights of all factors) for which the POCR score has been recalculated. Each of the 18 scenarios of changed weights has been applied to the analyzed wastewater pipe segments (633 total segments of VCP 8-inch). The POCR score of each segment has been recalculated for all scenarios. The changed weights of all factors for the 18 scenarios is found in Appendix C.

Table 3.14. Changing criteria weight for sensitivity analysis of POCR model.

Main Criterion	**Other Criteria**	**-50%**	**-25%**	**-10%**	**Original**	**10%**	**25%**	**50%**
Pipe Characteristics (PC)		**0.200**	**0.299**	**0.359**	**0.399**	**0.439**	**0.499**	**0.599**
	EF	0.525	0.464	0.419	0.394	0.368	0.329	0.263
	HOF	0.275	0.241	0.222	0.207	0.193	0.172	0.138
External Conditions (EC)		**0.197**	**0.296**	**0.355**	**0.394**	**0.434**	**0.493**	**0.592**
	PC	0.526	0.461	0.422	0.399	0.37	0.332	0.267
	HOF	0.277	0.243	0.223	0.207	0.197	0.175	0.142
Hydraulic & Other Factors (HOF)		**0.104**	**0.155**	**0.186**	**0.207**	**0.228**	**0.259**	**0.311**
	PC	0.447	0.422	0.407	0.399	0.386	0.37	0.345
	EF	0.449	0.423	0.407	0.394	0.386	0.371	0.311

The average percent differences between the baseline POCR calculated with the original PC, EC, and HOF weights, and the POCR scores calculated within each scenario of changed weights are summarized in Figure 3.3. The average differences were calculated between the cut-off values of the original POCR model, as presented in Figure 3.2, and the same cut-off values determined for each instance of changed criteria weight. Appendix D presents all calculated values for the computation of the average percent differences.

The most considerable difference of 9.48% is shown for the largest changes of the most important criteria's weight that is the PC. However, the statistical significance of this percent difference cannot be assessed. This is because, to be able to perform any type of statistical significance test, the experiment (in this case changing the criteria weights and recalculating the POCR score) must be repeated on the same sample, or model, which in this case does not happen. Because the POCR score is determined using a linear combination, any change in any of the factors will result in an obvious change of the outcome, change that cannot be determined if it is statistically significant or not.

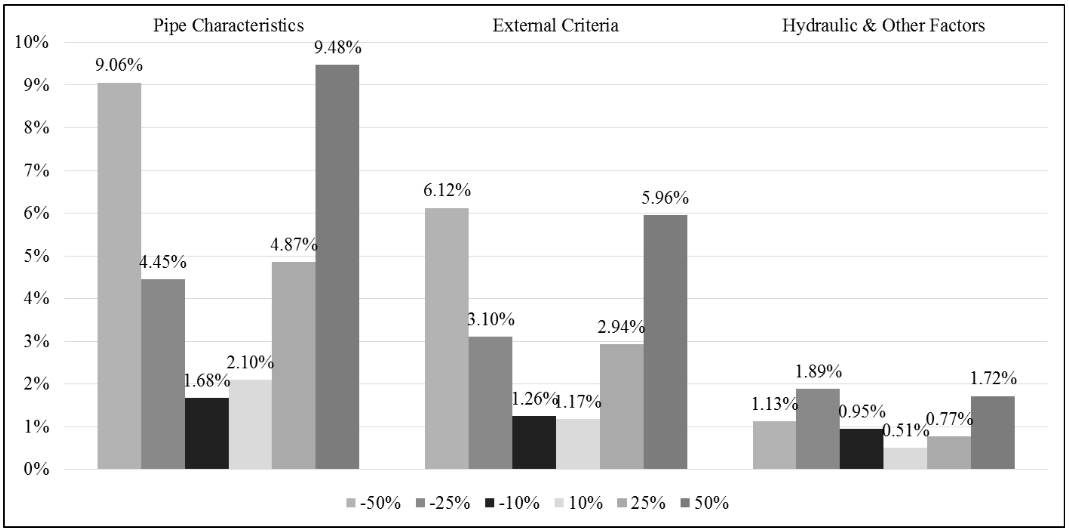

Figure 3.3. Average percent difference between original POCR score and changed criteria weight POCR score.

As a result, a cluster evaluation was performed between the changed weight POCR scores and the original POCR scores of the segments to determine how well the POCR scores agree between the original and the changed weights of the main criteria. For this, the Adjusted Rand Index (ARI) was used. The next section explains the process.

3.8.1 Adjusted Rand Index for Cluster Evaluation

The Adjusted Rand Index (ARI) is a performance measure of agreement between partitions, and it is a way to compare the results of clustering. It evaluates the consistency between two data sets in areas such as pattern recognition (Zhang & Wong, 2010).

Let $P = \{P_1, P_2, \ldots, P_r\}$ and $Q = \{Q, Q_2, \ldots, Q_s\}$ be two partitions on a data set X with N objects, where

- n_{ij} is the number of objects in partition P and in cluster Q_j in partition Q
- a_i is the number of objects in cluster P_i in partition P

- b_j is the number of objects in cluster Q_j in partition Q

Then, the overlap between these two partitions can be presented in the form of a contingency matrix. A contingency matrix, or contingency table, is typically used to show the frequency distribution of variables in statistical applications. The contingency table between the two partitions, P and Q, is presented in Table 3.15.

Table 3.15. Contingency table between two partitions, P and Q.

	Q_1	Q_2	…	Q_s	**Σ**
P_1	n_{11}	n_{12}	…	n_{1s}	$\boldsymbol{a_1}$
P_1	n_{21}	n_{22}	…	n_{2s}	$\boldsymbol{a_2}$
…	…	…	…	…	**…**
P_r	n_{r1}	n_{r2}	…	n_{rs}	$\boldsymbol{a_r}$
Σ	$\boldsymbol{b_1}$	$\boldsymbol{b_2}$	**…**	$\boldsymbol{b_s}$	$\boldsymbol{N}$

The Adjusted Rand Index, or ARI, is computed using Eq. (3.10):

$$ARI(P,Q) = \frac{Index - Expected\ Index}{Max\ Index - Expected\ Index} \quad (3.10)$$

Given the contingency matrix presented in Table 3.14, Eq. (3.11) shows the ARI.

$$ARI(P,Q) = \frac{\sum_{ij}\binom{n_{ij}}{2} - \left[\sum_{ij}\binom{a_i}{2}\sum_{ij}\binom{b_j}{2}\right]/\binom{n}{2}}{\frac{1}{2}\left[\sum_{ij}\binom{a_i}{2} + \sum_{ij}\binom{b_j}{2}\right] - \left[\sum_{ij}\binom{a_i}{2}\sum_{ij}\binom{b_j}{2}\right]/\binom{n}{2}} \quad (3.11)$$

Where:

$$\binom{n}{2} = \frac{n!}{2(n-2)!}$$

The value of the ARI is typically between 0 and 1; however, it can yield negative values as well. In cases when the assignment of labels is done randomly, the ARI is close to 0, meaning there is no similarity between the two data sets. The higher the ARI, the higher the agreement among the two analyzed partitions.

3.8.2 Adjusted Rand Index Results for Cluster Evaluation for POCR Model

To evaluate the consistency between the original POCR scores of all analyzed segments, and the POCR scores determined with the changed criteria weights (total of 18 changed weight scenarios), the ARI has been computed for each pair of partitions. As a result, a total of 19 data sets were obtained with 18 cases of ARI computations. The R code for this process is found in Appendix E. The data used for computing the ARI can be found on the CD accompanying this dissertation. Table 3.16 shows the ARI for assessing the agreements between the POCR scores of the pipe segments calculated with the considered weight change scenarios of the three main criteria, and the original POCR scores of the segments.

Table 3.16. Adjusted Rand Index results for POCR model sensitivity analysis.

	Percent Change from Original Weight					
	-50%	**-25%**	**-10%**	**10%**	**25%**	**50%**
Pipe Characteristics	0.753	0.855	0.942	0.932	0.804	0.626
External Conditions	0.417	0.703	0.857	0.866	0.784	0.592
Hydraulic & Other Factors	0.644	0.800	0.885	0.917	0.824	0.593

For differing relative importance weights of the criteria, the results summarize the ARI values that reflect the level of agreement between each case of condition scores calculated with the changed criterion weight and the original data set to assess the model's sensitivity to these changes. From the results shown in Table 3.16, it can be seen that the highest agreement between the original and the changed POCR scores is for the cases of ±

10% change of weight of PC criteria. Additionally, the ARI values are high for a ±10% change from the original weight of all three criteria. This might show that the POCR model is more robust when considering the criteria weights within the specified ± 10% interval from their original values, meaning that the resulted weights based on the AHP analysis are less sensitive to changes. The model is most sensitive to a -50% change of the EC criteria, the value of ARI being only 0.417. These results can prove to be useful for cases where a utility would re-assess the POCR model using the AHP method and consequently obtain different weights of the three main criteria.

3.9 Summary

This chapter presented the development of a wastewater pipe condition rating model that assesses the pipe's overall state of degradation by combining a series of structural, operational, and hydraulic factors. The novelty of this model is the incorporation of the PACP defect data into the final condition score. The POCR score is determined by using a linear combination between the relative importance weights of 16 factors and their respective ratings. The AHP method was used to obtain the relative importance weights of all criteria and factors. The process involved subject matter expert judgment in determining the relative importance weights of all 16 structural, operational, and hydraulic factors. The aggregation of experts' responses was achieved using the weighted geometric mean method, in which each expert had an importance weight calculated based on the consistency of their judgments. Results showed that the most important factor in determining the overall condition score of a sewer pipe is the corrosion resistance of the material, followed by the soil type. The least important factors were found to be the distribution of defects and the PACP O&M condition score.

The model was applied to a data set containing condition assessment information of wastewater pipes from a Northeastern Louisiana wastewater utility. VCP sewers of 8-inch diameter were selected for the case study. The results showed that the POCR score of the selected 633 VCP sewer segments was between 2.03 and 3.93. Based on these results, a categorization based on the POCR score of sewers was developed. Specifically, a pipe can be in condition 1, 2, or 3, and accordingly, some guidelines are provided for the action to be taken for a given segment based on its condition. A segment in condition 1 does not require any further action. For a pipe in condition 2, a re-inspection within one year is recommended for developing a rehabilitation design method. Finally, a pipe in condition 3 is in the worst overall condition and requires immediate attention.

A sensitivity analysis was performed to analyze how changing criteria and factor weights impact the outcome's overall condition score. For this, the POCR score was recalculated for all analyzed sewers, with changes of -50%, -25%, -10%, +10%, +25%, and +50% from the original weight for all three criteria. A similarity metric between data clusterings was used to compare the agreement between the original POCR scores and the POCR scores calculated with changed criteria weight. It was found that the model is most sensitive to a change of the EC factor weight by - 50%, while it showed the most agreement for all the cases of ± 10% of the three criteria weight change.

This comprehensive condition rating method can offer utilities a more in-depth overview of the factors that impact the overall condition of their sewer pipes, while still keeping track of the PACP structural and O&M condition scores. However, for ideal use of this model, more experimental applications to the case studies are needed for refining and improving the structural, operational, and hydraulic factors used in the model. The obtained POCR scores with the model presented in this chapter are used to develop a Continuous Time Markov chain deterioration model in Chapter 4.

CHAPTER 4

DETERIORATION MODEL USING CONTINUOUS TIME MARKOV CHAIN

4.1 Background

So far, a comprehensive wastewater pipe condition rating model has been developed. For a complete risk-based decision framework, the pipe's probability of failure (PoF) and consequence of failure (CoF) must also be determined. Having information about a given segment's CoF and PoF is mandatory to determine its risk of failure, at any given point in time. By having this information, decision-makers can make a more informed decision about current and future rehabilitation and replacement project planning and budgeting needs. The goal of this chapter is to present a sewer deterioration model that determines the probability of being in one of the three conditions previously derived with the model developed in Chapter 3, at any given age of the pipe. Specifically, a Continuous Time Markov Chain (CTMC) model is developed to model a pipe cohorts'[1] deterioration process over time, from existing condition assessment data. The model yields several outputs: first, a transition rate matrix is obtained, that is then used to compute the transition

[1] Pipe cohort, in this work, refers to a group of pipes that have the same characteristics, such as same pipe material, same diameter, and being part of the sewer basin.

probabilities from one condition to another at any given point in time; second, deterioration curves are developed to offer a visual representation of the pipe's conditions over time.

4.2 Markov Chain Deterioration Models for Wastewater Systems

Various studies used Markov Chain process to develop wastewater pipe deterioration models for decision-making purposes. Most research studies that focused on deterioration modeling consider the deterioration process occurring on a discrete timescale, meaning that condition changes occurred at discrete time steps (such as yearly, bi-yearly, or every five years). Some of the most known works include Abraham, Wirahadikusumah, Short, and Shahbahrami (1998), Wirahadikusumah *et al.* (2001), Kleiner (2001), Micevski *et al.* (2002) and Baik *et al.* (2006).

For example, Wirahadikusumah *et al.* (2001) developed a Discrete Time Markov Chain (DTMC) model for large combined sewers with the assumption that no more than one condition change occurs in a one year transition period. A nonlinear optimization was used to predict the transition probabilities among the five condition states, and several deterioration models were developed for various combinations between pipe material, backfill material, groundwater table elevation, and depth of cover. The conclusion of the study was that at least three consecutive data sets containing inspection data in different observation periods are needed to verify the Markovian property. In short, the Markovian property states that the conditional probability distribution of any future event is independent of past states and depends only on the current condition (Ross, 2007; Kulkarni, 1995).

Compared to a DTMC process, in a sewer pipe deterioration process modeled with Continuous Time Markov Chain (CTMC), the condition changes occur on a continuous time scale, rather than on a discrete. Kleiner (2001) used a semi-Markov process to model the deterioration of large diameter water and wastewater systems. A Markovian process in which the duration (time spent) in any state is independently distributed is called a semi-Markov model. In this particular study, the duration time was modelled as a random variable with a two-parameter Weibull probability distribution. Deterioration was assumed to occur as a one state change at a time. Inspection data was not available for the study; therefore, Monte Carlo simulation was used to generate data for calculating the duration times in each state. However, the study remains a theoretical framework due to the lack of actual data. Additionally, only the asset's age was considered as a factor affecting deterioration, and no other factors such as pipe material, diameter, soil type, or any other parameters were used to study the effect of these factors on the asset's deterioration (Baik *et al.*, 2006).

Micevski *et al.* (2002) developed a Markov model for stormwater pipes. This study differs from the previous ones in that it considered multiple state transitions over the one year transition period. The transition probabilities were estimated using the Metropolis-Hastings algorithm. The study concluded that different Markov deterioration models are required for different category pipes based on pipe diameter, pipe material, soil type, and adjacency to a coastline.

Baik *et al.* (2006) developed a Markov chain model for wastewater system deterioration. The transition probabilities were estimated using an ordered probit model separately for each of the five considered condition states. Their findings showed that longer sewer pipes are less likely to deteriorate than shorter ones, while older pipes in better condition are more likely to deteriorate at a faster pace. More so, a steeper slope of the pipe results in a higher probability of deterioration. Limitations of the model, as discussed by the authors, include the lack of integrity of the data set that led to smaller goodness of fit for the ordered probit model of conditions 4 and 5, and the subjectivity of interpreting the CCTV inspection data by certified inspectors. Additional shortcomings of the application of the ordered probit model in estimating transition probabilities of Markov chain models (i.e., Madanat, Mishalani, & Ibrahim, 1995; Baik *et al.*, 2006) has been presented by Kallen (2009). One of the most noteworthy drawbacks of estimating the transition probabilities for groups of assets using the ordered probit method is that these probabilities should be estimated directly using inspection data for all the assets and not by averaging transition probabilities of individual assets.

4.3 Markov Chain Process

4.3.1 Discrete Time Markov Chain Process

The Markov Chain (MC) process is a stochastic process in which the conditional probability distribution of any future event is independent of past states and depends only on the current condition (Ross, 2007; Kulkarni, 1995). This property of a stochastic process is called the Markovian property. According to Kallen and Van Noortwijk (2006), stochastic processes are especially useful for modeling dynamic systems that involve uncertainty over time.

Infrastructure deterioration is typically a function of the asset's age, as well as its structural and hydraulic condition over time. A Continuous Time Markov Chain (CTMC) model is useful in modeling the deterioration process of infrastructure systems such as bridges (Madanat *et al.*, 1995; Kallen & Van Noortwijk, 2006) and wastewater pipes

(Abraham *et al.*, 1998; Wirahadikusumah *et al.*, 2001; Micevski *et al.*, 2002; Kleiner *et al.*, 2004; Baik *et al.*, 2006; Sinha & McKim, 2007) over time.

Let X_n be a stochastic process $\{X_n, n=0, 1, 2 \ldots\}$ with a finite number of states. If the process is in state i at time t, then it is represented as $X_t = i$. The probability that the system will move to state j at time $t+1$ is expressed in Eq. (4.1). This is the definition of a Discrete Time Markov Chain (DTMC), where deterioration, or better said, change of condition is assumed to occur and are observed at discrete points in time.

$$P\{X_{t+1} = j | X_t = i, X_{t-1} = i_{n-1}, \ldots, X_1 = i_1, X_0 = i_0\} = p_{ij} \tag{4.1}$$

For all states i_0, $i_1 \ldots i_{n-1}$, i, j and all $n \geq 0$, and p_{ij} is the probability that, given the current condition i, the process will transition to condition j. The Markovian property is expressed in Eq. (4.2):

$$\begin{aligned} P\{X_{n+1} = j | X_n = i, X_{n-1} = i_{n-1}, \ldots, X_1 = i_1, X_0 = i_0\} &= \\ = P\{X_{n+1} = j | X_n = i\} = p_{ij} \end{aligned} \tag{4.2}$$

Sewer pipes are assumed to be installed in an excellent condition that is worsening as the pipe ages. The POCR score, previously determined in Chapter 3, describes this overall condition. So a sewer pipe will deteriorate from condition 1 at the time of installation, to a worse condition, either condition 2 or condition 3 as time passes, assuming no maintenance or rehabilitation actions are taken. Figure 4.1 presents the DTMC of a sewer deterioration process where there are three conditions the pipe can be in at any given time. The probabilities of moving from a better condition to a worse condition are shown as p_{ij}.

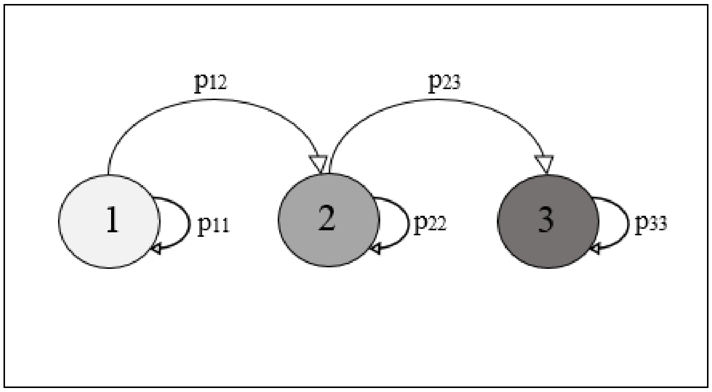

Figure 4.1. DTMC process of wastewater pipe deterioration with three condition states.

Considering the DTMC model and Eq. (4.2), the transition probabilities can be presented in a 3 x 3 transition probability matrix, P, where deterioration occurs entropically, meaning that the system can stay in the same condition, or move to a worse condition, but it cannot improve to a better condition. The transition probability matrix is presented in Eq. (4.3):

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ 0 & p_{22} & p_{23} \\ 0 & 0 & 1 \end{bmatrix} \tag{4.3}$$

Each element of matrix *P* represents the probability that a pipe that is currently in state *i* will deteriorate to state *j* at the next observation period. The transition probabilities in matrix *P* represent one-time step probabilities, depending on the condition inspection frequency (i.e., transition probabilities for one year, two years, or five years, depending on the considered observation time). Probabilities are always non-negative and the process always transitions in some other state; therefore, the following properties as shown in Eq. (4.4) are applicable:

$$p_{ij} \geq 0 \qquad i,j \geq 0; \qquad \sum_{j=0}^{\infty} p_{ij} = 1 \qquad i = 0,1,\dots,m \tag{4.4}$$

The element in the last row of matrix P represents the absorbing state; therefore, the probability is 1, meaning that once a sewer pipe enters condition state 3, it will remain there with probability 1 until it is rehabilitated or replaced. Once a sewer that is in condition 3 is replaced, it automatically moves to a better condition. For these instances, a new DTMC model must be developed, with inspection data on the conditions over time of the new replaced pipes. This aspect is not discussed in this research.

However, infrastructure deterioration occurs on a continuous time scale, as opposed to a discrete time scale. Even if deterioration is observed at discrete points in time, the process itself is still a continuous process. Therefore, it is warranted that the deterioration process is modeled as a Continuous Time Markov Chain (CTMC) model, as opposed to a DTMC.

As a result, in this research, a CTMC approach is used to model wastewater pipe deterioration. Arguments for using a DTMC rather than a CTMC for modeling infrastructure asset deterioration are that calculations are more straightforward using the former rather than the latter (Kallen & Van Noortwijk, 2006). According to Kallen and Van Noortwijk (2006), this is true, but the complexity of computations in a CTMC is not much higher than in a DTMC, thus making these simplifications is not warranted.

4.3.2 Continuous Time Markov Chain Process

4.3.2.1 Definition of a CTMC process

A CTMC is a stochastic model that describes a system with a countable state space that enters state i at time s and stays there for a random amount of time. In this study, the stochastic process $\{X(t), t \geq 0\}$ is a CTMC that describes the uncertain condition of a sewer segment over time. This is called the sojourn time, and it is exponentially distributed, with parameter q_i ($q_i \geq 0$).

Formally, a stochastic process $\{X(t), t \geq 0\}$ that has a countable state space, S, is a CTMC if it changes states at times $0 < S_1 < S_2 < \ldots$ and the embedded process $\{X_0,(X_n,Y_n), n \geq 1\}$ defined by $X_n = X(S_n+)$[2] $(n \geq 1)$, $Y_n = S_n$-S_{n-1} $(n \geq 1)$ with $S_0 = 0$ satisfies Eq. (4.5) (Kulkarni, 1995):

$$P\{X_{n+1} = j, Y_{n+1} > y, |X_n = i, Y_{n,} X_{n-1}, Y_{n-1}, \ldots, X_1, Y_1, X_0, Y_0\} = p_{ij} e^{-q_i y} \qquad (4.5)$$

where

- Y_n=S_n-S_{n-1} ($n \geq 1$) is the nth sojourn time
- S_n is the time of the nth ($n \geq 1$) transition

A CTMC, $\{X(t), t \geq 0\}$, has an embedded DTMC, $\{Xn, n \geq 0\}$, for which transition probabilities, given the sojourn times, can be expressed as shown in Eq. (4.5) (Kulkarni, 1995).

4.3.2.2 Transition Probabilities of a CTMC process

After spending exponentially distributed time in state i, the system jumps to state j with probability p_{ij} at time t. According to Kulkarni (1995, p.240), the sojourn time and the

[2] X_n=$X(S_n+)$ is the state of the system immediately after the nth transition, and is $X(S_n)$

new state depend only on the current state, that is state *i*, and not on any past states prior to time *t*. Thus, the past history impacts the future outcome through the current, present state of the system.

To find and solve the transition probability matrix at time *t*, *P(t)*, of such a process, the differential equation shown in Eq. (4.6) (forward Kolmogorov equation) must be solved:

$$\frac{\partial}{\partial \mathrm{t}} P(s,t) = P(s,t)Q(t) \tag{4.6}$$

In Equation (4.6), Q is called the transition intensity, transition rate, or generator matrix. It is important to note that *t* is the time since the process *X(t)* has started, and not the time since entering the last state (Kallen, 2009). Therefore, the transition intensities depend on the pipe's age, and not on the duration of the last state of the sewer. For a finite state space, computing the transition probability matrix *P(t)* associated with a CTMC is done using Eq. (4.7):

$$P(t) = \exp(Qt) \tag{4.7}$$

The generator matrix, *Q*, is defined as per Eq. (4.8).

$$Q = [q_{ij}] \qquad\qquad i,j \in S \tag{4.8}$$

For the generator matrix, *Q*, the sum of all elements in a row adds up to 1, as shown in Eq. (4.9):

$$\sum_{j \in S} q_{ij} = 0, \quad q_{ii} = -\sum_{j \neq i} q_{ij} = -\,q_i, \qquad i = 0, 1, \ldots, J \tag{4.9}$$

The CTMC that describes the wastewater deterioration model in this study is shown in Figure 4.2.

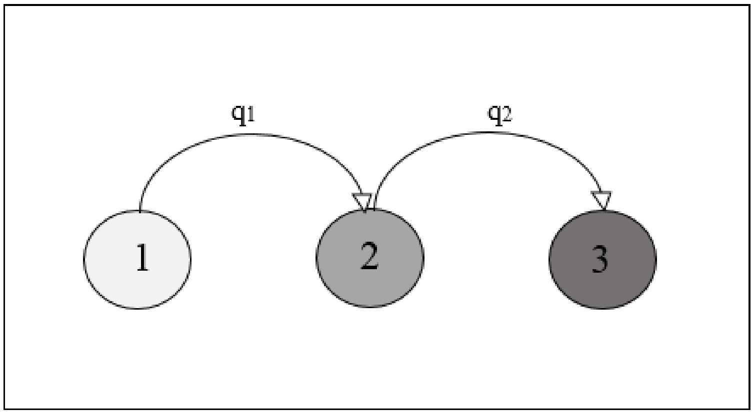

Figure 4.2. CTMC process of wastewater deterioration considered in this study.

The time spent in a state, before moving to a next state, the sojourn time *(Y_i)*, can be computed from the transition rates. As a result, the time spent in condition 1 before moving to condition 2 is calculated using the rate q_1, while the sojourn time in condition 2 is calculated using rate q_2 as shown in Eq. (4.10):

$$Y_i = \frac{1}{q_i} \tag{4.10}$$

It is said that a CTMC $\{X(t),\ t \geq 0\}$ is fully described by its initial distribution, a, and its transition probability matrix, $P(t)$. The initial distribution of a CTMC is a row vector that represents the probability mass function of the system being in state i at time $t=0$ (Kulkarni, 1995). So in the case of the CTMC presented in Figure 4.2, a is a row vector of three elements, each element representing the probability of being in any of the three states, at time 0, that is the time of installation of the pipes. Since it is assumed that the pipes were installed in almost perfect condition, the initial distribution of the CTMC in this study is the row vector shown in Eq. (4.11):

$$a = [1\ 0\ 0] \tag{4.11}$$

To find the transition probabilities at any age of the sewer pipe, the desired age must be inserted into Eq. (4.7). When observation data is available at age t of the pipe, transition probabilities to worse conditions at subsequent times are found from the transition probability matrix $P(t+s)$, where s is the time elapsed from the observation (i.e., the last CCTV inspection). However, the most difficult part of the solution is to find the generator matrix. The method to computationally find Q is described in Section 4.4.

4.4 Estimation of the Generator Matrix, Q, for CTMC

The goal of this research is to use a CTMC process to model wastewater pipe deterioration, not to develop computational methods to solve for the generator matrix. There is extensive literature across various disciplines such as medicine, business, or physics that have developed a variety of computational methods for determining Q and $P(t)$ (see for example the works of Bladt & Sørensen, 2005; 2009). In this work, estimation of the generator matrix, Q, was done by using the statistical software R, and implementing the "ctmcd" package (Pfeuffer, 2017).

The major difficulty when estimating the parameters of a CTMC is that continuously observed data is not available in most cases, but only discrete-time observations exist. This is the case of sewer condition assessment data as well. This drawback has been solved in the contributed research article of the "ctmcd" package by Pfeuffer (2017) who presents several methods to estimate the generator matrix of a CTMC.

In the current research work, the Gibbs sampling method has been used, and the following paragraphs will briefly describe it. For other computational methods available in R, the reader is referred to Pfeuffer (2017), and Bladt and Sørensen (2005, 2009).

Gibbs sampling is a Monte Carlo Markov Chain (MCMC) sampling method. MCMC methods are used in Bayesian inference to characterize a distribution by randomly drawing samples out of it without knowing all of its properties (van Ravenzwaaij, Cassey, & Brown, 2018). Any statistic of the posterior distribution can be, theoretically, computed by simulating a large number of samples from the distribution (Yildirim, 2012). As a note, prior and posterior distributions are used in Bayesian statistics where the prior distribution is an initial belief about the studied parameter, and it is updated based on the available data to obtain the posterior distribution of the parameter, using Bayes' theorem.

Gibbs sampling generates posterior distributions of the parameter (or parameters) by sequentially sampling through each parameter from its conditional distribution while the rest of the parameters' values remain fixed at their current value (Yildirim, 2012). To have an easier understanding of this process, Yildirim (2012) presented the generic algorithm of the Gibbs sampling method.

Algorithm 1 for Gibbs Sampler generalized by Yildirim (2012):

Initialize $x^{(0)} \sim q(x)$

for iteration i=1, 2,.... N **do**

$x_1^{(i)} \sim p(X_1 = x_1 | X_2 = x_2^{(i-1)}, X_3 = x_3^{(i-1)}, \dots, X_N = x_N^{(i-1)})$

$x_2^{(i)} \sim p(X_2 = x_2 | X_1 = x_1^{(i)}, X_3 = x_3^{(i-1)}, \dots, X_N = x_N^{(i-1)})$

…

$x_N^{(i)} \sim p(X_D = x_D | X_1 = x_1^{(i)}, X_2 = x_2^{(i)}, \dots, X_N = x_{N-1}^{(i)})$

end for

In the above generalized algorithm, the samples are generated by passing through all the conditional posterior distributions of the parameters, one random variable at a time. At the initialization, random samples are generated that might not be representative of the posterior distribution. As a result, these algorithms are typically run for a large number of iterations and early iterations are generally discarded. The discarded samples, or iterations, are called the burn-in period (Yildirim, 2012; Bladt & Sørensen, 2005; 2009).

To be specific, solving for the generator matrix Q in this study using the MCMC method, a prior density of the generator matrix is chosen, $\phi(Q)$, and the method is used to solve for the conditional distribution of Q given the existing data $x = \left\{x_i^k \middle| i = 1,2, \dots, n_k, k = 1,2, \dots, N\right\}$. Samples are drawn from the conditional distribution of (Q, X) given x, and by implementing the Gibbs sampler alternately X, is drawn given (Q, x) and Q is drawn given (X, x) by following the algorithm presented above. The continuous time sample paths of the process is represented by $X = \{X_t^k \big| 0 \leq t \leq \tau, k = 1,2, \dots, N\}$. Further detailed description of the Gibbs sampler is provided in Bland and Sørensen (2005) with an application to estimate transition rates between credit ratings from observations at discrete points in time.

Pfeuffer (2017) developed the “ctmcd” package for the R environment that allows for the implementation of the Gibbs sampling method to solve for the generator matrix of a CTMC, having only discrete observed data at times 0 and T. This is actually the case for many of the systems in the wastewater industry, where condition data is known at the time of installation ($t = 0$, assuming an almost perfect condition), and condition inspection is performed at another time in the future at age T of the pipe. The case study presented in Section 4.5 has this type of data as well.

Bladt and Sørensen (2005) proved that the Gamma distribution can be used as a prior distribution for estimating the off-diagonal elements of the generator matrix (Pfeuffer, 2017). As a result, the posterior distribution is derived as shown in Eq. (4.12):

$$
\begin{aligned}
& f(Q|\{s(0), s(T)\}) \\
& \qquad \propto L(Q|\{s(0), s(T)\}) \prod_{i=1}^{I} \prod_{j \neq i} q_{ij}^{\phi_{ij}-1} \exp\left(-q_{ij}\psi_i\right) \\
& \qquad \propto \prod_{i=1}^{I} \prod_{j \neq i} q_{ij}^{N_{ij}(T)+\phi_{ij}-1} \exp\left(-q_{ij}(R_i(T) + \psi_i)\right)
\end{aligned}
\tag{4.12}
$$

Briefly, the Gamma distribution is a two-parameter continuous probability distribution, where the first parameter, α, is called the shape parameter, and the second parameter, β, is the rate parameter. Both α and β are positive real numbers. In Eq. (4.12), Bladt and Sørensen (2005) define a Gamma distribution with parameters ϕ and ψ: Γ(ϕ,ψ). More details about this can be found in Bladt and Sørensen (2005, 2009).

Based on Eq. (4.12), the Gibbs sampler used in the "ctmcd" package samples at each iteration a full conditional distribution from the missing data, given the current parameter values and the existing observations at discrete times. The method simulates at each iteration the missing number of transitions from state *i* to state *j* and the cumulative sojourn times in a given state before the process moves to another state given the current parameter estimates. New parameter values are drawn then, based on the imputed data. The sampling is run for 10,000 iteration, the first 1,000 being discarded. After the 10,000 iterations, each element of the generator matrix is sampled.

4.5 Data Preparation and Implementation

The selected pipe cohort for developing the CTMC and subsequent deterioration model is Vitrified Clay (VC) sanitary sewer pipe of 8-inch diameter. To prepare the data for the R environment, a tabular format was used in a cvs file. For each pipe segment (PipeID), there were two consecutive rows of information: the first row contains data from the installation year (*t=0*), and the second row of information contains data from the inspection year (in this case 2016). Therefore, all pipe segments have two discrete time condition data points, one from the time of installation and one from the time of the only documented available inspection. The complete data set is found on the CD accompanying this dissertation. For each pipe segment, the POCR score was computed, as presented in Chapter 3. Part of the data file is shown in Table 4.1.

Table 4.1. Input data in R environment for generator matrix computation.

PipeID	Inspection ID	Flow_Control	Length_Surveyed [FT]	Insp_Year	Age [Yrs]	Pre-Cleaning	Location_Code	POCR
1	925	De-Watered using Jetter	86.8	1965	0	Jetting	Light Highway	3
1	925	De-Watered using Jetter	86.8	2016	51	Jetting	Light Highway	3
2	197	Not Controlled	49.6	1965	0	Jetting	Sidewalk	3
2	197	Not Controlled	49.6	2016	51	Jetting	Sidewalk	3
3	213	De-Watered using Jetter	527.3	1965	0	Jetting	Sidewalk	2
3	213	De-Watered using Jetter	27.3	2016	51	Jetting	Sidewalk	3
4	22	Bypassed	23	1965	0	Jetting	Light Highway	1
4	22	Bypassed	23	2016	51	Jetting	Light Highway	1
5	22	Bypassed	23	1965	0	Jetting	Light Highway	1
5	656	De-Watered using Jetter	46	2016	51	Jetting	Light Highway	2

After the data file was read into R, the absolute transition frequency matrix was calculated, as this is required as input for the Gibbs sampler algorithm. The R code is found in Appendix F. To use the method, the prior distribution must also be specified as a list object. After both the absolute transition frequency matrix and the prior distribution have been defined, the Gibbs method was called, using the following command:

Q ←gm(tm = abs_freq, te = 51, method = "GS", prior = pr, burnin = 1000)

where

- t_m is the absolute transition frequency matrix
- t_e is the average elapsed time between observations (in years)
- method stands for Gibbs sampler
- prior is the prior distribution defined in a list form
- burnin is the first 1000 iterations that are removed from the method
- Q is the 3x3 generator matrix obtained with using the Gibbs sampler method

The Gibbs sampler method runs for 10,000 iterations, from which the first 1,000 are removed due to them not being fully representative of the posterior distribution of the generator matrix elements (Bladt & Sørensen, 2005; 2009). The results are discussed in the next section.

4.6 Results

4.6.1 Generator Matrix

The code for obtaining the generator matrix of the CTMC is in Appendix F. Once the code was run, each element of the generator matrix Q was determined, following the

10,000 iterations of the Gibbs sampler. The generator matrix that shows the transition rates between conditions for the analyzed VC pipe cohort is presented in Eq. (4.13):

$$Q = \begin{bmatrix} -2.4980 & 2.4980 & 0 \\ 0 & -0.5167 & 0.5167 \\ 0 & 0 & 0 \end{bmatrix} \quad (4.13)$$

From the generator matrix, the sojourn times were calculated using Eq. (4.10). The results show that the time spent in condition 1, before moving to condition 2, is on average 20.42 years, and the time spent in condition 2, before moving to the worst condition 3, is 93.60 years. Based on the sojourn times, a VC pipe of 8-inch diameter from the analyzed cohort moves to the worst condition after 114.12 years. Figure 4.3 presents these results.

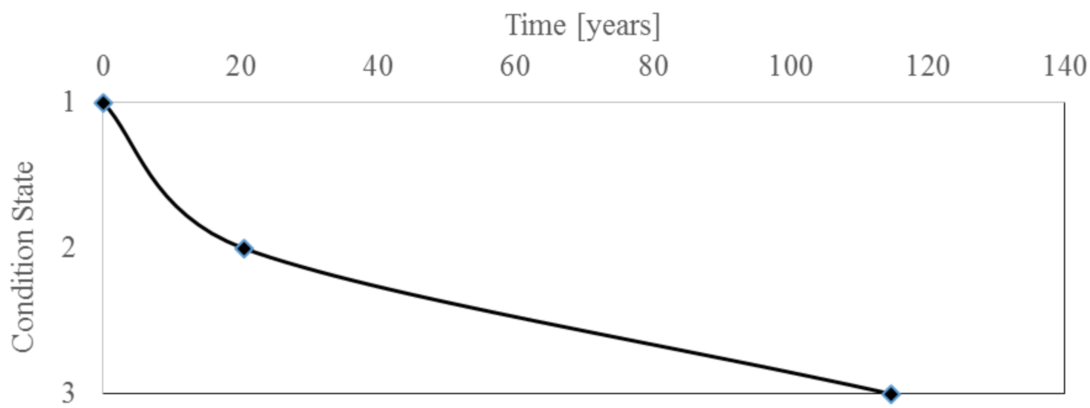

Figure 4.3. Sojourn times of VC pipe 8-inch.

4.6.2 Transition Probabilities

Once the generator matrix is found, transition probabilities for given age of pipe are easily found using Eq. (4.7). Note that the time interval between the observations is 51 years; therefore, a factor of (*t/51*) must be accounted in the exponential expression, where *t* is the time between the observation and desired time. The one-step transition probability matrix is therefore computed as shown in Eq. (4.14):

$$P(1) = \exp((\tfrac{1}{51})Q) = \begin{bmatrix} 0.952 & 0.047 & 0.001 \\ 0 & 0.989 & 0.011 \\ 0 & 0 & 1 \end{bmatrix} \tag{4.14}$$

Thus, Eq. (4.14) shows the one year transition probabilities between conditions from the last observation. The probability of failure is defined as the probability of entering the worst state that is condition 3 from any of the conditions 1 or 2. As a result, the one year probability of failure for a pipe that is in condition 1 is 0.001, and for a pipe that is in condition 2 is 0.011.

It can be verified that the sum of rows of matrix Q is 0, and the sum of rows of matrix *P(1)* is 1, as previously mentioned. Similarly as shown in Eq. (4.10), the 10 year, 20 year, 30 year, up until the 200 year transition probabilities were computed. According to the National Clay Pipe Institute's Vitrified Clay Pipe engineering manual, the maximum design life of VCP pipes is 200 years (National Clay Pipe Institute, 2015). Figure 4.4 shows the probability of being in any of the three states based on the pipe's age. The plot was obtained by iterating through 200 time steps (the 200 years of life of VCP) and computing *P(t)* at each time step, using Eq. (4.7), and knowing the initial distribution, *a* (Eq. 4.10).

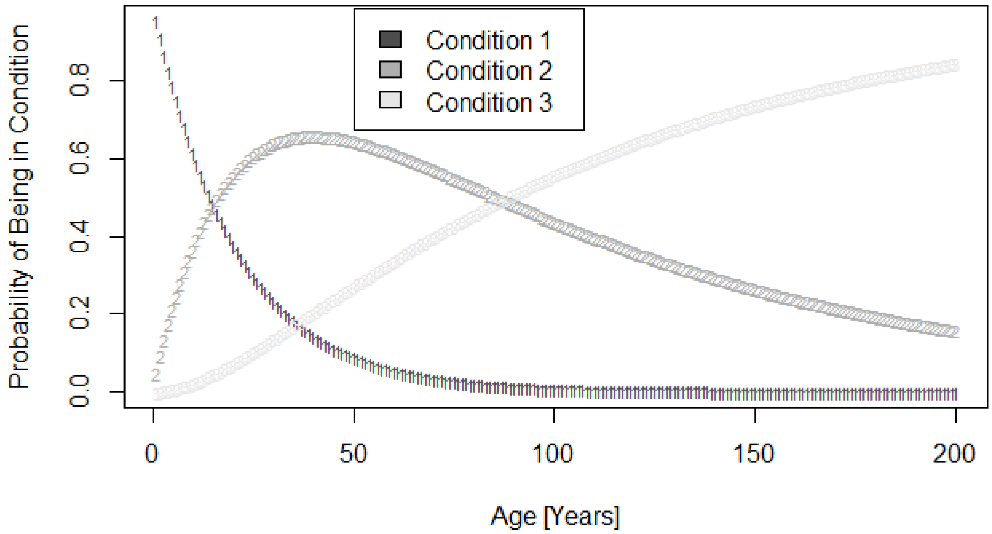

Figure 4.4. Probability of being in any of the three conditions based on the pipe's age for VC pipe of 8-inch.

From Figure 4.4 it can be seen that at the approximate age of a pipe of 87 years, the probability of being in the worst condition state (condition 3) increases, while the probability of being in the best condition state 1 is 0. The probability of failure at the age of 200 years is 0.85. The finding corroborates the results of Salman and Salem (2011), who developed a deterioration model for VCP with a 12-inch diameter. However, it is important to note that the large data gap of 51 years is not desirable and might lead to inaccurate estimations of the generator matrix that subsequently may lead to unreliable probability estimates. More details are discussed in the next section.

4.7 Summary

This chapter presented the application of the "ctmcd" R package to a set of wastewater pipe discrete time condition data. The analyzed pipes were selected from one sewer basin and are VC pipes with a diameter of 8-inch. The condition of the pipes was observed at two different times: observations at the time of pipe installation in 1965 (at time $t = 0$), and observations after 51 years in 2016 ($t = 51$). It was assumed that at time 0, almost all sewers were in excellent condition (condition 1). It was also assumed that a small percentage of the installed sewers reached conditions 2 and 3 very shortly after installation due to unforeseen problems, such as structural defect when installed, or poor workmanship upon installation. Specifically, 3% of the pipes were in condition 2 and 3% were in condition 3 shortly after installation (percentage by length). This was necessary to ensure that the probabilities p_{23} and p_{33}[3] exist in the matrix. The application of the model is presented in Chapter 6.

The R package "ctmcd" was used to find the generator matrix of the CTMC model which describes the pipes' deterioration process. The Gibbs sampling method was implemented to find the generator matrix. Once the generator matrix was found, transition probabilities were determined based on Eq. (4.7) starting from the observation time in 2016 to any desired future time. More importantly, PoF values from any observed condition in 2016 can be determined as the probability of transitioning from any condition to condition 3 during the analyzed time period. A limitation of the developed CTMC model is the fact that the available observation data has a large gap of 51 years. This makes the results of the elements of Q matrix obtained from the implementation of the Gibbs sampling uncertain in terms of how accurately the transition rates actually reflect the transition rates between the conditions. If more observation data were available at shorter time intervals, the accuracy of the Q matrix could be improved. Additionally, a larger data with multiple

[3] Note: p_{33} is the probability of being in condition 3 at time 0, and staying in condition 3 at the time of observation 51 years later. Similarly, p_{23} is the probability of being in condition 2 at time 0, and observing the pipe in condition 3 in 2016, 51 years later.

inspections at various points in time would allow for validation of the developed deterioration model. As of now, the developed CTMC model could not be validated due to insufficient data.

CHAPTER 5

PIPE CONSEQUENCE OF FAILURE

5.1 Background

This chapter presents the second critical components of the risk-based decision-making framework for sewer pipe rehabilitation and renewal planning, a comprehensive Consequence of Failure of Sewers (COFS) model. The COFS model is built using the TBL methodology and includes a total of 14 factors. The model is developed using multi-criteria decision-making by implementing the AHP method. Parts of this work have been presented in Vladeanu & Matthews (2018b). Having the COFS score, together with the PoF value obtained as previously presented in Chapter 4 allows for determining the risk of failure of the analyzed sewers for risk-based decision-making purposes. A sensitivity analysis was also performed for this model, similarly as in Chapter 3, using the ARI values. The goal of this model is to present a repeatable and robust technique to determine COFS scores of wastewater pipes to assess asset criticality for risk-based decision-making.

5.2 Consequence of Failure of Sewers (COFS) Model

The COFS model is based on the TBL method and it assesses the impact of a potential sewer failure from a combination of economic, social, and environmental perspectives. A total of 14 factors have been identified and used from the PACP CoF guidelines and extensive literature review. The resulting COFS score is on a continuous numerical scale between 1 and 5, given that a series of pipe parameters and demographics of the pipe are known. The 14 factors are arranged under the three main criteria (economic, social, and environmental) hierarchically, and their relative importance weights are computed using the multi-criteria decision-making method AHP.

To determine the relative importance weights of the three criteria and 14 factors, subject matter expert input from the public and private sector was used. Subject matter experts consisted of six experts with extensive experience in sewer pipe condition assessment and rehabilitation. Five of the questioned experts have PACP certification and have been working closely with NASSCO for at least ten years. The COFS model is presented in Figure 5.1.

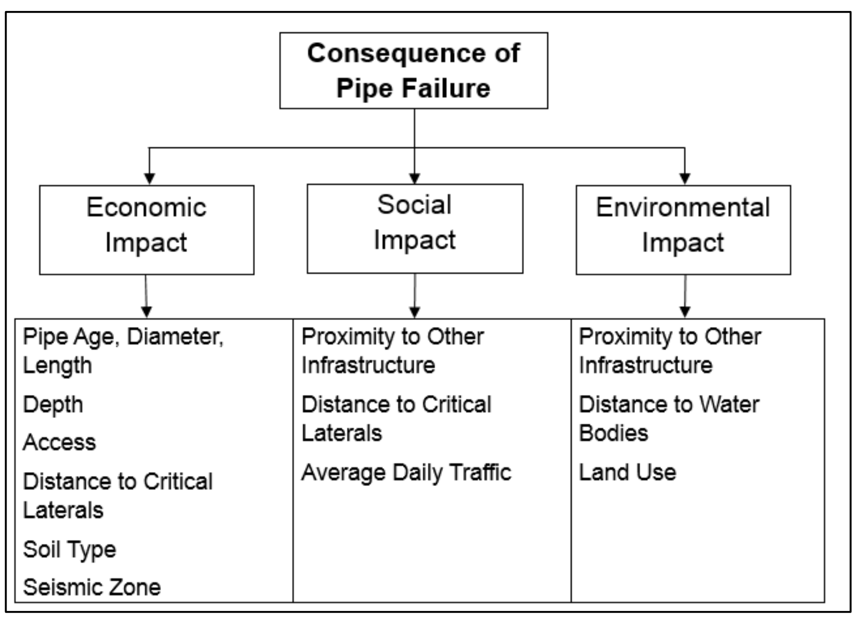

Figure 5.1. Hierarchical COFS model.

The AHP method has been implemented in the case of the COFS model as well, as previously presented in Chapter 3. Once the relative importance weights of all criteria and factors are obtained, Eqs. (5.1) through (5.4) are used to determine the COFS score of the individual sewer pipe segments:

$$\text{COFS} = w_{EC} \times \text{EC} + w_{SC} \times \text{SC} + w_{ENV} \times \text{ENV} \tag{5.1}$$

$$\text{EC} = \sum_{i=1}^{n} (w_i x R_i) \tag{5.2}$$

$$\text{SC} = \sum_{j=1}^{m} (w_j x R_j) \tag{5.3}$$

$$\text{ENV} = \sum_{k=1}^{o} (w_k x R_k) \tag{5.4}$$

Table 5.1 presents the COFS criteria and factors' description.

Table 5.1. Description of COFS model criteria and factors.

Criteria	Factor	Description and Importance
Economic Impact	Pipe Age	The time (in years), between pipe installation and inspection year. Aged pipes have higher probability for collapsing.
	Pipe Diameter	Nominal pipe diameter. Smaller diameter pipes are more likely to suffer beam failure.
	Pipe Length	Length of pipe segment. Bending stresses affect longer pipes.
	Depth	Higher depth sewers increase the consequence of failure.
	Access to Pipe	The ease of access of repair crews to the pipe in case of a potential failure: Right of way, public land, private land, behind structures, with and without vehicle access.
	Distance to Critical Laterals	The distance (ft.) from the affected sewer line to other critical buried infrastructure assets such as gas mains, water lines.

Criteria	Factor	Description and Importance
	Soil Type	Low, low to moderate, moderate, moderate-to-high, and high corrosiveness.
	Seismic Zone	Zone 1, Zone 2, Zone 3, Zone 4, and Zone 5*
Social Impact	Proximity to Other Infrastructure	Distance from affected sewer line to other major infrastructure component such as road (based on category of road), major collectors, buildings, and highways/waterways.
	Distance to Critical Laterals	The distance (ft.) from the affected sewer line to other critical buried infrastructure assets such as gas mains, water lines.
	Average Daily Traffic	Low, low-to-moderate, moderate, moderate-to-high, and high traffic.
Environmental Impact	Proximity to Other Infrastructure	Distance from affected sewer line to other major infrastructure component such as road (based on category of road), major collectors, buildings, and highways/waterways.
	Distance Between Pipe and Water Body	Distance (ft.) between the affected sewer line and major water bodies such as rivers, lakes, etc.
	Land Use	Type of use of the land/property the affected sewer line is on, such as recreational, residential, commercial, industrial, wetlands/preservation areas.

***** Based on 2017 USGS Seismic Maps:
Seismic Zone 1: ND, MN, WI, MI, IA, NE, FL, South LA, TX, Northeast MT, West KS, OK (except Central)
Seismic Zone 2: West NY and PA, OH, WV,VA, East NC, MD, DC, South GA, South AL, South MS, North LA, Southwest AR, Central OK, East KS, North IL, North IN, North KY, North and West MO, North TX, East CO, East NM, South SD, North NE, ME, North NH, North VT
Seismic Zone 3: Parts of East SC, AR and MO, Parts of South IL, Parts of West KY and TN, North of VT, Central WA, Large part of OR and NV, Central AK, Central CA, Parts of NM, AZ, Co and TN, MA, CT, RI, East NY, North NJ, East PA
Seismic Zone 4: Parts of West WA, OR, CA, NV, WY, and MT, Parts of East SC, AR and MO, Parts of South IL, Parts of West KY and TN, Parts of MT, West WY, East ID, Central UT
Seismic Zone 5: West and East CA, West NV, West WA, West OR, HI, South AK

Table 5.2 presents the rating of factors of the COFS model.

Table 5.2. Rating of COFS model factors.

Criterion	Factor	Attributes	Rating
Economic Cost	Pipe Age	< 10	1
		≥ 10 yrs and < 25 yrs	2
		≥ 25 yrs and < 40 yrs	3
		≥ 40 yrs and < 50 yrs	4
		≥ 50 yrs	5
	Pipe Diameter	≤ 6"	1
		> 6" and ≤ 12"	2
		> 12" and ≤ 18"	3
		> 18" and < 30"	4
		≥ 30"	5

Criterion	Factor	Attributes	Rating
	Pipe Length	> 20’	1
		≥ 20’ and < 40’	2
		≥ 40’ and < 60’	3
		≥ 60’ and < 80’	4
		≥ 80’	5
	Depth	≤ 4'	1
		> 4' and < 10'	2
		≥ 10' and < 18'	3
		≥ 18' and < 24'	4
		≥ 24'	5
	Access	Right-of-Way W-W/O Traffic Control	1
		Public Land W/Vehicle Access	2
		Public Land W/O Vehicle Access	3
		Private Land W/Vehicle Access	4
		Behind Structures W/O Vehicle Access	5
	Distance to Critical Laterals	≥ 20,000’	1
		12,000’ to 20,000’	2
		7,000’ to 12,000’	3
		1,000’ to 7,000’	4
		< 1,000’	5
	Soil Type	Granular (Crushed Stone/Gravel)	1
		Coarse Grained (Gravelly Sand)	2
		Silty/Clayey Gravels	3
		Fine Grained (Sands/Silts)	4
		Inorganic Silts/Clays	5
	Seismic Zone	Zone 1	1
		Zone 2	2
		Zone 3	3
		Zone 4	4
		Zone 5	5
Social Cost	Proximity to Other Infrastructure	Unpaved Road	1
		Major Local Road	2
		Collector	3
		Arterial/ Building	4
		Highway/ Waterway	5
	Distance to Critical Laterals	≥ 20,000’	1
		12,000’ to 20,000’	2
		7,000’ to 12,000’	3
		1,000’ to 7,000’	4
		< 1,000’	5
	Average Daily Traffic	Low	1
		Low to Moderate	2

Criterion	Factor	Attributes	Rating
		Moderate	3
		Moderate to Heavy	4
		Heavy	5
Environmental Cost	Proximity to Other Infrastructure Components	Unpaved road or minor local road	1
		Major local road	2
		Collector	3
		Arterial/Building/Pool	4
		Highway/Waterway	5
	Distance Between Pipe and Water Body	≥ 150’	1
		100’-150’	2
		60’-100’	3
		25’-60’	4
		< 25’	5
	Land Use	Recreational	1
		Residential	2
		Commercial	3
		Industrial	4
		Wetlands, preservation areas	5

5.3 Analytic Hierarchy Process Results

5.3.1 Aggregation of Individual Experts’ Judgments

The questionnaires have been filled out by six subject matter experts with extensive experience in wastewater pipe condition assessment and trenchless rehabilitation methods. However, after performing the AHP analysis on the individual responses, it was found that out of the six experts, only three had consistent answers. Therefore, the inconsistent results were not considered in this study.

The comparison matrices from three experts were analyzed. The CR of all of their comparison matrices were less than 0.1, meaning that their judgments were consistent. Local relative importance weights of factors affecting sewer pipe condition were obtained and are presented in Table 5.3.

Table 5.3. Relative importance weights and ranking of COFS model factors for all experts.

Criteria vs Goal	**Expert 1**		**Expert 2**		**Expert 3**	
	Weight	Rank	Weight	Rank	Weight	Rank
Economic Cost	0.648	1	0.633	1	0.334	1
Social Cost	0.122	3	0.26	2	0.333	2
Environmental Cost	0.23	2	0.106	3	0.333	3
Factors vs Criterion	**Expert 1**		**Expert 2**		**Expert 3**	
Economic Cost	Weight	Rank	Weight	Rank	Weight	Rank
Age	0.199	3	0.044	7	0.016	8
Diameter	0.056	5	0.228	2	0.213	4
Length	0.035	6	0.229	1	0.214	1
Depth	0.202	2	0.212	3	0.214	2
Access	0.026	8	0.098	4	0.213	3
DCL*	0.027	7	0.086	5	0.042	7
Soil Type	0.138	4	0.067	6	0.042	6
Seismic Zone	0.317	1	0.036	8	0.046	5
Social Cost	**Expert 1**		**Expert 2**		**Expert 3**	
	Weight	Rank	Weight	Rank	Weight	Rank
POI**	0.643	1	0.111	2	0.111	2
DCL*	0.074	3	0.111	3	0.111	3
Average Traffic	0.283	2	0.778	1	0.778	1
Environmental Cost	**Expert 1**		**Expert 2**		**Expert 3**	
	Weight	Rank	Weight	Rank	Weight	Rank
POI**	0.429	1	0.143	3	0.143	3
DWB***	0.428	2	0.714	1	0.429	1
Land Use	0.143	3	0.143	2	0.428	2

*Distance to Critical Laterals **Proximity to Other Infrastructure ***Distance to Water Bodies

There is a common agreement that the Economic Cost has the highest priority in determining the consequence of failure of a sewer pipe, followed by the Social and Environmental costs, respectively, as agreed by two of the experts. The importance of the factors under the criteria varies by expert, but there is a consensus between two of the experts in each of the following cases: the length of the pipe is the most important factor under the Economic Cost criterion, the average traffic is the top ranked factor among the factors that impact the Social Cost criterion, and the distance to water bodies is the most important factor under the Environmental Cost factors.

Next, the consistency measures CR and ED were computed for all three experts, based on Eq. (3.2) and (3.3), to find the individual weight of their judgments. This is presented in Table 5.4.

Table 5.4. Consistency Ratios (CR) and Euclidean Distances (ED) of expert judgments for the POCR model.

	Expert 1		**Expert 2**		**Expert 3**	
	CR	**ED**	**CR**	**ED**	**CR**	**ED**
Criteria vs Goal	0.003	0.355	0.033	1.247	0	0
Economic Cost	0.087	5.035	0.045	4.439	0.065	7.219
Social Cost	0.056	1.869	0	0	0.083	0.805
Environmental Cost	0	0	0	0	0	0
Σ	**0.146**	**7.258**	**0.078**	**5.686**	**0.148**	**8.024**

Once the consistency measures CR and ED are determined, the final judgment weights of the three experts are determined based on the method previously described in Section 3.4. The results are summarized in Table 5.5.

Table 5.5. Weights of expert judgments based on consistency measures CR and ED for COFS model.

	Expert 1	**Expert 2**	**Expert 3**
1/Σ CR	6.841	12.829	6.759
1/Σ ED	0.138	0.176	0.125
Normalized CR	0.259	0.485	0.256
Normalized ED	0.314	0.401	0.284
Expert's Judgment Weights, w_k	**0.287**	**0.443**	**0.270**

5.3.2 Relative Importance Weights of Factors Affecting Wastewater Consequence of Failure

The final and most important step is determining the relative importance weights of the 14 factors and three criteria. This is done by using Eq. (3.4) and all the information from Tables 5.4 and 5.5. The relative importance weights, global weights, and rankings of all factors and criteria are shown in Table 5.6.

Table 5.6. Relative importance weights of criteria and factors in the COFS model.

Criteria	Factors	Criteria Weight	Relative Importance Weight of Factor	Global Weight of Factors	Final Ranking of Factors
Economic Cost		**0.570**			
	Age		0.063	0.036	12
	Diameter		0.183	0.104	4
	Length		0.160	0.091	5
	Depth		0.256	0.146	2
	Access		0.100	0.057	7
	DCL		0.061	0.035	13
	Soil Type		0.089	0.051	8
	Seismic Zone		0.088	0.050	9
Social Cost		**0.238**			
	POI		0.246	0.059	6
	DCL		0.107	0.025	14
	Average Traffic		0.647	0.154	1
Environmental Cost		**0.192**			
	POI		0.211	0.041	10
	DWB		0.581	0.111	3
	Land Use		0.208	0.040	11

The global weights are obtained by multiplying the individual factor's relative importance weight with the weight of the criterion under which it falls. The sum of global weights is 1. The overall ranking of the 14 factors was obtained by ranking them based on their global weights. The first three most important factors, by weight, are each in one of the three main criteria: average traffic (Social), depth of burial (Economic), and distance to bodies of water (Environmental).

5.3.3 Application of the COFS Model

To apply the developed COFS model, the same VCP 8-inch cohort was selected as in the case of the POCR model application. For cases of missing information, the same process as for the POCR model was followed in which the ratings were distributed randomly, in equal proportions, among all 633 sewer pipes. There was no known information about the depth, distance to critical lateral, soil type, proximity to other infrastructure, distance to bodies of water, and land use. For all of these factors, 20% of all sewers have been randomly assigned the rating 1, then 20% of all sewers have been randomly assigned the rating 2, and so forth with the remaining ratings of 3, 4, and 5. This practice allowed for an unbiased representation of the factors for which there was no known information. However, due to not having this information about the geospatial characteristics of the assets, vital information related to the consequence of a potential failure is lost. This situation is almost always avoided by wastewater utilities with the use of the latest Geographic Information System (GIS) data. This type of data was not available for this research work.

Ratings of factors previously determined for the POCR model, such as depth and soil type, were the same for the corresponding pipes. The required information to compute the COFS score was previously presented in Tables 5.1 and 5.2. Existing information about the selected sewer segments can be found in Table 3.9. Economic impact factors of selected sewer segments are presented in Table 5.7., while social and environmental factors are shown in Table 5.8.

Table 5.7. COFS model economic cost factors of selected sewer pipes.

	Economic Cost				
Inspection ID	**Length [ft.]**	**Depth [ft.]**	**DCL* [ft.]**	**Soil Type**	**Seismic Zone**
925	> 80	≥ 10 and < 18	1,000 to 7,000	Inorganic silts and inorganic clays	Zone 2
197	> 80	≥ 10 and < 18	≥ 20,000	Fine grained soils (very fine sands and silts)	Zone 2
213	> 80	≥ 18 and < 24	1,000 to 7,000	Inorganic silts and inorganic clays	Zone 2
822	> 80	≤ 4	7,000 to 12,000	Silty gravels, clayey gravels	Zone 2
3656	> 80	≥ 10 and < 18	12,000 to 20,000	Granular soil (crushed stone, gravel)	Zone 2
343	> 80	> 4 and < 10	≥ 20,000	Granular soil (crushed stone, gravel)	Zone 2
334	> 80	≥ 24	7,000 to 12,000	Coarse grained soils (gravel-sand mixtures)	Zone 2

Table 5.8. COFS model social and environmental cost factors of selected sewer pipes.

	Social Cost			Environmental Cost		
InspectionID	**POI****	**DCL* [ft.]**	**Avg. Daily Traffic**	**POI****	**DWB*** [ft.]**	**Land Use**
925	Unpaved Road	1,000 to 7,000	Moderate	Unpaved Road	60-100	Commercial
197	Major Local Road	≥ 20,000	Low to Moderate	Major Local Road	25-60	Residential
213	Highway/ Waterway	1,000 to 7,000	Low to Moderate	Highway/ Waterway	< 25	Residential
822	Highway/ Waterway	7,000 to 12,000	Moderate	Highway/ Waterway	25-60	Commercial
3656	Major Local Road	12,000 to 20,000	Moderate	Major Local Road	100 -150	Commercial
343	Unpaved Road	≥ 20,000	Moderate	Unpaved Road	60 -100	Commercial
334	Highway/ Waterway	7,000 to 12,000	Moderate	Highway/ Waterway	≥ 150	Commercial

The COFS scores were calculated, using Eqs. (5.1) to (5.4) for all individual sewer segments. The obtained COFS scores for selected pipes are presented in Table 5.9.

Table 5.9. COFS scores of selected sewer pipes.

InspectionID	Economic Impact Score	Social Impact Score	Environmental Impact Score	COFS SCORE
925	3.350	2.614	2.577	3.026
197	3.039	1.893	3.162	2.790
213	3.568	2.952	4.377	3.577
822	2.599	3.492	4.004	3.081
3656	3.049	2.647	2.208	2.792
343	2.740	3.492	2.261	2.827
334	3.472	3.385	2.261	3.219

For the analyzed VCP cohort, the minimum COFS score was 1.750 and the maximum was 3.918. A more detailed analysis is presented in Chapter 6.

5.4 Consequence of Failure Categories Based on COFS Score

The COFS score of a wastewater pipe is a measure of its consequence of an unforeseen, potential failure. A score of 5 represents the highest consequence, while a score of 1 shows a pipe with a very low consequence of failure. However, reaching a score of 5 involves the fact that the majority of the 14 factors have a rating of 5. As seen from the results in Section 5.3.3, the maximum COFS score of the analyzed pipe cohort was 3.918. If the majority of the 14 factors have intermediate values of 2, 3, and 4, the COFS score will be in this interval, even if some remaining factors have a rating value of 5. Only in extreme cases will the COFS score reach the threshold of the maximum score of 5.

Therefore, to categorize each segment into a consequence of failure category based on the segment's COFS score, the following method was implemented.

The top ranked factor based on the AHP analysis is the Average Daily Traffic factor. For the purposes of this study, the selection criteria is this factor. Based on the average daily traffic, five cases were analyzed. In in each one, all but the average traffic factors were given the same rating. First, all factors were set to 1, then all were given a rating of 2, then a rating of 3, 4, and finally all factors' ratings were set to 5. The purpose of this process was to obtain an approximate interval variability of the COFS score, based on the value of the factor ratings, similarly as what was previously presented in Chapter 3, Section 3.7. The results are summarized in Table 5.10.

Table 5.10. COFS score by average daily traffic.

Average Daily Traffic	All 1's	All 2's	All 3's	All 4's	All 5's
1	1	1.846	2.692	3.538	4.384
2	1.154	2	2.846	3.692	4.538
3	1.308	2.154	3	3.846	4.692
4	1.462	2.308	3.154	4	4.846
5	1.616	2.462	3.308	4.154	5

Based on the values presented in Table 5.10, the following categories of consequence of failure were defined: a COFS score of less than or equal to 2.692 means the pipe has a low consequence of failure, a COFS score between the values of 2.692 and 3.538 means that the pipe has a moderate consequence, and all COFS score values that are larger than or equal to 3.538 mean that the pipe has a high consequence of failure. It can be seen that these critical values were defined based on the COFS values in the case of low daily traffic and were selected as a result of encompassing an average value of all 14 factors' ratings. A detailed case study is presented in Chapter 6. Figure 5.2 presents the consequence of failure categories of sewer pipes based on the thresholds of the COFS score values.

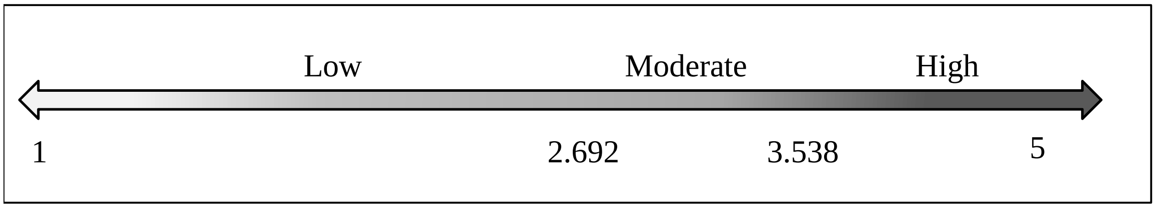

Figure 5.2. Categories of consequence of sewer pipe failure based on COFS score.

5.5. <u>Sensitivity Analysis of COFS Model</u>

The goal of the sensitivity analysis for the COFS model is to answer the following questions: How will the COFS score change if the relative importance weights of the three main criteria is changed? To answer this question, the relative importance weights of the criteria were incrementally changed from their original weights. Super Decisions software was used (Saaty & William, 2004). The same methodology as previously described in Chapter 3, Section 3.8 was followed.

To analyze the sensitivity of the COFS score to the changing factor weights, the weights of criteria EC, SC and ENV were changed from their original weights of 0.502, 0.266, and 0.232, respectively, as follows: -50%, -25%, -10%, +10%, +25%, and + 50%. This led to a change of values of the three criteria presented in Table 5.11.

Table 5.11. Changing criteria weight for sensitivity analysis of COFS model.

Criterion		-50%	-25%	-10%	Original	10%	25%	50%
Economic Cost	EC	**0.285**	**0.299**	**0.428**	**0.570**	**0.627**	**0.713**	**0.855**
	SC	0.396	0.317	0.269	0.238	0.206	0.159	0.080
	ENC	0.319	0.255	0.218	0.192	0.167	0.128	0.065
Social Cost	SC	**0.093**	**0.140**	**0.167**	**0.238**	**0.205**	**0.233**	**0.279**
	EC	0.681	0.646	0.625	0.570	0.596	0.576	0.541
	ENV	0.226	0.214	0.208	0.192	0.198	0.190	0.180
Environmental Cost	ENV	**0.091**	**0.137**	**0.164**	**0.192**	**0.201**	**0.228**	**0.274**
	EC	0.643	0.609	0.590	0.570	0.565	0.545	0.512
	SC	0.266	0.254	0.246	0.238	0.234	0.227	0.214

Using Super Decisions, at each change of the criteria's weight, all factors' weights are automatically recalculated. Based on the changed weights of the criteria, there are a total of 18 scenarios (six changed weights for each criteria with the corresponding weights of all factors) for which the COFS score has been recalculated. Each of the 18 scenarios of changed weights has been applied to the analyzed pipe segments (633 total segments of VC pipe with 8-inch diameter), and in each case, the COFS score of each individual segment has been recalculated. The changed weights of all factors for the 18 scenarios is found in Appendix G.

The average percent difference between the original COFS calculated with the initial EC, SC, and ENV weights, and the POCR scores calculated within each scenario of changed weights is summarized in Figure 5.3. The average differences were calculated between the cut-off values of the original COFS model, as presented in Figure 5.2, and the cut-off values determined for each instance of changed criteria weight. Appendix H presents all calculated values for the computation of the average percent differences.

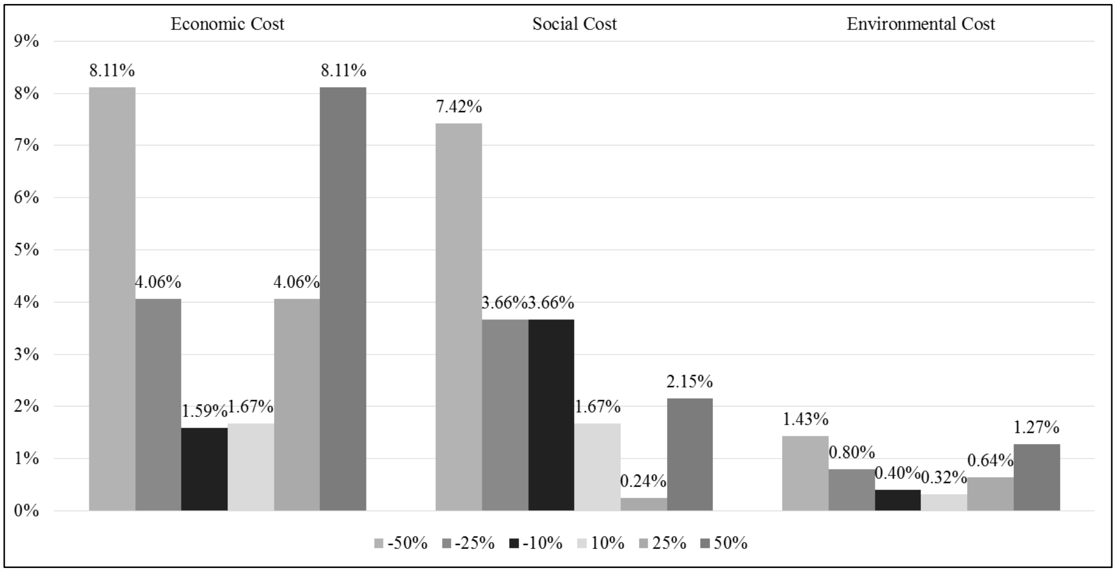

Figure 5.3. Average percent difference between original and changing criteria weight calculated COFS score.

The largest difference of 8.11% is shown for the largest changes for criteria EC. However, the statistical significance of this percent difference cannot be assessed. This is due to the fact that, to be able to perform any type of statistical significance test, the experiment, in this case, changing the criteria weights and recalculating the COFS score, must be repeated on the same sample, or model, which in this case does not happen. Because the COFS score is determined using a linear combination, any change in any of the factors will yield an obvious change in the outcome, change that cannot be determined if it is statistically significant or not.

As a result, a cluster evaluation was performed between the changed weight COFS scores and the original COFS scores of the segments to determine how well the COFS scores agree between the original and the changed weights of the main criteria. For this, the Adjusted Rand Index (ARI) was calculated. The ARI was previously detailed in

Chapter 3, Section 3.8.1. Therefore, the next section presents the results of the ARI values for the sensitivity analysis of the COFS model.

5.5.1 Adjusted Rand Index Results for Cluster Evaluation for COFS Model

To evaluate the consistency between the original COFS scores of all analyzed segments, and the COFS scores determined with the changed criteria weights (total of 18 changed weight scenarios), the ARI has been computed for each pair of partitions. As a result, a total of 19 data sets were obtained with 18 cases of ARI computations. The R code for this process is found in Appendix I. Table 5.12 shows the resulted ARI values for assessing the agreements between the COFS score of the analyzed segments calculated with the considered weight change scenarios of the three main criteria, and the original COFS scores of the segments.

Table 5.12. Adjusted Rand Index results for COFS model sensitivity analysis.

	Percent Change from Original Weight					
	- 50%	**- 25%**	**- 10%**	**10%**	**25%**	**50%**
Economic Cost	0.540	0.594	0.856	0.871	0.710	0.529
Social Cost	0.782	0.864	0.911	0.886	0.792	0.687
Environmental Cost	0.701	0.820	0.874	0.896	0.848	0.702

From the results summarized in Table 5.12, it can be seen that the highest agreement between the original and the changed COFS scores is for the cases of ± 10% change of weight of the Social Cost criterion. Additionally, the ARI values are high for a ± 10% change from the original weight of all three criteria. This might show that the COFS model is more robust when considering the criteria weights within the specified interval from their original values, meaning that the resulted weights based on the AHP analysis are less sensitive to changes.

The model is most sensitive to a ± 50% change of the Economic Impact criteria, where the ARI is approximately 0.53 between the original and the changed weight partitions. These results can prove to be useful for cases where a utility would re-assess the COFS model using the AHP method and consequently obtain different weights of the three main criteria.

5.6 Summary

This chapter presented the development of a consequence of failure model for wastewater pipes that assesses the impact of a potential failure using the TBL method, combining a series of economic, social, and environmental cost factors. The COFS score is determined using a linear combination between the relative importance weights of 14 factors and their respective ratings. The AHP method was used to obtain the relative importance weights of all criteria and factors. The process involved subject matter expert judgment in determining the relative importance weights of all 14 economic, social, and environmental cost impact factors. The aggregation of experts' responses was achieved using the weighted geometric mean method, in which each expert had an importance weight calculated based on the consistency of their judgments. Results showed that the most critical factor that impacts the consequence of sewer pipe failure is the average daily traffic, followed by the depth of pipe burial impacting the economic costs. The least important factor was found to be the pipe's age.

The model was applied to a data set containing pipe condition assessment information of wastewater pipes from a Northeastern Louisiana wastewater utility. VC pipes of 8-inch diameter were selected for the case study. The results showed that the COFS score of the selected 633 VC pipe segments was between 1.750 and 3.918. A categorization based on the COFS score of sewers was developed; specifically, a sewer pipe can have a low, moderate, or high consequence of failure.

A sensitivity analysis was performed to analyze how changing criteria and factor weights impact the COFS score. For this, the COFS score was recalculated for all analyzed sewers, with changes of - 50%, - 25%, - 10%, + 10%, + 25%, and + 50% from the original weight for all three criteria. A data clustering method was used to compare the agreement between the original COFS scores and the changed criteria weight COFS scores. It was found that the model is most sensitive to a change of the EC factor weight by ± 50%, while it showed the most agreement for the cases of ± 10% of the SC criteria weight change. Also, higher ARI values were determined for all weight changed in the interval ± 10%.

It is important to note that more applications to case studies are required to refine the TBL factors used in determining the COFS score. For a complete risk-based asset management tool, the proposed model has been incorporated with the CTMC deterioration model presented in Chapter 4 to determine the asset's risk of failure. A summary of all models presented in Chapters 3, 4, and 5, and their application to a sewer network is presented in Chapter 6. A risk-based decision-making framework is also presented with various renewal scenario analyses.

CHAPTER 6

CASE STUDY AND SCENARIO ANALYSIS

6.1 Background

This chapter summarizes the work presented in this dissertation so far, and presents an application-based case study of risk-based decision-making for wastewater pipe asset management. Risk of failure (RoF) is determined with a risk matrix that assesses the pipe's risk by combining PoF and CoF values determined in previous chapters. The developed framework was applied to a pipe cohort within a sewer basin for which data was obtained from a Northeastern Louisiana utility. A total of 633 segments totaling a length of 154,060 ft. of VC pipe of 8-inch were analyzed to determine the RoF. With the obtained results, two scenarios were analyzed: first, a yearly condition-based replacement was simulated considering all sewer segments that had a PACP code of 5. In the second scenario, all segments that had a POCR score of 3 were selected, and the same assumptions were applied to determine the time needed to replace all sewers in condition 3, as well as the costs associated with scheduled and emergency repairs. A comparison between the two scenarios was performed to determine cost differences and the time needed to address all pipes within the considered scenario.

A third and final scenario is also analyzed where replacement is based off of yearly calculated RoF values. In this case, the application of the proposed method in this research work is presented for a replacement scenario with a duration of 7 years, during which all high risk assets can be replaced. The chapter is ended with a comparison and discussion of the results.

6.2 Sewer Pipe Overall Condition Rating (POCR) Score

Chapter 3 presented the development of a comprehensive sewer condition rating model that incorporates information about pipe internal and external parameters, as well as structural, operational, and hydraulic condition data. The model includes a total of 16 factors into a linear weighted sum model to determine the segment's POCR score on a scale of 1 through 5. To determine the POCR score, the ratings of all 16 factors, as well as their relative importance weights are used. The ratings are on a scale of 1 through 5 as well, and the relative importance weights are normalized values between 0 and 1. The relative importance weights of all 16 factors were obtained from subject matter expert input through the AHP method. To summarize the results, Table 6.1 shows the importance weights of all 16 factors in the POCR model. The global weights of the factors are shown. The sum of all weights is 1.

Table 6.1. Summary of POCR model.

Factor	Relative Importance Weight	Factor	Relative Importance Weight
Age	0.113	Seismic Zone	0.074
Corrosion Resistance	0.219	Groundwater	0.067
Diameter	0.035	PACP Structural Score	0.078
Shape	0.03	PACP O&M Score	0.015
Depth	0.033	Defect Distribution	0.020
Soil Type	0.119	Repair History	0.045
Loading	0.059	Flow/Inflow	0.024
Waste Type	0.042	Pipe Surcharge	0.025

The formula to calculate the POCR score is presented in Eq. (6.1):

$$\text{POCR} = \sum_{i=1}^{16} (w_i x R_i) \tag{6.1}$$

where w_i is the global weight of the i^{th} factor, and R_i is its rating on a scale of 1 through 5. The rating criteria of all factors has been presented previously in Chapter 3.

6.2.1 Case Study

This section presents a case study where the POCR model has been applied to segments in a sewer basin using CCTV inspection data from a Northeastern Louisiana utility. Specifically, 633 VC pipe 8-inch segments were selected for the case study for which the total length is 154,060 ft. The data has been obtained in a Microsoft ACCESS database. For data analysis, the information has been transferred to Microsoft EXCEL, where the necessary data cleaning and analyis tasks have been performed to obtain useful information for calculating the POCR score.

There was no information related to burial depth, soil type, groundwater, defect distribution, repair history, and pipe surcharge in the MS ACCESS database. For each of these factors, there was a 20% random assignment of each of the ratings (1 through 5) among the 633 pipe segments. Randomly assigning each of the ratings for the factors with missing information to the pipe segments allows for an equal distribution of the ratings, and does not prioritize one factor over another. Table 6.2 presents the type of information available in the original database, and Tables 6.3 through 6.5 show the transferred information to the MS EXCEL database from where POCR scores were computed for all pipe segments.

Table 6.2. Available sewer pipe information in the database.

PipeID	Inspection ID	Date of inspection	Sewer_Use	Flow_Control	Height
Shape	Material	Length_Surveyed	Installation Year	Pre-cleaning	Location_Code

Table 6.3 presents the PC factor ratings of randomly selected pipes.

Table 6.3. Tabular data for POCR score calculation: Pipe Characteristics factor ratings.

PipeID	InspectionID	Age Grade	Corrosion Resistance	Diameter	Shape
1	925	4	2	2	1
2	197	5	2	2	1
3	213	5	2	2	1
4	822	4	2	2	1
5	3265	4	2	2	1

Table 6.4 presents the external factor ratings of the same segments as above.

Table 6.4. Tabular data for POCR score calculation: External Factors factor ratings.

PipeID	InspectionID	Depth	Soil Type	Loading	Waste Type	Seismic Zone	Ground water
1	925	3	5	3	3	2	2
2	197	3	4	4	3	2	3
3	213	4	5	2	3	2	1
4	822	1	3	3	3	2	4
5	822	3	3	3	3	2	4

Finally, Table 6.5 presents the hydraulic and other factors' ratings.

Table 6.5. Tabular data for POCR score calculation: Hydraulic & Other Factors factor ratings.

PipeID	**InspectionID**	**Structural Score**	**O&M Score**	**Defect Distribution**	**Repair History**	**Flow/Inflow**	**Pipe surcharge**
1	925	3	4	1	4	4	4
2	197	1	4	4	4	4	4
3	213	1	1	1	1	1	1
4	822	1	1	1	1	1	1
5	822	1	1	1	1	1	1

In this manner, using the information from Table 6.1, as well as all factor ratings from Tables 6.3, 6.4, and 6.5, the individual POCR score of all segments was calculated. As presented in Chapter 3, based on the POCR score, the segments are divided into three conditions (Table 6.6).

Table 6.6 Sewer condition based on POCR score

Condition of Pipe	**POCR Score**
Condition 1	≤ 2.562
Condition 2	$2.562 < \text{POCR} < 3.343$
Condition 3	≥ 3.343

It was found that in the observation year, 2016, 17% of the total length of the analyzed VC pipe 8-inch sewer cohort was in Condition 1, 75% was in Condition 2, and 8% were in Condition 3. The results are summarized in Figure 6.1.

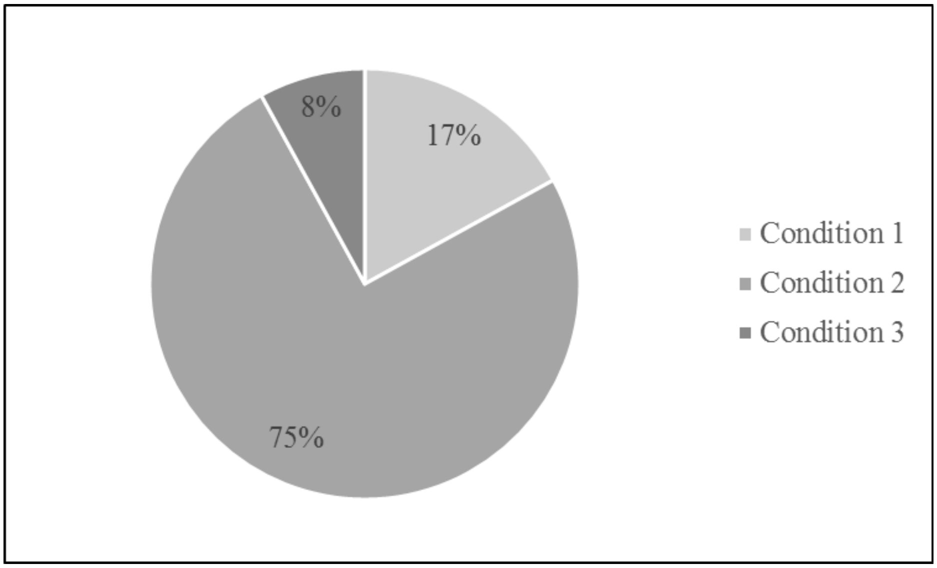

Figure 6.1. Length distribution by condition based on POCR score.

Once the individual POCR scores were determined at age 51 of the sewers, the CTMC model was developed using R software (RStudio Team, 2016). The next section will briefly summarize the method and results presented in Chapter 4.

6.3 Sewer Pipe Deterioration Model as CTMC

As previously presented in Chapter 4, for the CTMC sewer deterioration model, the R package "ctmcd" was used. The package was developed by Pfeuffer (2017). By implementing the package on the correctly formatted data, the generator matrix, Q, can be found, which is imperative in solving for the transition probabilities between conditions given the age of the pipe. Since there are three conditions that can describe the overall condition of the sewer pipe at a given time, both the Q and the $P(t)$ matrix are 3x3 matrices.

6.3.1 Generator Matrix and Transition Probability Matrix

All the results have been presented in Chapter 4. To be able to implement the "ctmcd" package, the data must be saved into a spreadsheet format (in this case, the data file was .cvs). For each inspection data (i.e., every observation), a separate row with the POCR score calculation is necessary because the final goal is to determine the transition probabilities between the three conditions. Obviously, it is desirable to have as many observations as possible at several points in time. Unfortunately, for this case study, only one observation was available and that was the CCTV inspection from 2016. As a result, some assumptions were made. It was assumed that almost all pipes were in condition 1 at the time of installation. It was also needed that a very small percentage of the segments were in conditions 2 and 3 at the time of installation, specifically 3% of the total length of the pipes in each of the conditions. This was needed to ensure the fact that the generator matrix will be of size 3 x 3, and that there are entries in the last row of the matrix as well. Table 4.1 previously presented the data format needed for reading the data. In the case where more observations are available, additional rows are inserted into the data table. However, it is important to mention the fact that the observation steps, or the time between observations, must be equal, or the considered elapsed time must be of same magnitude and unit.

After running the code, the generator matrix Q was found, from which various transition probability matrices could be calculated. To determine the pipe's PoF at the time when the observation was made (*t = 51* years), the *P(51)* transition probability matrix was computed using Eq. (5.7):

$$P(51) = \begin{bmatrix} 0.083 & 0.637 & 0.280 \\ 0 & 0.582 & 0.418 \\ 0 & 0 & 1 \end{bmatrix} \tag{6.2}$$

According to Eq. 6.2, in 51 years, a VC pipe of 8-inch from the analyzed sewer basin has a 28% probability to fail. For the scenario analysis that will be presented in

Section 6.6, a yearly replacement schedule was considered. For this, first the one-step transition probability matrix, *P(1),* was calculated based on Eq. (5.7). This was necessary to determine the length that will transition from 2016 to 2017 from condition 1 to conditions 2 and 3, and from condition 2 to condition 3. Then, the two-year transition probability was determined to find the length of pipe that transitions in the condition mentioned earlier, from 2016 to 2018. This process was repeated for a period of 25 years. This way, a more exact determination of the necessary budget for scheduled replacement, as well as emergency repairs can be done.

Note that because the elapsed time between the observations is 51 years, it is necessary to adjust the rate by *t/51,* where *t* is the considered time step (see Chapter 4). If there is available yearly CCTV inspection data, then the generator matrix can be calculated as the one-year transition rate matrix, and no further adjustments of the rate is required. The one year transition probability matrix is presented in Eq. (6.3):

$$P(1)=\begin{bmatrix} 0.952 & 0.047 & 0.001 \\ 0 & 0.989 & 0.011 \\ 0 & 0 & 1 \end{bmatrix} \tag{6.3}$$

6.4 Consequence of Failure of Sewers (COFS) Model

The last part of the risk assessment framework is the COFS model. It has already been discussed in much detail in Chapter 5. The COFS model uses the TBL approach to determine the CoF of a wastewater pipe. A total of 14 factors are incorporated into the linear weighted sum model, similar to the POCR model previously described. The same subject matter expert input as in the case of the POCR model was used to determine the relative importance weight of the factors. In a similar fashion, the factor ratings are on a scale of 1 through 5, and their relative importance weights are between 0 and 1. Table 6.7 summarizes the factor's global weights.

Table 6.7. Summary of COFS model.

Factor	Relative Importance Weight	Factor	Relative Importance Weight
Age	0.022	Seismic Zone	0.039
Diameter	0.098	POI**	0.064
Length	0.088	DCL*	0.027
Depth	0.126	Average Traffic	0.175
Access	0.063	POI**	0.046
DCL*	0.028	DWB***	0.126
Soil Type	0.038	Land Use	0.061

The formula to calculate the COFS score is shown in Eq. (6.4):

$$\text{COFS} = \sum_{j=1}^{14} \left(v_j x S_j\right) \tag{6.4}$$

where v_j is the global weight of the j^{th} factor, and S_j is its rating on a scale of 1 through 5. The rating criteria of all factors has been presented in Chapter 4.

<u>6.4.1 Case Study</u>

This section presents a case study where the COFS model has been applied to the same 633 VC pipe 8-inch segments as the POCR model in Section 6.2.1. In this case again, there was no available GIS information to be able to determine the POI or DCL factor ratings; for example there was no information related to DCL, POI, and DWB. For each of these factors, there was a 20% random assignment of each of the ratings (one through five) among the 633 pipe segments. Previously used information for the POCR model, such as depth of burial and soil type, was the same. Randomly assigning each of the ratings for those factors with missing information to the pipe segments ensures an equal distribution of the ratings to not prioritize one factor over another. Tables 6.8 through 6.10 show the data used in MS EXCEL to compute the COFS score of each of the analyzed sewer segments.

Table 6.8. Tabular data for COFS score calculation: Economic impact factor ratings.

InspectionID	Age Grade	Diameter	Length	Depth	Access to Pipe	DCL	Soil Type	Seismic Zone
925	4	2	5	1	3	4	5	2
197	5	2	5	1	2	1	4	2
213	5	2	5	1	2	4	5	2
822	4	2	5	1	3	3	3	2
3265	4	2	5	1	3	2	3	2

Table 6.9. Tabular data for COFS score calculation: Social Impact factor ratings.

InspectionID	POI	DCL	Avg. Traffic
925	1	4	3
197	2	1	2
213	5	4	2
822	5	3	3
3265	2	2	3

Table 6.10. Tabular data for COFS score calculation: Environmental impact factor ratings.

InspectionID	POI	DWB	Land Use
925	1	3	3
197	2	4	2
213	5	5	2
822	5	4	3
3265	2	2	3

In this manner, all individual COFS scores of the 633 pipe segments were calculated. As presented in Chapter 5, based on the COFS score, the segments can be grouped into three consequence of failure categories. These categories are summarized in Table 6.11.

Table 6.11. Sewer consequence of failure based on COFS score.

Consequence of Failure	**COFS Score**
Low	≤ 2.692
Moderate	2.692 > COFS < 3.538
High	≥ 3.538

It was found that 36% of the total length of the analyzed VCP 8-inch sewer cohort has a low COFS score, 61% has a moderate, and the remaining 3% has a high COFS score (Figure 6.2).

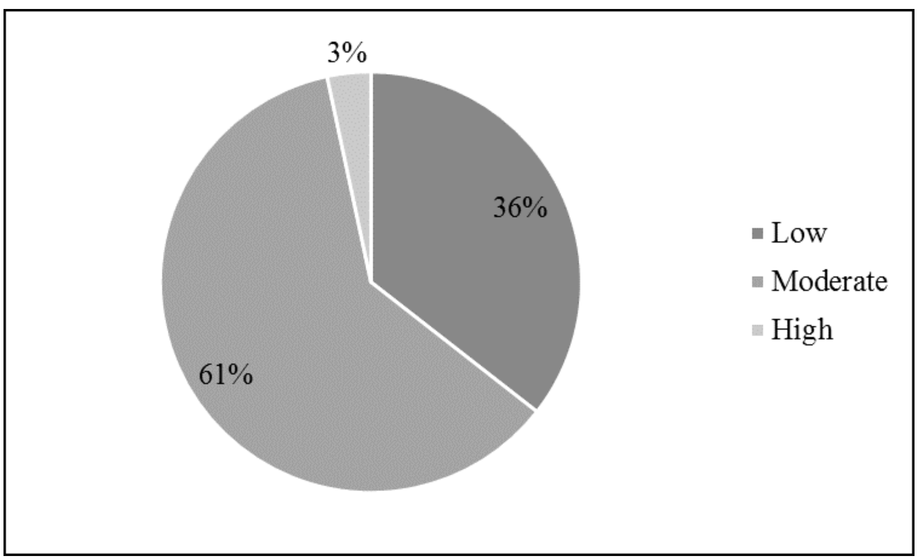

Figure 6.2. Length distribution by consequence of failure based on COFS score.

6.5 <u>Assessment of Risk of Failure</u>

The Risk of Failure (RoF) is determined as the multiplication between the PoF (Chapter 4) and COFS scores. Note that the PoF can be determined at any desired time in the future using the developed CTMC model. The COFS score will most probably not change significantly as the pipe ages, since the majority of the factors have a constant rating. Unless some major changes take place in the vicinity of the sewer (for example, the construction of a new road, highway, or building that would impact some of the factors), all factor ratings are constant, except the age. However, once the pipe has been in use for more than 50 years, the age rating stays at a constant value of 5 as well. Therefore, the RoF can also be determined at any age of the pipe, considering the PoF and the COFS values.

To determine the RoF of the pipe at the time of observation, the 51-year probabilities must be used, and multiplied with the COFS scored determined in the previous section. By obtaining a RoF value for each individual segment, a ranking and subsequent prioritization of the most critical assets is obtained. Figure 6.3 presents a risk matrix specifically developed for the critical values of PoF and COFS scores determined in this study.

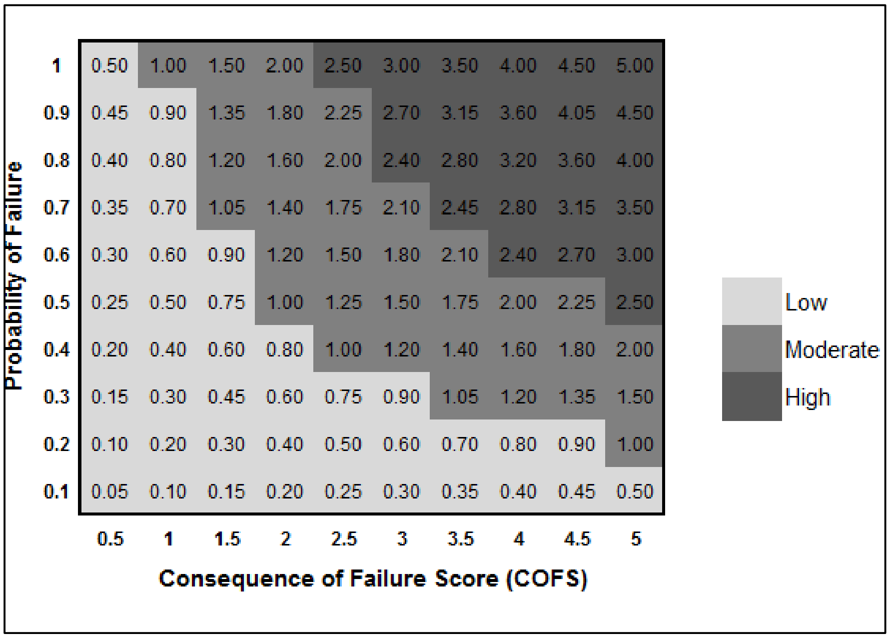

Figure 6.3. Risk matrix.

From the risk matrix presented in Figure 6.3, it can be seen that the Low, Moderate, and High regions of RoF are clearly differentiated. Generally, to determine a sewer's RoF, Table 6.12 summarizes the critical values.

Table 6.12. Sewer RoF based on PoF and COFS scores.

Risk of Failure	**PoF**	**COFS Score**	**RoF Value**
Low	≤ 0.33	≤ 2.692	≤ 0.88
Moderate	0.33 > PoF < 0.66	2.692 > COFS < 3.538	0.88 > RoF < 2.33
High	≥ 0.66	≥ 3.538	≥ 2.33

To determine yearly RoF of the segments for planning purposes, one year transition probability values are needed (Eq. 5.7). The *P(1)* transition probability matrix has been summarized in Section 6.3.1 of this chapter. Accordingly, the observation data at $t = 0$ and $t = 51$ has been used to find the generator matrix, Q, to determine the desired transition probabilities for any given time steps. Since observation data is available for 2016, the 1-year PoF of each individual pipe segment can be determined from the *P(1)* matrix for 2017. Having the one year PoF values and the COFS score of each individual pipe segment, the RoF for 2017 is determined by multiplying these values. From the total length of VC pipe 8-inch pipes, 91% have a low risk of failure, while 9% have a high risk of failure. None of the segments fell into the moderate RoF category. Figure 6.4 shows the distribution, by length, of the RoF of the analyzed sewer cohort.

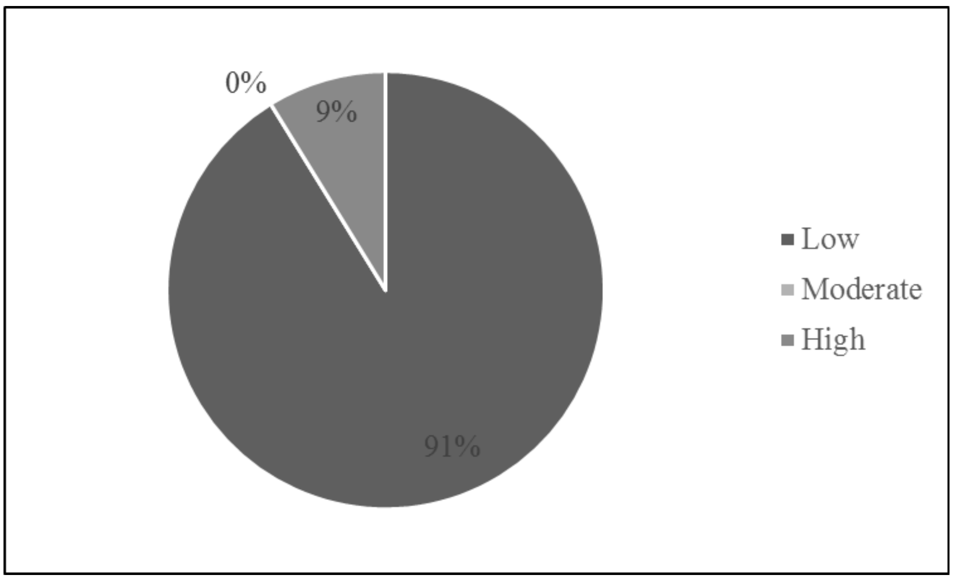

Figure 6.4. Length distribution by RoF of the analyzed VCP 8-inch sewer cohort (2017).

Based on the risk assessment, approximately 13,600 ft. of the cohort have a high RoF. These sewers are prioritized on a decreasing scale based on the RoF values, from highest risk to lowest risk, for replacement and rehabilitation project planning.

With the obtained results, two scenarios were analyzed: first, a yearly condition-based replacement was simulated considering all sewer segments that had a PACP defect severity of 5. In the second scenario, all segments that had a POCR score of 3 were selected, and the same replacement assumptions were applied to determine the time needed to replace all sewers in condition 3, as well as the costs associated with scheduled and emergency repairs. A comparison between the two scenarios was performed to determine cost differences and the time needed to address all sewers within the considered scenario. In both cases, a fixed yearly budget of $600,000, starting with 2017, was allocated. The budget was used to first cover all emergency repairs, for both scenarios. With the remaining yearly budget, replacement of the segments was maximized in both cases, meaning that as many feet as possible of the sewers were replaced in each year. To establish the same emergency repair rate between the analyzed scenarios, it was assumed that each year 1% of the total length of the cohort in the worst condition in both cases (i.e., PACP = 5, or POCR = 3, respectively) had an unexpected failure and required emergency repairs. This equals to 1,541 ft. of sewer pipe annually, in each of the scenarios.

6.6 Scenario Analyses

6.6.1 Cost Considerations for VC pipe Renewal

Cost information about VC pipe renewal (replacement and rehabilitation) was obtained from the report by Simicevic and Sterling (2002). For replacement, the open-cut method was considered, and for rehabilitation, the Cured-In-Place-Pipe (CIPP) technology was selected. To determine cost estimates, the survey analyzed bidding summaries cost data collected from 67 municipalities across 39 states on pipeline construction and rehabilitation methods. The cost estimates for various technologies have been determined with non-linear regression. Accordingly, Eq. (6.5) presents the equation for the best curve fit for open-cut pipe replacement, where D is the diameter of the pipe:

$$Cost_{open\ cut} = 0.60 \times D^{3/2} + 76.24 \tag{6.5}$$

Eq. (6.5) considers the data points only for successful bids. Similarly, Eq. (6.6) presents the best fit curve for CIPP technology, where *D* is the diameter of the pipe. This too is representative for successful bids only:

$$Cost_{CIPP} = 0.77 \times D^{3/2} + 25.90 \tag{6.6}$$

Both costs are in $/foot of pipe. As a result, using Eq. (6.5) and (6.6), the open-cut replacement of an 8-inch VC pipe cost was $ 89.82 /ft., while rehabilitation using CIPP for the same pipe costs $ 43.32/ft.. It is important to note that these costs are for 2002 data. Therefore, the value of both the replacement and rehabilitation costs need to be determined for the current observation year 2016, using Eq. (6.7):

$$FV = P_0(1 + r)^n \tag{6.7}$$

where

- *FV* is the future value of P_0
- P_0 is the original amount
- *r* is the rate of interest, or discount value
- *n* is the number of compounding periods (in years)

For determining the discount value, we used historic information from the U.S. Federal Reserve. The long-term average discount rate was used in this study, which on 25 April 2018 was 2.03%[4] (Ycharts, 2018).

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[4] Information was retrieved from https://ycharts.com/indicators/us_discount_rate on 25th April, 2018.

As a result, the 2016 value of the cost items were determined to be $119/ft. for open-cut replacement and $57.40/ft. for CIPP rehabilitation technology. For both costs, future value will be determined starting from 2017 until the year 2035. Additionally, emergency replacement costs are considered double the amount of scheduled replacement costs, i.e., $238/ft. in 2016. This information is summarized in Table 6.13.

Table 6.13. Future value of scheduled and emergency renewal costs of VCP 8-inch.

Year	Future Value of Open-Cut Replacement [$/ft.]	Future Value of Emergency Replacement [$/ft.]	Future Value of CIPP Rehabilitation Technology [$/ft.]
2017	121.42	242.83	58.56
2018	123.88	247.76	59.75
2019	126.40	252.79	60.97
2020	128.96	257.92	62.20
2021	131.58	263.16	63.47
2022	134.25	268.50	64.76
2023	136.98	273.95	66.07
2024	139.76	279.51	67.41
2025	142.59	285.19	68.78
2026	145.49	290.97	70.18
2027	148.44	296.88	71.60
2028	151.45	302.91	73.05
2029	154.53	309.06	74.54
2030	157.67	315.33	76.05
2031	160.87	321.73	77.59
2032	164.13	328.26	79.17
2033	167.46	334.93	80.78
2034	170.86	341.73	82.42
2035	174.33	348.66	84.09

6.6.2 Yearly Condition-Based Replacement Scenario Based on the PACP method

The PACP condition rating method is a well-established method widely used in the U.S. wastewater industry. The first scenario considers all sewers that have the worst condition as per the PACP method that is a defect score of 5. So, all VC pipe 8-inch segments from the analyzed sewer basin with at least one PACP defect of severity 5 were selected totaling a length of 47,494 ft. It is assumed that during the CCTV inspection performed in 2016 there was no other maintenance, repair, or renewal action performed, but all capital improvement planning was scheduled starting with 2017. A fixed budget of $600,000 is to be used each year to address a maximum length of the wastewater pipes in the worst condition, and the costs should fit within the yearly allocated budget. With the initial fixed budget, yearly emergency repairs and scheduled replacements are considered to estimate the total time (in years) needed to replace all sewers with a PACP score of 5. The yearly budget has to cover the scheduled replacement of as many feet of sewer as possible while addressing all emergency repairs first.

It was assumed that emergency repairs would cover one percent of the total length of the system each year. This equals to roughly 1,541 ft. of pipe length requiring emergency repairs. The emergency repairs are considered at this fixed rate each year and are addressed first. The remaining amount from the yearly budget is then used to replace as many feet of pipe as possible. To fully replace the 47,494 ft. of sewer with a PACP score of 5, approximately 18 years are needed. During this time, no other improvement projects can be done due to the budget constraints. Table 6.14 summarizes the results of the yearly replacement scenario analysis for all sewer pipes with a PACP score of 5.

Table 6.14. Yearly replacement scenario analysis for PACP method.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Cost [$]	Remaining Budget[5] [$/ft.]	Scheduled Replacement Length [ft.]	Total Length Replaced[6] [ft.]	Remaining Length [ft.]
2017	600,000	47,493.5	374,106.46	225,893.5	1,860.50	3,401.10	44,092.4
2018	600,000	44,092.4	381,700.82	218,299.1	1,762.18	3,302.78	40,789.6
2019	600,000	40,789.6	389,449.34	210,550.6	1,665.81	3,206.42	37,583.1
2020	600,000	37,583.1	397,355.17	202,644.8	1,571.37	3,111.97	34,471.2
2021	600,000	34,471.2	405,421.48	194,578.5	1,478.80	3,019.40	31,451.8
2022	600,000	31,451.8	413,651.53	186,348.4	1,388.07	2,928.68	28,523.1
2023	600,000	28,523.1	422,048.66	177,951.3	1,299.15	2,839.76	25,683.3
2024	600,000	25,683.3	430,616.25	169,383.7	1,212.00	2,752.60	22,930.7
2025	600,000	22,930.7	439,357.75	160,642.2	1,126.58	2,667.19	20,263.6
2026	600,000	20,263.6	448,276.72	151,723.2	1,042.86	2,583.47	17,680.1
2027	600,000	17,680.1	457,376.73	142,623.2	960.81	2,501.41	15,178.7
2028	600,000	15,178.7	466,661.48	133,338.5	880.39	2,420.99	12,757.7
2029	600,000	12,757.7	476,134.71	123,865.2	801.57	2,342.17	10,415.5
2030	600,000	10,415.5	485,800.25	114,199.7	724.32	2,264.92	8,150.63
2031	600,000	8,150.63	495,661.99	104,338.0	648.60	2,189.21	5,961.43
2032	600,000	5,961.43	505,723.93	94,276.07	574.39	2,115.00	3,846.43
2033	600,000	3,846.43	515,990.12	84,009.88	501.66	2,042.26	1,804.17
2034	600,000	1,804.17	526,464.72	28,502.22	263.56	1,804.17	-

As seen from Table 6.14, over a period of 18 years, all wastewater pipe segments with a PACP score of 5 from the analyzed network will be replaced, considering the one percent of the total length that require emergency replacement as well. The remaining budget in each year was calculated as the difference between the initial budget and the emergency replacement cost. The total length replaced is the summation of the emergency length and the scheduled replacement length. Finally, the remaining length at the end of each year was calculated as the initial length minus the total length replaced.

[5] Remaining budget is calculated as the difference between the yearly budget and the cost of the 1,541 ft. of sewer replaced each year at the corresponding emergency cost.
[6] Total length replaced is the sum between the yearly emergency length (1,541 ft) and the yearly scheduled replacement length.

6.6.3 Yearly Condition-Based Replacement Scenario Based on POCR model

The second scenario is based on the condition rating model developed in Chapter 3. This scenario considers all sewers that have a POCR score of 3 as this is considered the worst state in which a sewer pipe requires immediate attention. For this, all sewer segments with a POCR score of 3 were selected with 12,240 ft. of total length. This is the total length of the pipes that are in condition 3 in 2017. Using the deterioration model presented in Chapter 4, yearly transitions from better to worse condition can also be estimated. As a result, the yearly transitioned length of VC pipe of 8-inch from conditions 1 and 2 to condition 3 are also added to the yearly length of worst condition pipes.

The budget considerations and cost estimates are the same as for the first scenario and have been previously presented in Table 6.13. The yearly budget should cover the scheduled replacement of as many feet of sewer as possible while addressing all emergency repairs first. The considerations for the emergency replacement rate are the same as for the first scenario: one percent of the total length of the system each year requires emergency replacement due to unforeseen failure. This equals to roughly 1,541 ft. of sewer. To fully replace the 12,240 ft. of sewer with a POCR score of 3, and adding to this the yearly transitioned length of sewer pipes that deteriorate to condition 3, a total of seven years approximately are needed. During this time period, no other improvement projects can be done due to the budget constraints. Table 6.15 summarizes the results of the yearly replacement scenario analysis for all sewers with a POCR score of 3.

Table 6.15. Yearly replacement scenario analysis for POCR model.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Cost [$]	Remaining Budget[7] [$/ft.]	Scheduled Replacement Length [ft.]	Total Length Replaced[8] [ft.]	Remaining Length [ft.]
2017	600,000	13,467.55	374,106.46	225,893.54	1,860.50	3,401.10	10,066.45
2018	600,000	11,308.34	381,700.82	218,299.18	1,762.18	3,302.78	8,005.56
2019	600,000	9,239.42	389,449.34	210,550.66	1,665.81	3,206.42	6,033.00
2020	600,000	7,265.46	397,355.17	202,644.83	1,571.37	3,111.97	4,153.49
2021	600,000	5,384.03	405,421.48	194,578.52	1,478.80	3,019.40	2,364.62
2022	600,000	3,592.71	413,651.53	186,348.47	1,388.07	2,928.68	664.03
2023	600,000	1,889.19	422,048.66	130,203.30	348.59	1,889.19	-

As seen from Table 6.15, in seven years, all sewer pipes that are in condition 3, as per the POCR model including the length of the system will transition to condition 3 during those seven years. At the end of this period, there is an available sum of $130,203 remaining. As compared to the PACP scenario analysis, the replacement of all pipes with a POCR score of 3 is accomplished 11 years sooner.

Therefore, during the remaining 11 years, a yearly rehabilitation program can be implemented so that the entire timeline of the first scenario is matched here as well for comparison purposes. Starting from year seven, the yearly rehabilitation program will first address all emergency repairs. With the remaining budget, wastewater pipes that have a POCR score of 2 are rehabilitated. For the remaining 11 years, the emergency repairs address all sewers that are transitioning each year from conditions 1 and 2 to condition 3. This information is presented in Appendix J.

[7] Remaining budget is calculated as the difference between the yearly budget and the cost of the 1,541 ft. of sewer replaced each year at the corresponding emergency cost.
[8] Total length replaced is the sum between the yearly emergency length (1,541 ft) and the yearly scheduled replacement length.

First, the total length of VC pipes of 8-inch that are in condition 2 in year seven (the year 2023) is determined. For this, the initial distribution of the sewers observed in conditions 1, 2 and 3 in 2016 and the *P(7)* transition probability matrix are used. Next, the length that requires emergency repair each year is determined. In this case, there is no fixed yearly rate that is assumed to fail unexpectedly, but because of the transition probabilities known from the deterioration model, the length of the sewer transitioning from conditions 1 and 2 to condition 3 can be determined. As a result, to determine the sewer pipe's length that requires emergency repair in 2023, the transitioned length from conditions 1 and 2 to condition 3 is determined by using the *P(7)* transition probability matrix (the number of years elapsed from 2016 to 2023). Then, the emergency repair cost is calculated based on this length; the remaining budget is used to maximize the length of VC pipe 8-inch sewers in condition 2 that will be rehabilitated in that year. Table 6.16 summarizes the results of the yearly rehabilitation scenario analysis for all sewers with a POCR score of 2.

Table 6.16. Yearly rehabilitation scenario analysis for POCR model.

Year	Initial Length [ft.]	Emergency Repair [ft.]	Emergency Cost [$]	Remaining Budget [$]	Scheduled Rehab Length [ft.]	Total Length Replaced [ft.]	Remaining Length [ft.]
2023	114,623.15	-	0.00	130,203.30	1,970.68	-	112,652.46
2024	113,455.69	1,221.79	341,502.98	258,497.02	3,834.62	1,221.79	108,399.28
2025	109,152.02	1,217.99	347,351.63	252,648.37	3,673.29	1,217.99	104,260.74
2026	104,965.53	1,213.79	353,181.78	246,818.22	3,517.13	1,213.79	100,234.61
2027	100,893.87	1,209.22	358,995.58	241,004.42	3,365.95	1,209.22	96,318.69
2028	96,934.70	1,204.30	364,793.78	235,206.22	3,219.62	1,204.30	92,510.78
2029	93,085.74	1,199.06	370,579.23	229,420.77	3,077.94	1,199.06	88,808.74
2030	89,344.72	1,193.52	376,353.47	223,646.53	2,940.77	1,193.52	85,210.43
2031	85,709.42	1,187.69	382,118.48	217,881.52	2,807.97	1,187.69	81,713.77
2032	82,177.65	1,181.60	387,874.86	212,125.14	2,679.39	1,181.60	78,316.66
2033	78,747.23	1,175.26	393,625.99	206,374.01	2,554.88	1,175.26	75,017.09
2034	75,416.05	1,168.69	399,371.03	200,628.97	2,434.34	1,168.69	71,813.02

At the end of year 2034, a total of 36,077 ft. of pipe can be rehabilitated, in addition to the total of 34,032 ft. replaced since 2017. As a result, a potential benefit of implementing the POCR model arises from the fact that during the same time period of 18 years, in addition to replacing all sewers that require immediate attention, a rehabilitation program can also be implemented, allowing for an improvement of the overall condition of the network at a faster pace compared to the PACP method. The results will be discussed more in-depth in the following section.

It is important to note the fact that the segments that are replaced and rehabilitated in each year will automatically transition to condition 1. However, the transition probabilities of these new pipes cannot be considered the same ones as for the pipes installed in 1965 because the new pipes might be of a different material. As an example, for the CIPP rehabilitation method, the new pipe is not clay. Even if the replaced pipe is clay, the manufacturing process might be different, the composition of the material might also differ from the pipes' installed in 1965. Therefore, all these conditions and differing characteristics will impact the deterioration process of the new pipes. As a result, for these new pipes, the transition probabilities must be determined using historical condition assessment data collected over time. Since this is not yet possible, it is difficult to validate the deterioration model developed in this work.

One possible way to validate the model is to assume different transition probabilities for the new pipes. The model could run for the 51-year period to validate the predictions by checking if the predictions match the observed data at age 51 of the original pipes. However, this involves a significant amount of additional assumptions and uncertainties, and at this point would not yield any proper validation.

6.6.4 Comparison of Results

In the first scenario, the PACP condition scoring method was used to determine the time needed, in years, to replace all segments that required immediate attention, given a fixed yearly budget allocated for both emergency and scheduled replacements. Although in the PACP method the Quick Rating Index is used to prioritize the most deteriorated assets first, in this work, all PACP segments that had at least one defect of severity 5 were considered needing immediate replacement. It has been found that using the worst defect score is a better indicator of the remaining useful life of a sewer pipe than the PACP Quick Rating Index (Koo & Ariaratnam, 2006), which is an indicator of the current condition of the pipe. Using the long-term average discount rate of 2.03% to calculate the future value of replacement and rehabilitation costs (see Table 6.13), and a fixed yearly budget of $600,000, it was determined that replacement of all analyzed VC pipe 8-inch segments with PACP defects of severity 5 would be accomplished in approximately 18 years. As a result, 18 years was considered as the baseline comparison timeline for the replacement scenario analysis with the developed POCR condition rating model, also.

For the second scenario, all VC pipe of 8-inch segments that had a POCR condition score of 3 were selected to be replaced with the same budgetary considerations as the first case. It was found that seven years would be required to replace all segments that had a POCR score of 3. Therefore, in the next 11 years, a rehabilitation program was implemented where segments with a POCR score of 2 were rehabilitated using the remaining yearly budget after all emergency replacements have been considered. These results were presented in Tables 6.15 and 6.16. To summarize all results, Figure 6.5 shows the total length replaced and rehabilitated over the course of 18 years, for both methods, given the fixed yearly budget of $600,000.

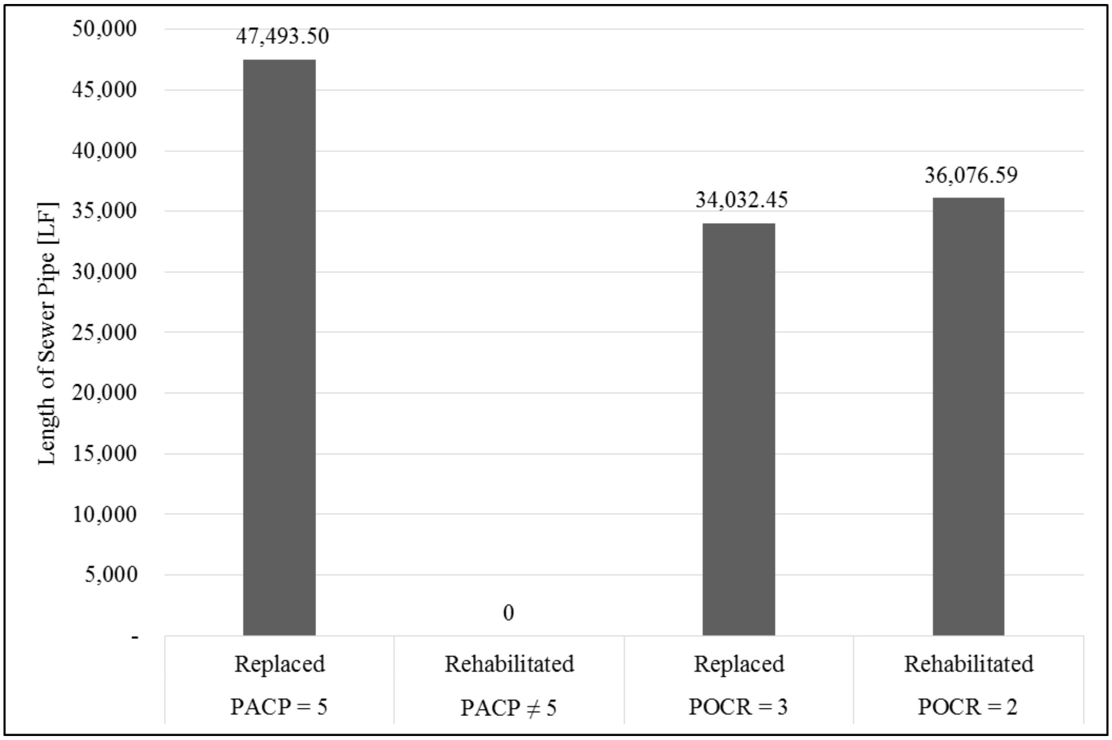

Figure 6.5. Total length replaced and/or rehabilitated in 18 years given a fixed yearly budget.

Based on the results summarized in Figure 6.5, using the POCR condition rating model, a larger portion of the analyzed sewer network can be addressed and improved in the same time period as using PACP condition scoring method for prioritizing replacement actions. Replacing all sewers that had at least one PACP defect of severity 5 results in improving 31% of the analyzed network over 18 years, not allowing for any other improvement projects due to budget constraints. Compared to this, the POCR model implementation results in addressing 46% of the analyzed network over the same time period with the same budget constraints.

When calculating a yearly replacement rate for both scenarios, a 1.72% yearly replacement rate is achieved by implementing the PACP method. This means that it would take approximately 58 years to replace the entire length of the analyzed sewer network. Compared to this, using the developed POCR condition rating method, a yearly replacement rate of 2.55% is achieved; this means that in approximately 39 years, the entire sewer network length can be replaced. These replacement rates are based on the assumption that the same yearly percent length of the system is replaced each year, at a constant rate. However, this assumption might not be of a practical use since once the worst condition segments are replaced, replacing or rehabilitating the ones in a better condition might be performed at a different rate, as needed. Still, obtaining another set of inspection data for the analyzed network from a future inspection would enable us to validate, as well as improve upon the accuracy of these predictions.

It is important to note the fact that the most severe POCR score of only 10.5% of the segments matches the most severe PACP scores, and the majority of the segments that have a PACP score of 5 require only rehabilitation design as per the POCR model having a score of 2. Figure 6.6 summarizes the POCR score distribution for all VC pipe 8-inch segments with a PACP score of 5. As a result, rehabilitation is recommended for 82% of all pipes that have a PACP score of 5, if implementing the POCR model. This obviously results in cost saving over a long-term planning period and allows for a larger scale improvement by incorporating both replacement of the most critical assets, as well as rehabilitation of those that require it.

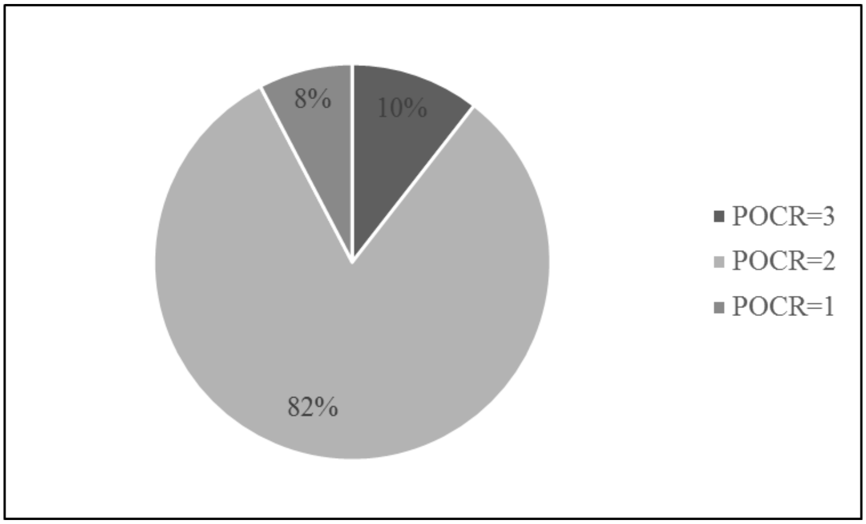

Figure 6.6. Length distribution of POCR condition scores for all VC pipe 8-inch segments with PACP = 5 defect severity.

However, it must be noted that the POCR model might be underestimating the true condition of the pipe, therefore, being much less conservative than the PACP method. More application to case studies and a refinement of the factors used to determine the condition score must be performed to establish a reliable and robust condition scoring model. Additionally, larger data sets for model validation would help improving the reliability and accuracy of the model. The work presented herein is a good starting point for further research work.

6.7. Risk-Based Decision-Making

This section presents a practical application of the risk-based framework developed in this work. To determine all segments' RoF, their PoFs were multiplied with their COFS score, and arranged in descending rank to determine the most at-risk segments. Figure 6.4 already presented the distribution of RoF of the analyzed network in 2017[9].

For this scenario, no comparison to the PACP method was done because there was no information related to the CoF of the segments. Additionally, the PACP method uses a different scale (0 through 6) for determining the PoF of sewers, and the author did not want to misrepresent any information.

This scenario considers all sewers that have a high RoF. High RoF, as per Table 6.12, means that the RoF values is higher than 2.33. For this, all segments with a high RoF were selected with a total length of 13,552 ft. With an initial fixed budget of $600,000 in 2017, yearly unforeseen emergency repairs and scheduled replacements are considered to evaluate the time needed to replace all sewers with a high RoF. The yearly budget should cover the scheduled replacement of as many feet of sewer as possible while addressing all emergency repairs first.

It was assumed that emergency repairs would cover one percent of the total length of the system each year. This equals to roughly 1,541 ft. of sewer length requiring emergency repairs. The emergency repairs are considered at a fixed rate each year. The cost of emergency repairs is determined by multiplying the 1,541 ft. of sewer pipe length with double the cost of the scheduled replacement. The yearly scheduled replacement cost values have been previously presented in Table 6.13. The remaining amount from the yearly budget is then used to replace as many feet of pipe as possible. To fully replace the 13,552 ft. of initial pipe with a high RoF (plus the additional that transition from low

[9] Available observation data is from 2016. To determine the PoF for each subsequent year, the 1-year, 2-year …, n-year transition probability matrices were determined. Based on what condition a segment was in 2016, the PoF is the probability of transitioning to condition 3 in the given time period.

and moderate to high RoF each year), approximately seven years are needed. In this time period, no other improvement projects can be performed due to budget constraints. Similar to the previously presented scenarios, the cost considerations and discount rate for this scenario are the same. Table 6.17 summarizes the results of the yearly replacement scenario analysis for all sewers with high RoF.

Table 6.17. Yearly replacement scenario analysis for risk-based decision-making.

Year	**Initial Length [LF]**	**Emergency Cost [$]**	**Remaining Budget[10] [$/LF]**	**Scheduled Replacement Length [FT]**	**Total Length Replaced[11] [FT]**	**Remaining Length [FT]**
2017	13,551.90	374,106.46	225,893.54	1,860.50	3,401.10	10,150.80
2018	11,417.80	381,700.82	218,299.18	1,762.18	3,302.78	8,115.01
2019	9,401.81	389,449.34	210,550.66	1,665.81	3,206.42	6,195.39
2020	7,389.69	397,355.17	202,644.83	1,571.37	3,111.97	4,277.72
2021	5,230.72	405,421.48	194,578.52	1,478.80	3,019.40	2,211.32
2022	3,638.82	413,651.53	186,348.47	1,388.07	2,928.68	710.14
2023	1,669.84	422,048.66	177,951.34	129.24	1669.84	-

As seen from Table 6.17, over a period of seven years, all pipe segments from the analyzed network that had initially a high RoF will be replaced, assuming the one percent of the total length that is required for emergency replacement and the yearly transitioned length from low and moderate to high RoF. The remaining budget in each year was calculated as the difference between the initial budget and the emergency replacement cost. The total length replaced is the summation of the emergency length replaced and the

[10] Remaining budget is calculated as the difference between the yearly budget and the cost of the 1,541 ft. of sewer replaced each year at the corresponding emergency cost.
[11] Total length replaced is the sum between the yearly emergency length (1,541 ft) and the yearly scheduled replacement length.

scheduled replaced length. Finally, the remaining length was calculated as the initial length minus the total length replaced.

Note that with the yearly remaining budget, a rehabilitation program can be implemented in the remaining 11 years. After the observation year of 2016, there are no pipe segments with moderate RoF until 2027. This means that in the first ten years after observing the system, only the high risk assets are addressed (either by scheduled or emergency replacement), but none of the analyzed segments need rehabilitation. Starting with year 11, a small percentage of segments will have a moderate RoF due to the increasing PoF values (the COFS scores remain constant). Therefore, in the remaining period from year 11 until year 18, a rehabilitation program is implemented in this third scenario as well. Table 6.18 presents the results of the rehabilitation implementation for the risk-based scenario analysis.

Table 6.18. Yearly rehabilitation scenario analysis for risk-based decision-making.

Year	Initial Length [ft.]	Emergency Repair [ft.]	Emergency Cost [$]	Remaining Budget [$]	Scheduled Rehab Length [ft.]	Total Length Improved[12] [ft.]	Remaining Length in moderate RoF [ft.]
2024	0	1,157.30	323,478.44	276,521.56	0.00	1,157.30	0.00
2025	0	1,198.40	341,766.17	258,233.83	0.00	1,198.40	0.00
2026	0	1,156.70	336,570.38	263,429.62	0.00	1,156.70	0.00
2027	911.30	1,266.80	376,089.41	223,910.59	911.30	2,178.10	0.00
2028	1,053.20	1,044.70	316,448.13	283,551.87	1,053.20	2,097.90	0.00
2029	1,350.00	1,035.90	320,152.32	279,847.68	1,350.00	2,385.90	0.00
2030	1,459.63	1,569.70	494,975.12	105,024.88	1,380.99	2,950.69	78.64
2031	1,863.64	1,242.00	399,591.45	200,408.55	1,863.64	3,105.64	0.00
2032	2,035.60	976.20	320,450.74	279,549.26	2,035.60	3,011.80	0.00
2033	2,436.30	1,113.27	372,864.36	227,135.64	2,436.30	3,549.57	0.00
2034	2,895.30	1,020.73	348,810.17	251,189.83	2,895.30	3,916.03	0.00

[12] Total length improved is the summation between the yearly emergency replaced length and the scheduled rehab length.

As a result, in the considered time period of 18 years, a total of 44,501 feet of sewer can be improved, from which 33,422 feet are pipes with high RoF that are replaced, and the remaining 14,079 feet are pipes with moderate RoF that are rehabilitated. Compared to the condition-based replacement scenario using the POCR model (scenario 2), a total of $1.7 M is saved during the 18 years related to rehabilitation costs. This is due to the fact that significantly less pipes will move into a moderate RoF within the analyzed time period than pipes that are in condition 2 according to the POCR, and that requires rehabilitation. Table 6.19 summarizes the results of all three scenarios, showing the years needed to replace worst condition assets, and the total cost of replacements and rehabilitation.

Table 6.19. Comparison of scenario analyses results.

	Scenario 1 (PACP method)	**Scenario 2 (POCR model)**	**Scenario 3 (Risk of failure)**
Time Needed to Replace All Assets in Worst Condition [Years]	18	7	7
Remaining Time to Implement Rehabilitation Program [Years]	0	11	11
Total Cost Replacement [$]	10.8 M	8.15 M	8.00 M
Total Cost Rehabilitation [$]	0	2.65 M	1.10
Total Cost [$]	**10.8 M**	**10.8 M**	**9.10 M**

Table 6.19 shows that using a risk-based decision-making approach for planning renewal actions can lead to cost savings due to making decisions based on risks and not based solely on the pipe's condition. In this case, $1.7 M is the potential cost savings as a result of implementing a risk-based decision-making approach over a period of 18 years.

6.8. Summary and Discussion

This chapter provided a comparison between the well-established PACP condition rating method and the POCR condition rating model developed herein. A scenario analysis was used to compare the time needed to replace all pipe segments that had the worst PACP condition score with those that had the worst POCR condition score. It was found that approximately 26% of wastewater pipes with the worst PACP score had also the worst POCR score. The time needed to replace all segments using the model developed in this work was significantly less, seven years as compared to 18 years if replacing based on the PACP grading method. In the remaining 11 years, therefore, a rehabilitation program can be implemented, thus allowing for a more significant scale improvement as compared to only replacing the worst sewers each year.

The results can be summarized twofold. First, it can be concluded that considering all segments with the worst PACP score is a more conservative approach, and a more careful approach is needed before assuming that all pipes with a score of 5 need to be replaced. This is true, however, as per the PACP explanation of the defect code severities, a segment with a score of 5 needs “immediate attention”; therefore, it is not unwarranted to assume replacement for all sewers with a PACP defect of severity 5.

Second, it can also be concluded that the POCR model is less conservative, and it underestimates the true condition of the pipe. This too might be true; however, the POCR model is not only a structural or only a hydraulic condition rating model, but rather a comprehensive rating model that assesses the overall condition of the pipe considering a total of 16 factors. A short article published in NASSCO’s newsletter in 2008 highlighted this exact same issue with the existing PACP method. As per Thornhill (2008), the PACP condition grading system expresses how severe a defect is, but it should not be used to determine which segments should be rehabilitated or replaced because it does not use depth, soil type, surface conditions, capacity, criticality, or any other factors and parameters that must be considered for rehabilitation planning. Accordingly, the POCR model solves this issue and considers the pipe's internal and external factors, including PACP structural and O&M defects and their severity codes, as well as a series of hydraulic parameters in determining the overall condition of the pipe. However, more applications to case studies are needed to refine the number and quality of the factors used. Additionally, larger data sets are needed to validate the model's accuracy in determining the pipe's condition.

The final part of the chapter presented the application of the risk-based decision-making framework for pipe replacement planning. The advantage of using the full risk-based decision-making framework for renewal decision-making is that it considers both the PoF and the COFS scores of each pipe segment. If a pipe has a higher PoF but a low COFS, it will not be prioritized over a segment that has a lower PoF but a much higher COFS. Therefore, this framework allows for the most critical assets that are at a high risk of failure to be prioritized for replacement planning or rehabilitation design.

It was found that in approximately seven years, all sewers that had an initial high RoF will be replaced, including the transitioned high RoF segments as well. The primary advantage of using the risk of failure of wastewater pipes as opposed to only the condition score when making renewal decisions is that sewers that are in an intermediate condition state might not need rehabilitation after all if their COFS scores are also considered when making decisions. As shown in Figure 6.4, there are no sewers with a moderate RoF in the first observation year. All sewers are in a low RoF zone, except those that are in condition 3, for which the PoF is 1; therefore, the overall RoF of these assets is high RoF.

In the first ten years, there are no sewers that need rehabilitation (i.e., that have a moderate RoF). Starting from year 11 until year 18, there is a small percentage of pipes that move into a moderate RoF and that need rehabilitation. When comparing the POCR model results with the risk-based decision-making framework, it can be seen that the rehabilitation costs incurred from years seven to 18 with the condition-based POCR model are higher than in the risk-based decision-making scenario. Therefore, potential savings of approximately $1.70 M resulting from implementation of risk of failure could be allocated to other projects during that time period. A limitation of the model is, however, the inability to validate future predictions due to lack of historical data. More observation data is required for validation purposes, and to improve the reliability of the predictions. Additionally, similarly as for the POCR and COFS models, application to more case studies is needed to test the reliability and robustness of the decision-making framework.

CHAPTER 7

CONCLUSIONS AND RECOMMENDATIONS

7.1 Summary

A review of the relevant literature on risk-based decision-making for sewer pipe renewal including a review of condition rating methods and models allowed for the development of the POCR condition rating model. Furthermore, an in-depth review of methods and models determining the consequence of failure, as well as practical applications by wastewater utilities provided the background for developing the COFS model. A CTMC model was developed to determine the PoF at any given age of the pipe, using the POCR conditions as states of the Markov chain at two separate observation times. Finally, the PoF and COFS values were multiplied to determine the RoF of sewer segments for risk-based decision-making purposes.

7.2 Conclusions

The following conclusions are presented from the research work of this dissertation:

1. The POCR model incorporates a total of 16 factors that include the pipe's internal and external conditions, as well as structural, operational, and hydraulic parameters. These factors incorporate the PACP structural and O&M defect scores as well. These parameters were compiled based on a comprehensive literature review and subject matter expert input.

2. The COFS model incorporates a total of 14 factors that include pipe characteristics and demographic parameters. These factors were compiled based on the guidelines provided in NASCCO's PACP manual, as well as a comprehensive literature review.
3. A CTMC deterioration model was developed using the POCR scores of VC pipe of 8-inch diameter to determine the PoF at any age of the pipe.
4. A risk-based decision-making framework was developed incorporating the PoF and COFS scores for performing pipe renewal decision planning.

7.3 Future Work

This section presents future research work to be done to improve the reliability, accuracy, and robustness of the risk-based decision-making framework presented in this work:

1. More experimental applications to case studies are recommended for both the POCR and COFS models to refine and improve the number and type of factors used in the models.
2. Increasing the number of subject matter experts to determine the relative importance weights of factors and criteria using the AHP method would provide a better accuracy of the derived weights.
3. More CCTV inspection data at closer time intervals is needed to improve the reliability of the CTMC deterioration model and to validate the predictions of the model.

4. Automation of the risk-based decision-making framework should be implemented to allow for automation of data input, data analysis, result display, and decision-making process.

APPENDIX A

AHP QUESTIONNAIRE

The purpose of this questionnaire is to ask you, as a subject matter expert in sewer pipe conditions, to perform a pairwise comparison between several factors and sub-factors. The aim of Section 1 of the questionnaire is to establish a weighted rating scale of structural, operational and hydraulic factors as they relate to deterioration of sewer pipe condition. Questions 1 through 4 are related to establishing priorities among a variety of factors and sub-factors as they relate to the condition of the sewer pipe. The aim of Section 2 of the questionnaire is to establish a weighted rating scale of several economic, social and environmental costs relative to the consequence of failure of sewer pipes. Questions 5 through 8 are asked to compare the relative importance of various factors as they relate to the consequences of sewer pipe failure. The scores presented in Table A-1 must be used for the pair wise comparison.

Table A-1. Pairwise comparison scale.

Importance	Explanation
1 – Equal Importance	Two activities contribute equally to the objective.
2 - Weak	Represents compromise between importance 1 and 3.
3 – Moderate Importance	Experience and judgment slightly favor one factor (row component) over the other (column component).
4 - Moderate to Strong	Represents compromise between importance 3 and 5.
5 – Strong Importance	Experience and judgment strongly favor one factor (row component) over the other (column component).
6 - Strong to Very Strong	Represents compromise between importance 5 and 7.

Importance	Explanation
7 - Very Strong Importance	An activity is favored very strongly over another and its dominance is demonstrated in practice.
8 - Very Strong to Extreme	Represents compromise between importance 7 and 9.
9 – Extreme Importance	The evidence favoring one activity over another is of the highest possible order of affirmation.

When performing the pairwise comparisons, please compare the row component to the column component. For example, (Ex. 1), if Pipe Characteristics is extremely more important than External Pipe Conditions with respect to the condition of a sewer pipe, the importance for the Pipe Characteristics row would be an Extreme Importance of 9. Alternatively, if External Pipe Conditions are extremely more important than Pipe Characteristics with respect to the condition of a sewer pipe, the importance for the Pipe Characteristics would be the inverse of Extreme Importance or 1/9 (see example in Table A-2 below).

Table A-2. Example pairwise comparison between two factors.

Condition of Sewer Pipe	Pipe Characteristics	External Pipe Conditions
Ex. 1: Pipe Characteristics	1	9
Ex. 2: Pipe Characteristics	1	1/9

The following figures are presented as reference for the questions. Additionally, the last two tables in this questionnaire are for detailing the factors shown in the figures below (see Figures A-1 and A-2) and are for your reference only.

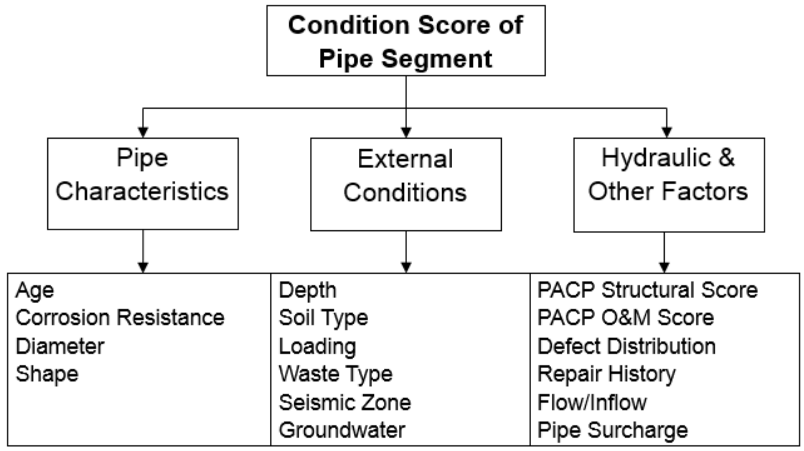

Figure A-1. Factors affecting the overall condition of the sewer pipe.

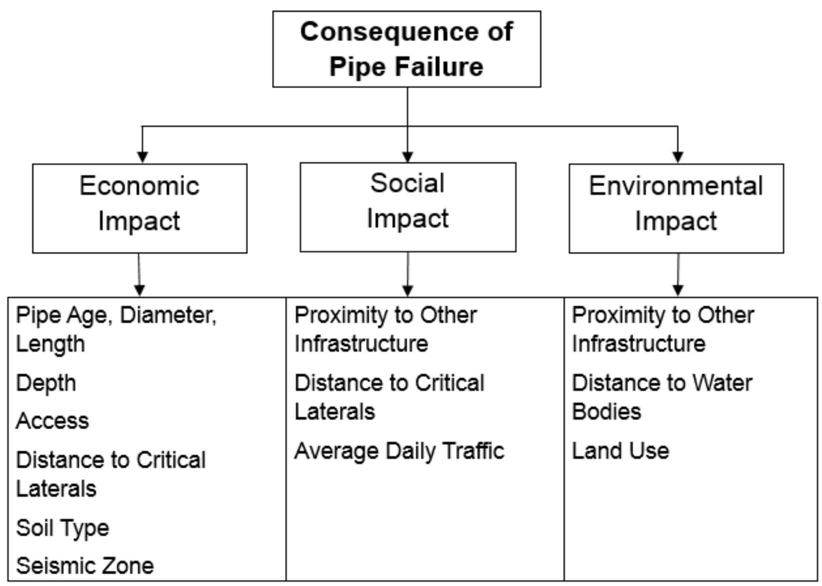

Figure A-2. Factors affecting the consequence of failure of sewer pipe.

SECTION 1: CONDITION OF PIPE SEGMENTS

1. What is the relative importance of pipe characteristics, external conditions, and other factors (see Figure 1 on Pg. 2) relative to the overall condition of the sewer pipe?

Condition	Pipe Characteristic	External Conditions	Other Factors
Pipe Characteristics	1		
External Conditions		1	
Other Factors			1

2. What is the relative importance of the age, corrosion resistance, diameter, and shape of the pipe relative to pipe characteristics that accelerate the structural degradation?

Pipe Characteristics	Age	Corrosion Resistance	Diameter	Shape
Age	1			
Corrosion Resistance		1		
Diameter			1	
Shape				1

3. What is the relative importance of depth, soil type, loading, waste type, seismic zone, and groundwater relative to the external conditions that accelerate the structural degradation?

External Conditions	Depth	Soil Type	Loading	Waste Type	Seismic Zone	Groundwater
Depth	1					
Soil Type		1				
Loading			1			
Waste Type				1		
Seismic Zone					1	
Groundwater						1

4. What is the relative importance of the PACP structural score, PACP O&M score, defect distribution, repair history, flow/inflow, and pipe surcharge relative to other factors that accelerate structural degradation?

Other Factors	Structural Score	O&M Score	Defect Distribution	Repair History	Flow/ Inflow	Pipe Surcharge
Structural Score	1					
O&M Score		1				
Defect Distribution			1			
Repair History				1		
Flow/Inflow					1	
Pipe Surcharge						

SECTION 2: CONSEQUENCE OF PIPE FAILURE

5. What is the relative importance of economic, social, and environmental costs (see Figure A-2) relative to the consequence of sewer pipe failure?

Consequence	Economic Cost	Social Cost	Environmental Cost
Economic Cost	1		
Social Cost		1	
Environmental Cost			1

6. What is the relative importance of the economic cost sub-factors relative to the economic costs involved in a sewer pipe failure?

Economic Costs	Pipe Age	Pipe Diameter	Pipe Length	Depth	Access	DCL*	Soil Type	Seismic Zone
Pipe Age	1							
Pipe Diameter		1						
Pipe Length			1					
Depth				1				
Access					1			
DCL*						1		
Soil Type							1	
Seismic Zone								1

*DCL – Distance to Critical Laterals

7. What is the relative importance of the social cost sub-factors relative to the social costs involved in a sewer pipe failure?

Social Costs	POI*	DCL**	Average Daily Traffic
POI*	1		
DCL**		1	
Average Daily Traffic			1

*POI-Proximity to Other Infrastructure; **DCL – Distance to Critical Laterals

8. What is the relative importance of the environmental cost sub-factors relative to the environmental costs involved in a sewer pipe failure?

Environmental Costs	POI*	DWB**	Land Use
POI*	1		
DWB**		1	
Land Use			1

*POI-Proximity to Other Infrastructure; ***DWB-Distance to Water Bodies

SUPPORTING INFORMATION FOR SECTION 1: OVERALL CONDITION OF SEWER PIPE

FACTOR SCORE	**PIPE CHARACTERISTICS**				**EXTERNAL CONDITIONS**					
	Pipe Age [yrs]	**Corrosion Resistance**	**Diameter [inch]**	**Shape**	**Depth [feet]**	**Soil Type**	**Loading**	**Waste Type**	**Seismic Zone***	**Groundwate r**
1	< 10 yrs	Plastic/ GRP	≤ 6	Circular	≤ 4	Granular (Crushed	No/Very Light Traffic	Mildly Corrosive	Zone 1	Low
2	≥ 10 yrs & < 25 yrs	Clay	> 6 & ≤ 12	Oval	> 4 & <10	Coarse Grained (Gravelly Sand)	Light Traffic	Mildly to Moderately	Zone 2	Low to Moderate
3	≥ 25 yrs & < 40 yrs	NRCP/AC	> 12 & ≤ 18	Horseshoe	≥ 10 & <18	Silty/Clayey Gravels	Medium Traffic	Moderately Corrosive	Zone 3	Moderate
4	≥ 40 yrs & < 50 yrs	RCP	> 18 & <30	Semi-elliptic	≥ 18 & < 24	Fine Grained (Sands/Silts)	Moderate to Heavy Traffic	Moderately to Highly	Zone 4	Moderate to High
5	≥ 50 yrs	Metallic	≥ 30	Arch	≥ 24	Inorganic Silts/Clays	Heavy Traffic	Highly Corrosive	Zone 5	High

*Based on 2017 USGS Seismic Maps:
Seismic Zone 1: ND, MN, WI, MI, IA, NE, FL, South LA, TX, Northeast MT, West KS, OK (except Central)
Seismic Zone 2: NY,PA, OH, WV,VA, East NC, MD, DC, South GA, South AL, South MS, North LA, Southwest AR, Central OK, East KS, North IL, North IN, North KY, North and West MO, North TX, East CO, East NM, South SD, North NE
Seismic Zone 3: Parts of East SC, AR and MO, Parts of South IL, Parts of West KY and TN, North of VT, Central WA, Large part of OR and NV, Central AK, Central CA, Parts of NM, AZ, Co and TN
Seismic Zone 4: Parts of West WA, OR, CA, NV, WY, and MT, Parts of East SC, AR and MO, Parts of South IL, Parts of West KY and TN, Parts of MT, West WY, East ID, Central UT
Seismic Zone 5: West and East CA, West NV, West WA, West OR, HI, South AK

FACTOR SCORE	**OTHER FACTORS**						
	Structural Score	**O&M Score**	**Defect Distribution [feet]**	**Repair History**	**Flow**	**Inflow**	**Pipe Surcharge**
1	1	1	> 4	No Significant Events/Year	Sufficient	No Inflow	Full Pipe
2	2	2	> 3 & ≤ 4	Minor Events/Year	Moderately Sufficient	Minor Inflow	N/A
3	3	3	> 2 & ≤ 3	Moderate Events/Year	Moderately Insufficient	Moderate Inflow	Height Difference Between Burial & Water Depths ≥ 5 ft.
4	4	4	≥ 1 & ≤ 2	Significant Events/Year	Insufficient	Significant Inflow	N/A
5	5	5	< 1	Extremely Abrasive	Insufficient	Extreme Inflow	Height Difference Between Burial & Water Depth < 5 ft.

SUPPORTING INFORMATION FOR SECTION 2: CONSEQUENCE OF PIPE FAILURE

FACTOR SCORE	Economic Cost Factors								Social Cost Factors		
	Pipe Age [yrs]	**Diameter [inch]**	**Length [feet]**	**Depth [feet]**	**Access**	**DCL[1] [feet]**	**Soil Type**	**Seismic Zone***	**POI[2]**	**DCL [feet]**	**Avg. Daily Traffic**
1	< 10	< 8	> 20	< 6	Right-of-Way W-W/O Traffic Control	≥ 20,000	Granular (Crushed Stone/Gravel)	Zone 1	Unpaved Road	≥ 20,000	Low
2	≥ 10 & < 25	≥8 & < 14	≥ 20 & <40’	≥ 6 & < 12	Public Land W/Vehicle Access	12,000 to 20,000	Coarse Grained (Gravelly Sand)	Zone 2	Major Local Road	12,000 to 20,000	Low to Moderate
3	≥ 25 & < 40	≥ 14 & < 18	≥ 40 & < 60	≥ 12 & < 18	Public Land W/O Vehicle Access	7,000 to 12,000	Silty/Clayey Gravels	Zone 3	Collector	7,000 to 12,000	Moderate
4	≥ 40 & < 50	≥ 18 & < 30	≥ 60 & < 80	≥ 18 & < 24	Private Land W/Vehicle Access	1,000 to 7,000	Fine Grained(Sands/Silts)	Zone 4	Arterial/ Building	1,000 to 7,000	Moderate to Heavy
5	≥ 50	≥ 30	≥ 80	≥ 24	Behind Structures W/O Vehicle Access	< 1,000	Inorganic Silts/Clays	Zone 5	Highway/ Waterway	< 1,000	Heavy

[1]Distance to Critical Lateral [2]Proximity to Other Infrastructure

*Based on 2017 USGS Seismic Maps:
Seismic Zone 1: ND, MN, WI, MI, IA, NE, FL, South LA, TX, Northeast MT, West KS, OK (except Central)
Seismic Zone 2: NY,PA, OH, WV,VA, East NC, MD, DC, South GA, South AL, South MS, North LA, Southwest AR, Central OK, East KS, North IL, North IN, North KY, North and West MO, North TX, East CO, East NM, South SD, North NE
Seismic Zone 3: Parts of East SC, AR and MO, Parts of South IL, Parts of West KY and TN, North of VT, Central WA, Large part of OR and NV, Central AK, Central CA, Parts of NM, AZ, Co and TN
Seismic Zone 4: Parts of West WA, OR, CA, NV, WY, and MT, Parts of East SC, AR and MO, Parts of South IL, Parts of West KY and TN, Parts of MT, West WY, East ID, Central UT
Seismic Zone 5: West and East CA, West NV, West WA, West OR, HI, South AK

COF	Environmental Costs Factors		
	POI	**DWB[3] [feet]**	**Land Use**
1	Unpaved Road	≥ 150	Recreational
2	Major Local Road	100 to 150	Residential
3	Collector	60 to 100	Commercial
4	Arterial/Building	25 to 60	Industrial
5	Highway/ Waterway	< 25	Wetlands/Preservations

[3]Distance to Water Bodies

APPENDIX B

EXAMPLE CALCULATION OF EUCLIDEAN DISTANCE AND CONSISTENCY RATIO

This appendix presents an example calculation of the Consistency Ratio (CR) and Euclidean Distance (ED) for a decision-maker.

Step 1. Pair wise comparison

For this, the comparison matrix of the criteria is presented in Table B-1. Each entry of the upper diagonal is based on Table 3.1, where the row component is evaluated against the column component based on the following questions: What is the relative importance of pipe characteristics, external conditions, and other factors relative to the overall condition of the sewer pipe?

Table B-1. Pairwise comparison matrix.

	Pipe Characteristic	External Condition	Hydraulic & Other Factors
Pipe Characteristic	**1.00**	0.33	3.00
External Condition	3.00	**1.00**	5.00
Hydraulic & Other Factors	0.33	0.20	**1.00**
Σ	**4.33**	**1.53**	**9.00**

Step 2. Normalization

The next step is to normalize the matrix by calculating the sum of all the column components and then dividing each individual column component by the sum of the column components. As a result, a new matrix is obtained. For example, the first component of the first row is obtained as $\frac{1}{4.33} = 0.23$. For this matrix, the sum of all rows is calculated, and the average value of the rows is also computed, as shown in Table B-2.

Table B-2. Normalized matrix.

	Pipe Characteristic	External Condition	Other Factors	**Sum**	**Average**
Pipe Characteristic	0.23	0.22	0.33	**0.26**	**3.03**
External Condition	0.69	0.65	0.56	**1.90**	**0.63**
Other Factors	0.08	0.13	0.11	**0.32**	**0.11**

Step 3. Consistency Index (CI) calculation

There are three steps to arrive to the *CI*. First, a Consistency Measure (CM) is calculated for each component, by multiplying the row of the pairwise comparison matrix by the column vector of the average values of the normalized matrix, and then dividing this value by the corresponding average weight. For example, the *CM* of Pipe Characteristics was obtained as follows:

$$CM_{Pipe\ Characteristic} = \frac{1.00 \times 0.26 + 0.33 \times 0.63 + 3.00 \times 0.11}{0.26} = 3.03$$

CM values for the three criteria are presented in Table B-3.

Table B-3. Calculation of the Consistency Measure (CM) for the three criteria in the POCR model.

	Σ	Average	CM
Pipe Characteristic	0.26	3.03	3.03
External Condition	1.90	0.63	3.07
Other Factors	0.32	0.11	0.11

The Consistency Index is calculated as a next step as presented in Eq. (B-1):

$$CI = \frac{(\lambda_{max} - n)}{(n-1)} \tag{B-1}$$

where

$$\lambda_{max} = \frac{3.03 + 3.07 + 3.01}{3} = 3.04$$

Then

$$CI = \frac{3.04 - 3}{2} = 0.02$$

Step 4. Calculation of the Consistency Ratio (CR)

The *CR* is calculated as presented in equation (5):

$$CR = \frac{CI}{RCI}$$

where *RCI* is found in Table 5 and is 0.58 in this case. The value of *CR* is:

$$CR = \frac{0.02}{0.58} = 0.03$$

The *CR* is less than 0.1, meaning that the judgment of this decision-maker is consistent.

Step 5. Calculation of the Euclidean Distance (ED)

Equation (6) is used for this computation:

$$ED = \left[\sum_{i=1}^{n}\sum_{j=1}^{m}\left(a_{ij} - \frac{w_i}{w_j}\right)^2\right]^{1/2}$$

The *ED* compares each entry of the comparison matrix, a_{ij}, and the related ratios of the obtained weights of factors, w_i/w_j. For this case, the *ED* is computed as follows:

$$ED = \sqrt{\left(\frac{0.33 - 0.26}{0.63}\right)^2 + \left(\frac{3.00 - 0.26}{0.11}\right)^2 + \left(\frac{5.00 - 0.63}{0.11}\right)^2} = 1.11$$

The rest of the calculations are simple to follow starting from Table 3.8.

APPENDIX C

CHANGED FACTOR WEIGHTS OF POCR MODEL FOR SENSITIVITY ANALYSIS

Table C-1. Factor weights and ranks with changing Pipe Characteristics criteria weight.

Factor	**Percent Weight Change of Pipe C Criteria**						
	-50%	**-25%**	**-10%**	**BASELINE**	**10%**	**25%**	**50%**
Weight PC	***0.200***	***0.299***	***0.359***	***0.399***	***0.439***	***0.499***	***0.599***
Age	0.056	0.084	0.101	0.113	0.123	0.14	0.168
Corrosion Resistance	0.111	0.166	0.199	0.219	0.244	0.277	0.332
Diameter	0.017	0.026	0.031	0.035	0.038	0.043	0.052
Shape	0.016	0.023	0.028	0.032	0.034	0.039	0.047
Depth	0.044	0.039	0.035	0.033	0.031	0.028	0.022
Soil Type	0.157	0.137	0.125	0.119	0.110	0.098	0.079
Loading	0.078	0.069	0.063	0.059	0.055	0.049	0.039
Waste Type	0.057	0.05	0.045	0.042	0.040	0.036	0.028
Seismic Zone	0.096	0.084	0.077	0.074	0.067	0.06	0.048
Groundwater	0.093	0.081	0.074	0.067	0.065	0.058	0.047
Structural Score	0.105	0.092	0.084	0.078	0.073	0.065	0.052
O&M Score	0.019	0.016	0.016	0.015	0.013	0.012	0.009
Defect Distribution	0.027	0.023	0.021	0.020	0.019	0.017	0.013
Repair History	0.060	0.053	0.048	0.045	0.041	0.038	0.030
Flow/Inflow	0.033	0.029	0.027	0.024	0.024	0.02	0.018
Pipe Surcharge	0.031	0.028	0.026	0.025	0.023	0.02	0.016

Table C-2. Factor weights and ranks with changing External Condition criteria weight.

Factor	Percent Weight Change of External Conditions Criteria						
	-50%	-25%	-10%	BASELINE	10%	25%	50%
Weight EC	***0.197***	***0.296***	***0.355***	***0.394***	***0.433***	***0.493***	***0.591***
Age	0.147	0.129	0.118	0.113	0.104	0.093	0.075
Corrosion Resistance	0.292	0.256	0.234	0.219	0.205	0.184	0.148
Diameter	0.046	0.04	0.037	0.035	0.032	0.029	0.023
Shape	0.041	0.036	0.033	0.032	0.029	0.026	0.021
Depth	0.016	0.025	0.030	0.033	0.034	0.040	0.050
Soil Type	0.059	0.089	0.106	0.119	0.135	0.147	0.177
Loading	0.029	0.044	0.052	0.059	0.060	0.074	0.087
Waste Type	0.022	0.032	0.038	0.042	0.047	0.053	0.063
Seismic Zone	0.036	0.054	0.066	0.074	0.080	0.091	0.109
Groundwater	0.035	0.052	0.063	0.067	0.077	0.088	0.105
Structural Score	0.105	0.092	0.085	0.078	0.074	0.065	0.052
O&M Score	0.019	0.017	0.015	0.015	0.014	0.012	0.010
Defect Distribution	0.027	0.023	0.022	0.020	0.020	0.018	0.014
Repair History	0.061	0.053	0.048	0.045	0.042	0.038	0.030
Flow/Inflow	0.033	0.03	0.027	0.024	0.024	0.022	0.019
Pipe Surcharge	0.032	0.028	0.026	0.025	0.023	0.020	0.017

Table C-3. Factor weights and ranks with changing Hydraulic and Other Factors criteria weight.

Factors	Percent Weight Change of Hydraulic and Other Factors Criteria						
	-50%	-25%	-10%	BASELINE	10%	25%	50%
Weight HOF	***0.104***	***0.155***	***0.186***	***0.207***	***0.228***	***0.259***	***0.311***
Age	0.125	0.118	0.114	0.113	0.108	0.104	0.096
Corrosion Resistance	0.248	0.234	0.226	0.219	0.214	0.205	0.191
Diameter	0.039	0.037	0.035	0.035	0.034	0.032	0.030
Shape	0.035	0.033	0.032	0.032	0.030	0.029	0.028
Depth	0.038	0.036	0.034	0.033	0.032	0.031	0.029
Soil Type	0.134	0.126	0.122	0.119	0.115	0.111	0.103
Loading	0.067	0.063	0.061	0.059	0.058	0.055	0.051
Waste Type	0.049	0.046	0.043	0.042	0.042	0.040	0.037
Seismic Zone	0.082	0.077	0.075	0.074	0.071	0.068	0.063
Groundwater	0.079	0.075	0.072	0.067	0.068	0.066	0.061
Structural Score	0.040	0.059	0.071	0.078	0.087	0.098	0.118
O&M Score	0.007	0.011	0.012	0.015	0.016	0.018	0.021
Defect Distribution	0.010	0.015	0.018	0.020	0.022	0.025	0.030

Factors	Percent Weight Change of Hydraulic and Other Factors Criteria						
	-50%	**-25%**	**-10%**	**BASELINE**	**10%**	**25%**	**50%**
Weight HOF	***0.104***	***0.155***	***0.186***	***0.207***	***0.228***	***0.259***	***0.311***
Repair History	0.023	0.034	0.041	0.045	0.050	0.057	0.068
Flow/Inflow	0.012	0.018	0.022	0.024	0.027	0.031	0.037
Pipe Surcharge	0.012	0.018	0.022	0.025	0.026	0.030	0.037

APPENDIX D

CALCULATED VALUES OF POCR SCORES

WITH CHANGED CRITERIA WEIGHTS

Table D-1. Values of POCR score for - 50% change from the original PC criteria weight.

Pipe Material	All 1s	All 2s	All 3s	All 4s	All 5s
Plastic/GRP	1	1.889	2.778	3.667	4.556
Clay	1.111	2	2.889	3.778	4.667
NRCP/AC	1.222	2.111	3	3.889	4.778
RCP	1.333	2.222	3.111	4	4.889
Metallic	1.444	2.333	3.222	4.111	5

Table D-2. Values of POCR score for - 25% change from the original PC criteria weight.

Pipe Material	All 1s	All 2s	All 3s	All 4s	All 5s
Plastic/GRP	1	1.834	2.668	3.502	4.336
Clay	1.166	2	2.834	3.668	4.502
NRCP/AC	1.332	2.166	3	3.834	4.668
RCP	1.498	2.332	3.166	4	4.834
Metallic	1.664	2.498	3.332	4.166	5

Table D-3. Values of POCR score for - 10% change from the original PC criteria weight.

Pipe Material	All 1s	All 2s	All 3s	All 4s	All 5s
Plastic/GRP	1	1.801	2.602	3.403	4.204
Clay	1.199	2	2.801	3.602	4.403
NRCP/AC	1.398	2.199	3	3.801	4.602
RCP	1.597	2.398	3.199	4	4.801
Metallic	1.796	2.597	3.398	4.199	5

Table D-4. Values of POCR score for 10% change from the original PC criteria weight.

Pipe Material	All 1s	All 2s	All 3s	All 4s	All 5s
Plastic/GRP	1	1.756	2.512	3.268	4.024
Clay	1.244	2	2.756	3.512	4.268
NRCP/AC	1.488	2.244	3	3.756	4.512
RCP	1.732	2.488	3.244	4	4.756
Metallic	1.976	2.732	3.488	4.244	5

Table D-5. Values of POCR score for 25% change from the original PC criteria weight.

Pipe Material	All 1s	All 2s	All 3s	All 4s	All 5s
Plastic/GRP	1	1.723	2.446	3.169	3.892
Clay	1.277	2	2.723	3.446	4.169
NRCP/AC	1.554	2.277	3	3.723	4.446
RCP	1.831	2.554	3.277	4	4.723
Metallic	2.108	2.831	3.554	4.277	5

Table D-6. Values of POCR score for 50% change from the original PC criteria weight.

Pipe Material	All 1s	All 2s	All 3s	All 4s	All 5s
Plastic/GRP	1	1.668	2.336	3.004	3.672
Clay	1.332	2	2.668	3.336	4.004
NRCP/AC	1.664	2.332	3	3.668	4.336
RCP	1.996	2.664	3.332	4	4.668
Metallic	2.328	2.996	3.664	4.332	5

Table D-7. Values of POCR score for - 50% change from the original EC criteria weight.

Pipe Material	All 1s	All 2s	All 3s	All 4s	All 5s
Plastic/GRP	1	1.708	2.416	3.124	3.832
Clay	1.292	2	2.708	3.416	4.124
NRCP/AC	1.584	2.292	3	3.708	4.416
RCP	1.876	2.584	3.292	4	4.708
Metallic	2.168	2.876	3.584	4.292	5

Table D-8. Values of POCR score for - 25% change from the original EC criteria weight.

Pipe Material	All 1s	All 2s	All 3s	All 4s	All 5s
Plastic/GRP	1	1.744	2.488	3.232	3.976
Clay	1.256	2	2.744	3.488	4.232
NRCP/AC	1.512	2.256	3	3.744	4.488
RCP	1.768	2.512	3.256	4	4.744
Metallic	2.024	2.768	3.512	4.256	5

Table D-9. Values of POCR score for - 10% change from the original EC criteria weight.

Pipe Material	All 1s	All 2s	All 3s	All 4s	All 5s
Plastic/GRP	1	1.766	2.532	3.298	4.064
Clay	1.234	2	2.766	3.532	4.298
NRCP/AC	1.468	2.234	3	3.766	4.532
RCP	1.702	2.468	3.234	4	4.766
Metallic	1.936	2.702	3.468	4.234	5

Table D-10. Values of POCR score for 10% change from the original EC criteria weight.

Pipe Material	All 1s	All 2s	All 3s	All 4s	All 5s
Plastic/GRP	1	1.795	2.59	3.385	4.18
Clay	1.205	2	2.795	3.59	4.385
NRCP/AC	1.41	2.205	3	3.795	4.59
RCP	1.615	2.41	3.205	4	4.795
Metallic	1.82	2.615	3.41	4.205	5

Table D-11 Values of POCR score for a 25% change from the original EC criteria weight

Pipe Material	All 1s	All 2s	All 3s	All 4s	All 5s
Plastic/GRP	1	1.816	2.632	3.448	4.264
Clay	1.184	2	2.816	3.632	4.448
NRCP/AC	1.368	2.184	3	3.816	4.632
RCP	1.552	2.368	3.184	4	4.816
Metallic	1.736	2.552	3.368	4.184	5

Table D-12. Values of POCR score for 50% change from the original EC criteria weight.

Pipe Material	All 1s	All 2s	All 3s	All 4s	All 5s
Plastic/GRP	1	1.852	2.704	3.556	4.408
Clay	1.148	2	2.852	3.704	4.556
NRCP/AC	1.296	2.148	3	3.852	4.704
RCP	1.444	2.296	3.148	4	4.852
Metallic	1.592	2.444	3.296	4.148	5

Table D-13. Values of POCR score for - 50% change from the original HOF criteria weight.

Pipe Material	All 1s	All 2s	All 3s	All 4s	All 5s
Plastic/GRP	1	1.752	2.504	3.256	4.008
Clay	1.248	2	2.752	3.504	4.256
NRCP/AC	1.496	2.248	3	3.752	4.504
RCP	1.744	2.496	3.248	4	4.752
Metallic	1.992	2.744	3.496	4.248	5

Table D-14. Values of POCR score for - 25% change from the original HOF criteria weight.

Pipe Material	All 1s	All 2s	All 3s	All 4s	All 5s
Plastic/GRP	1	1.766	2.532	3.298	4.064
Clay	1.234	2	2.766	3.532	4.298
NRCP/AC	1.468	2.234	3	3.766	4.532
RCP	1.702	2.468	3.234	4	4.766
Metallic	1.936	2.702	3.468	4.234	5

Table D-15. Values of POCR score for - 10% change from the original HOF criteria weight.

Pipe Material	All 1s	All 2s	All 3s	All 4s	All 5s
Plastic/GRP	1	1.774	2.548	3.322	4.096
Clay	1.226	2	2.774	3.548	4.322
NRCP/AC	1.452	2.226	3	3.774	4.548
RCP	1.678	2.452	3.226	4	4.774
Metallic	1.904	2.678	3.452	4.226	5

Table D-16. Values of POCR score for 10% change from the original HOF criteria weight.

Pipe Material	All 1s	All 2s	All 3s	All 4s	All 5s
Plastic/GRP	1	1.786	2.572	3.358	4.144
Clay	1.214	2	2.786	3.572	4.358
NRCP/AC	1.428	2.214	3	3.786	4.572
RCP	1.642	2.428	3.214	4	4.786
Metallic	1.856	2.642	3.428	4.214	5

Table D-17. Values of POCR score for 25% change from the original HOF criteria weight.

Pipe Material	All 1s	All 2s	All 3s	All 4s	All 5s
Plastic/GRP	1	1.795	2.59	3.385	4.18
Clay	1.205	2	2.795	3.59	4.385
NRCP/AC	1.41	2.205	3	3.795	4.59
RCP	1.615	2.41	3.205	4	4.795
Metallic	1.82	2.615	3.41	4.205	5

Table D-18. Values of POCR score for a 50% change from the original HOF criteria weight.

Pipe Material	All 1s	All 2s	All 3s	All 4s	All 5s
Plastic/GRP	1	1.809	2.618	3.427	4.236
Clay	1.191	2	2.809	3.618	4.427
NRCP/AC	1.382	2.191	3	3.809	4.618
RCP	1.573	2.382	3.191	4	4.809
Metallic	1.764	2.573	3.382	4.191	5

APPENDIX E

CODE FOR ADJUSTED RAND INDEX CALCULATION IN R SOFTWARE FOR POCR MODEL

```
library(mclust)
library(NMI)
data<- read.csv("C:/Users/Greta/ Data/ARI.csv")
data<-as.data.frame(data)
head(data)
POCR<-data[["POCR"]]
                    ### Pipe Characteristics weight change ###
PCminus50<-data[["PC50MIN"]]
PCminus25<-data[["PC25MIN"]]
PCminus10<-data[["PC10MIN"]]
PCplus10<-data[["PC10PLUS"]]
PCplus25<-data[["PC25PLUS"]]
PCplus50<-data[["PC50PLUS"]]
                    ###Adjusted Rand Index PC###
```

```
adjustedRandIndex(POCR,PCminus50)
adjustedRandIndex(POCR,PCminus25)
adjustedRandIndex(POCR,PCminus10)
adjustedRandIndex(POCR,PCplus10)
adjustedRandIndex(POCR,PCplus25)
adjustedRandIndex(POCR,PCplus50)
                    ### External Factors Weight Change ###
EFminus50<-data[["EF50MIN"]]
EFminus25<-data[["EF25MIN"]]
EFminus10<-data[["EF10MIN"]]
EFplus10<-data[["EF10PLUS"]]
EFplus25<-data[["EF25PLUS"]]
EFplus50<-data[["EF50PLUS"]]
                    ###Adjusted Rand Index EF###
adjustedRandIndex(POCR,EFminus50)
adjustedRandIndex(POCR,EFminus25)
adjustedRandIndex(POCR,EFminus10)
adjustedRandIndex(POCR,EFplus10)
adjustedRandIndex(POCR,EFplus25)
adjustedRandIndex(POCR,EFplus50)
                    ### Hydraulic and Other factors weight change ###
HOFminus50<-data[["HOF50MIN"]]
HOFminus25<-data[["HOF25MIN"]]
```

```
HOFminus10<-data[["HOF10MIN"]]

HOFplus10<-data[["HOF10PLUS"]]

HOFplus25<-data[["HOF25PLUS"]]

HOFplus50<-data[["HOF50PLUS"]]

###Adjusted Rand Index HOF###

adjustedRandIndex(POCR,HOFminus50)

adjustedRandIndex(POCR,HOFminus25)

adjustedRandIndex(POCR,HOFminus10)

adjustedRandIndex(POCR,HOFplus10)

adjustedRandIndex(POCR,HOFplus25)

adjustedRandIndex(POCR,HOFplus50)
```

APPENDIX F

CODE FOR FINDING THE GENERATOR MATRIX OF THE CONTINUOUS TIME MARKOV CHAIN MODEL

```
library(ctmcd)

library(msm)

library(expm)

library(markovchain)

require(ctmcd)

require(msm)

require(expm)

require(markovchain)

require(survival)

require(mstate)

                    ### READ THE DATA ###

data<- read.csv("C:/Users/Greta/ Data/VCP8BROADMOOR.csv")

data<-as.data.frame(data)


    ### ABSOLUTE VALUES OF CONDITION STATE CHANGES ###

statetable<-statetable.msm(POCRFINAL, PipeID, data=data)
```

```
statetable
### RELATIVE TRANSITION FREQUENCIES ###
reltransfreq <-rbind((statetable/rowSums(statetable))[1:2,],c(rep(0,2),1))
reltransfreq
### ESTIMATION OF RATE MATRIX USING GIBBS SAMPLER###
pr<-list()                    #list of prior parameters for Gamma distribution
pr[[1]]<-matrix(1,3,3)    #needed in the Gibbs sampling method
pr[[1]][3,]<-0
pr[[2]]<-c(rep(1,2),Inf)
pr
### GIBBS SAMPLER WITH FIRST 1000 ITERATIONS REMOVED
gmgs<-gm(tm=statetable,te=51,method="GS",prior=pr,burnin=1000)
gmgs
### TRANSITION RATE MATRIX
Q<-as.matrix(gmgs[[1]])
## ONE YEAR TRANSITION PROBABILITY MATRIX
P1<-expm((1/51)*Q)
### SOJOURN TIME IN CONDITION 1 ###
q12<-(1/(Q[[1]]))
### SOJOURN TIME IN CONDITION 2 ###
q23<-1/(Q[[2]])
### PROBABILITY OF FAILURE CURVE PLOT WHEN STARTING ON
CONDITION 1 AT TIME T=0 ###
```

```
V1<-c(1,0,0)  #initial probability distribution
for (step in 1:200) {
  matplot(t(sapply(1:200, function(step) {V1 %*% (P %^% step)})),
        cex=0.7,
        main="Probability of being in any of the conditions based on the pipe's age", xlab="Time [Years]", ylab="Probability")
legend("center",colnames(POCRFINAL),col=seq.len(nn),cex=0.7,fill=seq_len(nn))
}
```

APPENDIX G

CHANGED FACTOR WEIGHTS OF COFS MODEL FOR SENSITIVITY ANALYSIS

Table G-1. Factor weights and ranks with changing Economic Cost criteria weight.

Factor	**Percent Weight Change of Economic Cost Criteria**						
	-50%	**-25%**	**-10%**	**BASELINE**	**10%**	**25%**	**50%**
Weight EC	***0.285***	***0.428***	***0.513***	***0.570***	***0.627***	***0.713***	***0.855***
Age	0.017	0.025	0.030	0.036	0.037	0.042	0.050
Depth	0.075	0.112	0.135	0.104	0.165	0.187	0.224
Diameter	0.052	0.077	0.093	0.091	0.114	0.129	0.155
Seismic Zone	0.024	0.036	0.044	0.146	0.053	0.061	0.073
Soil Type	0.028	0.043	0.051	0.057	0.062	0.071	0.085
Length	0.045	0.068	0.081	0.035	0.099	0.113	0.135
Access	0.028	0.042	0.051	0.051	0.062	0.071	0.084
DCL-Econ	0.016	0.025	0.028	0.050	0.035	0.039	0.049
POI-Social	0.100	0.08	0.068	0.059	0.052	0.040	0.020
DCL-Social	0.040	0.032	0.027	0.025	0.021	0.016	0.008
Avg. Daily Traffic	0.256	0.205	0.174	0.154	0.133	0.103	0.052
POI-Environmental	0.067	0.054	0.046	0.041	0.035	0.027	0.014
DWB	0.185	0.148	0.126	0.111	0.096	0.074	0.038
Land Use	0.067	0.053	0.046	0.040	0.036	0.027	0.013

Table G-2. Factor weights and ranks with changing Social Cost criteria weight.

Factor	Percent Weight Change of Social Cost Criteria						
	-50%	**-25%**	**-10%**	**BASELINE**	**10%**	**25%**	**50%**
Weight SC	***0.093***	***0.140***	***0.167***	***0.238***	***0.205***	***0.233***	***0.279***
Age	0.040	0.038	0.037	0.036	0.035	0.034	0.032
Depth	0.178	0.169	0.164	0.104	0.156	0.151	0.142
Diameter	0.123	0.117	0.113	0.091	0.108	0.104	0.098
Seismic Zone	0.058	0.055	0.053	0.146	0.051	0.049	0.046
Soil Type	0.068	0.064	0.062	0.057	0.059	0.057	0.054
Length	0.108	0.102	0.099	0.035	0.094	0.091	0.085
Access	0.067	0.064	0.062	0.051	0.059	0.057	0.053
DCL-Economic	0.039	0.037	0.035	0.050	0.034	0.033	0.031
POI-Social	0.023	0.035	0.042	0.059	0.052	0.059	0.070
DCL-Social	0.009	0.015	0.017	0.025	0.021	0.024	0.028
Avg. Daily Traffic	0.061	0.09	0.108	0.154	0.133	0.151	0.181
POI-Environmental	0.048	0.046	0.044	0.041	0.042	0.041	0.038
DWB	0.131	0.123	0.121	0.111	0.115	0.111	0.105
Land Use	0.047	0.045	0.043	0.040	0.041	0.038	0.037

Table G-3. Factor weights and ranks with changing Environmental Cost criteria weight.

Factor	Percent Weight Change of Environmental Cost Criteria						
	-50%	**-25%**	**-10%**	**BASELINE**	**10%**	**25%**	**50%**
Weight ENV	***0.091***	***0.137***	***0.164***	***0.192***	***0.201***	***0.228***	***0.274***
Age	0.038	0.036	0.035	0.036	0.034	0.032	0.030
Depth	0.168	0.16	0.155	0.104	0.148	0.143	0.134
Diameter	0.116	0.11	0.107	0.091	0.102	0.099	0.093
Seismic Zone	0.054	0.051	0.050	0.146	0.048	0.046	0.044
Soil Type	0.067	0.061	0.059	0.057	0.056	0.054	0.051
Length	0.101	0.096	0.092	0.035	0.089	0.086	0.081
Access	0.063	0.06	0.058	0.051	0.056	0.054	0.050
DCL-Econ	0.036	0.035	0.034	0.050	0.032	0.031	0.029
POI-Social	0.067	0.064	0.062	0.059	0.059	0.058	0.054
DCL-Social	0.027	0.026	0.025	0.025	0.024	0.023	0.022
Avg. Daily Traffic	0.172	0.164	0.159	0.154	0.151	0.146	0.138
POI-Environmental	0.019	0.029	0.035	0.041	0.043	0.048	0.058
DWB	0.053	0.080	0.095	0.111	0.117	0.132	0.159
Land Use	0.019	0.028	0.034	0.040	0.041	0.048	0.057

APPENDIX H

CALCULATED VALUES OF COFS SCORES

WITH CHANGED CRITERIA WEIGHTS

Table H-1. Values of COFS score for - 50% change from the original EC criteria weight

.Average Traffic	All 1s	All 2s	All 3s	All 4s	All 5s
Low	1	1.744	2.488	3.232	3.976
Low to Moderate	1.265	2	2.753	3.497	4.241
Moderate	1.530	2.221	3	3.762	4.506
Moderate to Heavy	1.795	2.222	3.283	4	4.771
Heavy	2.060	2.333	3.548	4.292	5

Table H-2. Values of COFS score for - 25% change from the original EC criteria weight.

Average Traffic	All 1s	All 2s	All 3s	All 4s	All 5s
Low	1	1.795	2.590	3.385	4.180
Low to Moderate	1.205	2	2.795	3.590	4.385
Moderate	1.410	2.205	3	3.795	4.590
Moderate to Heavy	1.615	2.410	3.205	4	4.795
Heavy	1.820	2.615	3.410	4.205	5

Table H-3. Values of COFS score for –10% change from the original EC criteria weight.

Average Traffic	All 1s	All 2s	All 3s	All 4s	All 5s
Low	1	1.826	2.652	3.478	4.304
Low to Moderate	1.174	2	2.826	3.652	4.478
Moderate	1.348	2.174	3	3.826	4.652
Moderate to Heavy	1.522	2.348	3.174	4	4.826
Heavy	1.696	2.522	3.348	4.174	5

Table H-4. Values of COFS score for 10% change from the original EC criteria weight.

Average Traffic	All 1s	All 2s	All 3s	All 4s	All 5s
Low	1	1.867	2.734	3.601	4.468
Low to Moderate	1.133	2	2.867	3.734	4.601
Moderate	1.266	2.133	3	3.867	4.734
Moderate to Heavy	1.399	2.266	3.133	4	4.867
Heavy	1.532	2.399	3.266	4.133	5

Table H-5. Values of COFS score for a 25% change from the original EC criteria weight.

Average Traffic	All 1s	All 2s	All 3s	All 4s	All 5s
Low	1	1.897	2.794	3.691	4.588
Low to Moderate	1.103	2	2.897	3.794	4.691
Moderate	1.206	2.103	3	3.897	4.794
Moderate to Heavy	1.309	2.206	3.103	4	4.897
Heavy	1.412	2.309	3.206	4.103	5

Table H-6. Values of COFS score for 50% change from the original EC criteria weight.

Average Traffic	All 1s	All 2s	All 3s	All 4s	All 5s
Low	1	1.948	2.896	3.844	4.792
Low to Moderate	1.052	2	2.948	3.896	4.844
Moderate	1.104	2.052	3	3.948	4.896
Moderate to Heavy	1.156	2.104	3.052	4	4.948
Heavy	1.208	2.156	3.104	4.052	5

Table H-7. Values of COFS score for - 50% change from the original SC criteria weight.

Average Traffic	All 1s	All 2s	All 3s	All 4s	All 5s
Low	1	1.939	2.878	3.817	4.756
Low to Moderate	1.061	2	2.939	3.878	4.817
Moderate	1.122	2.061	3	3.939	4.878
Moderate to Heavy	1.183	2.122	3.061	4	4.939
Heavy	1.244	2.183	3.122	4.061	5

Table H-8. Values of COFS score for - 25% change from the original SC criteria weight.

Average Traffic	All 1s	All 2s	All 3s	All 4s	All 5s
Low	1	1.892	2.784	3.676	4.568
Low to Moderate	1.108	2	2.892	3.784	4.676
Moderate	1.216	2.108	3	3.892	4.784
Moderate to Heavy	1.324	2.216	3.108	4	4.892
Heavy	1.432	2.324	3.216	4.108	5

Table H-9. Values of COFS score for - 10% change from the original SC criteria weight.

Average Traffic	All 1s	All 2s	All 3s	All 4s	All 5s
Low	1	1.892	2.784	3.676	4.568
Low to Moderate	1.108	2	2.892	3.784	4.676
Moderate	1.216	2.108	3	3.892	4.784
Moderate to Heavy	1.324	2.216	3.108	4	4.892
Heavy	1.432	2.324	3.216	4.108	5

Table H-10. Values of COFS score for 10% change from the original SC criteria weight.

Average Traffic	All 1s	All 2s	All 3s	All 4s	All 5s
Low	1	1.867	2.734	3.601	4.468
Low to Moderate	1.133	2	2.867	3.734	4.601
Moderate	1.266	2.133	3	3.867	4.734
Moderate to Heavy	1.399	2.266	3.133	4	4.867
Heavy	1.532	2.399	3.266	4.133	5

Table H-11. Values of COFS score for 25% change from the original SC criteria weight.

Average Traffic	All 1s	All 2s	All 3s	All 4s	All 5s
Low	1	1.849	2.698	3.547	4.396
Low to Moderate	1.151	2	2.849	3.698	4.547
Moderate	1.302	2.151	3	3.849	4.698
Moderate to Heavy	1.453	2.302	3.151	4	4.849
Heavy	1.604	2.453	3.302	4.151	5

Table H-12. Values of COFS score for 50% change from the original SC criteria weight.

Average Traffic	All 1s	All 2s	All 3s	All 4s	All 5s
Low	1	1.819	2.638	3.457	4.276
Low to Moderate	1.181	2	2.819	3.638	4.457
Moderate	1.362	2.181	3	3.819	4.638
Moderate to Heavy	1.543	2.362	3.181	4	4.819
Heavy	1.724	2.543	3.362	4.181	5

Table H-13. Values of COFS score for - 50% change from the original ENV criteria weight.

Average Traffic	All 1s	All 2s	All 3s	All 4s	All 5s
Low	1	1.828	2.656	3.484	4.312
Low to Moderate	1.172	2	2.828	3.656	4.484
Moderate	1.344	2.172	3	3.828	4.656
Moderate to Heavy	1.516	2.344	3.172	4	4.828
Heavy	1.688	2.516	3.344	4.172	5

Table H-14. Values of COFS score for - 25% change from the original ENV criteria weight.

Average Traffic	All 1s	All 2s	All 3s	All 4s	All 5s
Low	1	1.836	2.672	3.508	4.344
Low to Moderate	1.164	2	2.836	3.672	4.508
Moderate	1.328	2.164	3	3.836	4.672
Moderate to Heavy	1.492	2.328	3.164	4	4.836
Heavy	1.656	2.492	3.328	4.164	5

Table H-15. Values of COFS score for - 10% change from the original ENV criteria weight.

Average Traffic	All 1s	All 2s	All 3s	All 4s	All 5s
Low	1	1.841	2.682	3.523	4.364
Low to Moderate	1.159	2	2.841	3.682	4.523
Moderate	1.318	2.159	3	3.841	4.682
Moderate to Heavy	1.477	2.318	3.159	4	4.841
Heavy	1.636	2.477	3.318	4.159	5

Table H-16. Values of COFS score for 10% change from the original ENV criteria weight.

Average Traffic	All 1s	All 2s	All 3s	All 4s	All 5s
Low	1	1.850	2.700	3.550	4.400
Low to Moderate	1.150	2	2.850	3.700	4.550
Moderate	1.300	2.150	3	3.850	4.700
Moderate to Heavy	1.450	2.300	3.150	4	4.850
Heavy	1.600	2.450	3.300	4.150	5

Table H-17. Values of COFS score for 25% change from the original ENV criteria weight.

Average Traffic	All 1s	All 2s	All 3s	All 4s	All 5s
Low	1	1.854	2.708	3.562	4.416
Low to Moderate	1.146	2	2.854	3.708	4.562
Moderate	1.292	2.146	3	3.854	4.708
Moderate to Heavy	1.438	2.292	3.146	4	4.854
Heavy	1.584	2.438	3.292	4.146	5

Table H-18. Values of COFS score for 50% change from the original ENV criteria weight.

Average Traffic	All 1s	All 2s	All 3s	All 4s	All 5s
Low	1	1.862	2.724	3.586	4.448
Low to Moderate	1.138	2	2.862	3.724	4.586
Moderate	1.276	2.138	3	3.862	4.724
Moderate to Heavy	1.414	2.276	3.138	4	4.862
Heavy	1.552	2.414	3.276	4.138	5

APPENDIX I

CODE FOR ADJUSTED RAND INDEX CALCULATION IN R SOFTWARE FOR COFS MODEL

```
library(mclust)

library(NMI)
data<- read.csv("C:/Users/Greta/ Data/ARI.csv")
data<-as.data.frame(data)
head(data)
COFS<-data[["COFS"]]
                    ### Economic Cost weight change ###
ECminus50<-data[["EC50MIN"]]
ECminus25<-data[["EC25MIN"]]
ECminus10<-data[["EC10MIN"]]
ECplus10<-data[["EC10PLUS"]]
ECplus25<-data[["EC25PLUS"]]
ECplus50<-data[["EC50PLUS"]]
                    #Adjusted Rand Index EC#
adjustedRandIndex(COFS,ECminus50)
```

```
adjustedRandIndex(COFS,ECminus25)
adjustedRandIndex(COFS,ECminus10)
adjustedRandIndex(COFS,ECplus10)
adjustedRandIndex(COFS,ECplus25)
adjustedRandIndex(COFS,ECplus50)
                    ### Social Cost weight change ###
SCminus50<-data[["SC50MIN"]]
SCminus25<-data[["SC25MIN"]]
SCminus10<-data[["SC10MIN"]]
SCplus10<-data[["SC10PLUS"]]
SCplus25<-data[["SC25PLUS"]]
SCplus50<-data[["SC50PLUS"]]
                    #Adjusted Rand Index SC#
adjustedRandIndex(COFS,SCminus50)
adjustedRandIndex(COFS,SCminus25)
adjustedRandIndex(COFS,SCminus10)
adjustedRandIndex(COFS,SCplus10)
adjustedRandIndex(COFS,SCplus25)
adjustedRandIndex(COFS,SCplus50)
                    ### Environmental Cost weight change ###
ENVminus50<-data[["ENV50MIN"]]
ENVminus25<-data[["ENV25MIN"]]
ENVminus10<-data[["ENV10MIN"]]
```

```
ENVplus10<-data[["ENV10PLUS"]]

ENVplus25<-data[["ENV25PLUS"]]

ENVplus50<-data[["ENV50PLUS"]]

                    #Adjusted Rand Index ENV#

adjustedRandIndex(COFS,ENVminus50)

adjustedRandIndex(COFS,ENVminus25)

adjustedRandIndex(COFS,ENVminus10)

adjustedRandIndex(COFS,ENVplus10)

adjustedRandIndex(COFS,ENVplus25)

adjustedRandIndex(COFS,ENVplus50)
```

APPENDIX J

YEARLY TRANSITIONED LENGTH OF

SEWER PIPE FROM POCR

CONDITIONS 1 AND 2

TO CONDITION 3

Table J-1. Transition probabilities from condition i to condition j over a period of 25 years.

Time elapsed	**Transition Probabilities**		
	p_{12}	p_{13}	p_{23}
t = 1	0.047	0.000	0.011
t = 2	0.092	0.001	0.021
t = 3	0.134	0.002	0.032
t = 4	0.174	0.004	0.042
t = 5	0.211	0.006	0.052
t = 6	0.246	0.008	0.062
t = 7	0.278	0.011	0.072
t = 8	0.309	0.014	0.082
t = 9	0.338	0.018	0.092
t = 10	0.365	0.021	0.101
t = 11	0.390	0.026	0.111
t = 12	0.414	0.030	0.120
t = 13	0.436	0.034	0.130
t = 14	0.456	0.039	0.139
t = 15	0.475	0.044	0.148
t = 16	0.493	0.049	0.157
t = 17	0.509	0.055	0.166
t = 18	0.525	0.060	0.175
t = 19	0.539	0.066	0.184
t = 20	0.552	0.072	0.192
t = 21	0.564	0.078	0.201

Time elapsed	Transition Probabilities		
	p_{12}	p_{13}	p_{23}
t = 22	0.575	0.084	0.209
t = 23	0.585	0.090	0.218
t = 24	0.594	0.096	0.226
t = 25	0.602	0.103	0.234

Table J-2. Length of wastewater pipe in each condition over a period of 25 years.

Time elapsed	TOTAL LENGTH [ft.]		
	Condition 1	Condition 2	Condition 3
2016	26,147	115,674	12,240
t = 1	24,901	115,692	13,468
t = 2	23,714	115,637	14,709
t = 3	22,584	115,533	15,943
t = 4	21,508	115,376	17,176
t = 5	20,483	115,171	18,406
t = 6	19,507	114,919	19,634
t = 7	18,578	114,623	20,860
t = 8	17,692	114,287	22,081
t = 9	16,849	113,912	23,299
t = 10	16,047	113,501	24,513
t = 11	15,282	113,056	25,722
t = 12	14,554	112,580	26,927
t = 13	13,860	112,075	28,126
t = 14	13,200	111,541	29,319
t = 15	12,571	110,983	30,507
t = 16	11,972	110,400	31,689
t = 17	11,401	109,795	32,864
t = 18	10,858	109,170	34,032
t = 19	10,335	108,531	35,194
t = 20	9,848	107,863	36,349
t = 21	9,379	107,185	37,497
t = 22	8,932	106,491	38,638
t = 23	8,506	105,784	39,771
t = 24	8,101	105,064	40,896
t = 25	7,715	104,332	42,013

Table J-3. Total length of wastewater pipe transitioned from better to worse condition.

Years elapsed from observation	Transition from 1 to 2	Transition from 1 to 3	Transition from 2 to 3
	[ft.]	[ft.]	[ft.]
t = 1	1,239	7	1,221
t = 2	2,406	26	2,443
t = 3	3,505	58	3,646
t = 4	4,538	101	4,835
t = 5	5,509	154	6,012
t = 6	6,421	218	7,176
t = 7	7,278	291	8,328
t = 8	8,081	373	9,468
t = 9	8,834	464	10,596
t = 10	9,538	562	11,711
t = 11	10,198	667	12,815
t = 12	10,814	779	13,907
t = 13	11,389	898	14,988
t = 14	11,925	1,022	16,057
t = 15	12,424	1,152	17,115
t = 16	12,888	1,287	18,161
t = 17	13,318	1,427	19,197
t = 18	13,717	1,572	20,221
t = 19	14,091	1,720	21,234
t = 20	14,427	1,872	22,237
t = 21	14,740	2,028	23,229
t = 22	15,028	2,187	24,211
t = 23	15,292	2,349	25,182
t = 24	15,533	2,513	26,143
t = 25	15,752	2,680	27,093

Table J-4. Yearly transitioned length of wastewater pipe from better to worse condition.

Years elapsed from observation	Transition from 1 to 2	Transition from 1 to 3	Transition from 2 to 3
	[ft.]	[ft.]	ft.]
t = 1	1,239	7	1,221
t = 2	1,167	20	1,222
t = 3	1,098	32	1,202
t = 4	1,033	43	1,189
t = 5	971	54	1,177
t = 6	912	64	1,164
t = 7	856	73	1,152
t = 8	803	82	1,140
t = 9	753	90	1,128
t = 10	705	98	1,116
t = 11	659	105	1,104
t = 12	616	112	1,092
t = 13	575	119	1,081
t = 14	536	124	1,069
t = 15	499	130	1,058
t = 16	464	135	1,046
t = 17	431	140	1,035
t = 18	399	144	1,024
t = 19	374	148	1,013
t = 20	335	152	1,003
t = 21	314	156	992
t = 22	288	159	982
t = 23	264	162	971
t = 24	241	165	961
t = 25	219	167	951

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