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Risk-Based Decision-Making Modeling for Wastewater Pipes

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RISK-BASED DECISION-MAKING MODELING FOR WASTEWATER PIPES

by

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ABSTRACT

The dissertation research work described here has three primary objectives under risk-based decision making. (1) The development of a comprehensive sewer pipe condition rating model that incorporates many environmental, structural, and hydraulic parameters. (2) The development of a sewer 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 sewer pipe failure using economic, social, and environmental cost factors.

The Pipeline Assessment and Certification Program (PACP) was developed by the National Association of Sewer Service Companies, the industry-accepted protocol for condition rating sewer pipes in the US. The PACP method relies exclusively on visual inspections performed using 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, capacity, the distribution of structural defects, or history of preventative maintenance to determine the condition rating of the sewer pipe segment. Therefore, a comprehensive rating model with pipe characteristics, external characteristics, and hydraulic characteristics was developed. The calculating of a comprehensive rating is an entirely manual process.

Therefore, this research work addresses this limitation of Analytical Hierarchy Process (AHP) and suggests AHP is not a suitable method to calculate comprehensive rating. Develops a faster calculation of a comprehensive rating model using and *K*-NN that incorporates pipe characteristics, environmental characteristics, and information about PACP structural score and PACP O&M score in hydraulic factors. Factors such as pipe age, pipe material, diameter, shape, depth, soil type, loading, carried waste, seismic zone, PACP structural score, and PACP O&M score are used. Our proposed model is applied to the data received from the City of Shreveport, LA, which is currently under a Federal Consent Decree. The results of a comprehensive rating model showed a below-average validity percentage because linear regression assumes a linear relationship between the input and output variables. Still, the relationship between response and the predictor is not linear for AHP to prove AHP is not a suitable method and satisfactory results for *K*-NN.

As part of decision-making, for capital improvement planning and budgeting, the capacity to predict future sewer pipe conditions and potential breakdowns is essential. In contrast to the often-used Discrete Time Markov Chain approaches in the literature, the deterioration model created here uses a Continuous Time Markov Chain method to calculate the likelihood that a pipe will change from a better to a worse condition at given age.

The consequence of the pipe's failure is established to ascertain the risk of failure and to create a comprehensive framework for risk-based decision-making. To estimate the impact of the asset's failure, the established consequence of failure model considers a significant number of economic, social, and environmental cost elements. For budgeting future capital projects and improvements, the CTMC model and failure consequences for sewers are useful.

APPROVAL FOR SCHOLARLY DISSEMINATION

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DEDICATION

This work is dedicated to my grandmother Sesharatnam Chekuri, my mother Dr. Naga Parameshwari Betgeri, and my sister Sai Seshu Betgeri, Shashank Reddy Vadyala who encouraged and supported me every step of the way during my studies, and I am forever grateful for their love and support.

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CHAPTER 1

INTRODUCTION

1.1 Background

Aging wastewater infrastructure is a growing source of concern for utilities all over the country. The US water sector earned a worrying C- (Report, 2021) but got an upgrade from the previous D score(USEPA, 2004), US wastewater sector earned a worrying D+ (ASCE, 2021) in the most recent Infrastructure Report Card. Over the next 25 years, $271 billion will be needed to run and manage these networks at the required level of operation. In addition, it is expected that demand for wastewater collection and treatment will increase by 23% by the end of the year 2032 (ASCE, 2021). Sewer systems are made up of several parts that carry wastewater from residences and businesses to a treatment facility. In the United States, there are two types of wastewater networks: gravity lines and force mains. Gravity is usually the dominant force moving wastewater from its origin to its eventual treatment destination. This implies that no mechanical or electrical power is required to move the wastewater (Atalah and Ampadu, 2006). But force mains are used when wastewater moves from low-lying areas to higher altitudes through steep hills. They produce the necessary pressure to push wastewater up to higher elevations, and force mains rely on mechanical pumps or compressors situated in a lift station. Risk-based asset management entails recognizing the most critical properties to pursue the most effective course of action in rehabilitating and replacing these structures.

Firstly, CCTV (Closed-circuit television) crawler inspection is an industry go-to for pipe interior inspection. The Pipeline Assessment and Certification Program (PACP), established by the National Association of Sewer Service Companies, is the industry-accepted and used protocol for rating the condition of sewer pipes in the United States (DeBoda and Bayer, 2015). Since the initial development of the method, several updated versions exist, the most current one is PACP version 7.0.4, released on October 1, 2020 (Version, 2021, DeBoda and Bayer, 2015, Kumar et al., 2020b, Kumar et al., 2020a, Kumar et al., 2018). PACP Ratings are listed in Table 1-1. Some utilities develop their in-house defect rating methods, but typically these are also some variations of the PACP method (Angkasuwansiri and Sinha, 2015).

Table 1-1: PACP Ratings And Description.

PACP Ratings	Description
Defect rating 1	Unlikely in the foreseeable future.
Defect rating 2	Rehabilitate or replace in 20 years or more.
Defect rating 3	Rehabilitate or replace in ten to twenty years.
Defect rating 4	Rehabilitate or replace in five to ten years.
Defect rating 5	Rehabilitate or replace in next five years

The PACP method is entirely based on visual inspections utilizing closed-circuit television (CCTV), in which qualified operators examine existing structural and operation and maintenance (O&M) problems. A CCTV camera is mounted on an IBAK crawler with a 1000' cable which transmits the high-resolution images to an above-ground computer and display. Continuous video is recorded as the crawler carries the CCTV unit through the pipe. The crawler can be stopped at any time and the CCTV camera can be rotated and the area of interest "zoomed" to reveal fine details. The inner surface images of the pipe are recorded in real-time for the period of the inspection and the videos are then analyzed by the contractors immediately. The contractors make pipe assessment reports using the CCTV inspection and the inspectors calculate the final rating of a pipe using the industry accepted PACP protocol for all the pipe assessment reports. The overall Rating assessment is shown in Figure 1-1.

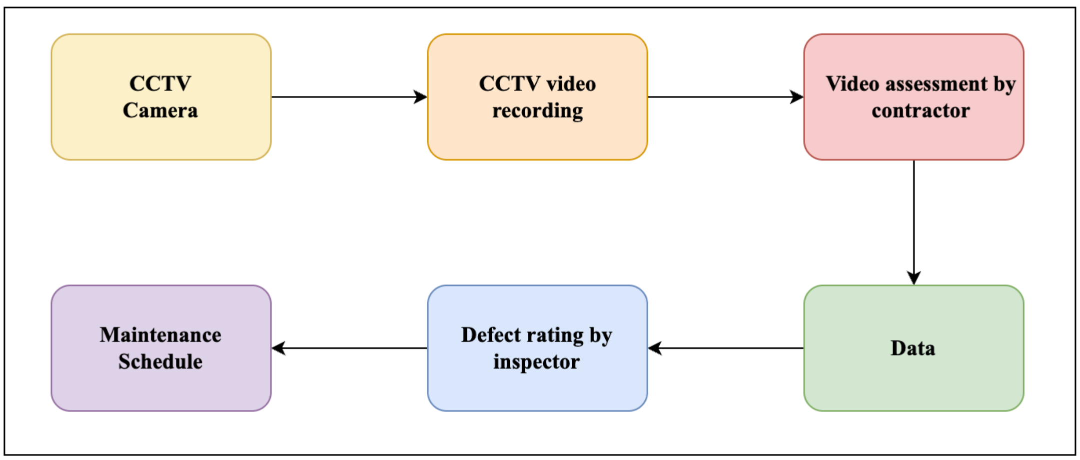

Figure 1-1: Overall Video Assessment

A limitation of the PACP method, according to Thornhill, is that it does not consider environmental characteristics such as depth, soil type, surface conditions, pipe criticality, and capacity, nor the distribution of structural defects or the history of preventative maintenance when determining the condition rating of a gravity sewer pipe segment. Some utilities create defect rating methods in-house, but these are mostly versions of the PACP method (PACP, 2021). Several studies address the need to incorporate pipe, structural, operational, and environmental factors with visual pipe inspection data to evaluate the performance of sewer collection systems better and developed many Overall Condition assessments for both machine learning and statistical models (Velayutham

Kandasamy and Sinha, 2018, Ennaouri and Fuamba, 2013, Chughtai and Zayed, 2007, Tabesh and Madani, 2006, Yan and Vairavamoorthy, 2003, Vladeanu and Matthews, 2019a, Vladeanu and Matthews, 2019b, Sai Nethra Betgeri, 2021, Betgeri et al., 2022a, Betgeri et al., 2022b). In all the previous studies, pipe conditions from a structural, hydraulic, or operational perspective, or some combination of these, fail to consider a more comprehensive variety of parameters that affect pipe conditions (Opila and Attoh-Okine, 2011, Opila, 2011).

As a result, in addition to the PACP defect ratings, numerous other factors such as sewer pipe diameter, pipe material, burial depth, pipe bedding, load transfer, pipe joint type and material, surface loading, ground conditions, groundwater level, and soil type, type of waste carried, pipe age, sediment level, surcharge, and poor maintenance practices were assessed to provide a more precise assessment and these Rating, and it is listed as comprehensive rating by the utility department of Shreveport. Comprehensive rating descriptions are listed in Table 1-2.

Table 1-2: Comprehensive Ratings And Description.

PACP Ratings	Description
Defect rating 1	Reassess in ten years.
Defect rating 2	Rehabilitate or replace in six to ten years.
Defect rating 3	Rehabilitate or replace in three to five years.
Defect rating 4	Rehabilitate or replace in zero to two years.
Defect rating 5	Rehabilitate or replace immediately.

Few pipes defects leakage; partial blockage; deformation; corrosion, detachment. are shown in Figure 1-2.

Figure 1-2: Different Pipe Deficiencies.

A developed Pipe Overall Conditional Rating model (POCR) consists of several factors related to pipe characteristics, external characteristics, and hydraulic characteristics to assess overall pipe rating using Analytic Hierarchy Process (AHP) to reduce the manual efforts to the inspector In addition, the AHP for decision-making is considered for prioritization in which many variables or criteria are considered. 16 assumed factors related to pipe characteristics, external characteristics, and hydraulic characteristics were used in calculating comprehensive Rating in POCR model. The factors used in POCR model is shown in Figure 1-3. We have compared the final ratings obtained from the POCR model using AHP with Comprehensive ratings given by the inspector and the overall accuracy of the model is 8.45%.

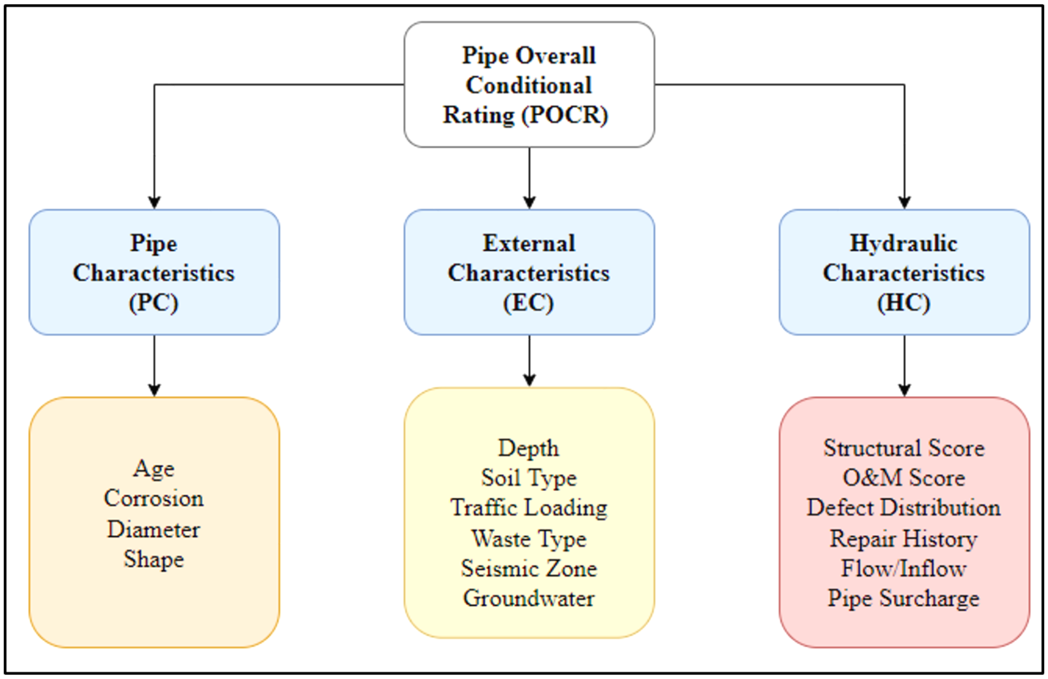

Figure 1-3: Factors Under Each Criterion For POCR AHP Model.

Secondly, the likelihood that the pipe will fail is necessary for a full decision framework (POF). To assess a POF's risk of failure at any given time, knowledge about it is essential. Decision-makers can more effectively plan for and allocate funds for present and upcoming rehabilitation and replacement projects with the use of this information. Till now the POF model developed are used to calculate the pipe probability after one year using DTMC. To calculate the pipe probability for large diameters using CTMC. To calculate the pipe probability based on pipe age using CTMC. Additionally, no other variable related pipe characteristics, external characteristics or hydraulic characteristics are considered.

Thirdly, the consequence of failure is based on Tripe Bottom Line (TBL) method to assess the impact of pipe failure based on social, economic, and environmental impact. Previously the Consequence of failure (COF) model is built only based on pipe characteristics. It did not consider external or hydraulic characteristics under social, economic, and environmental impact. The other COF model developed using AHP has factors related to pipe characteristics, external characteristics, and hydraulic characteristics under social, economic, and environmental impact but it has limitations because of the subject matter expert. Whenever subject matter expert opinion is varying the COF model consequence is getting changed and whenever factors are added or removed entire AHP process must be redone.

1.2 Objective

The objective of this research is to build a comprehensive rating model upon the previous POCR version using AHP with exact factors used in comprehensive rating by utilities of Shreveport and to suggest AHP cannot be used in comprehensive rating. Build a model using *K*-NN with exact factors used in the comprehensive rating. 12 exact factors related to pipe characteristics, external characteristics, and hydraulic characteristics, are used in the actual comprehensive Rating. The second objective of this research is to build a Continuous Time Markov Chain (CTMC) Probability of Failure (POF) model using 12 factors related to pipe characteristics, external characteristics, and hydraulic characteristics. The third objective of this research is to build a weighted ranking based on the weighted average consequence of failure (COF) model for the sewer to know the consequence of failure using 12 factors related to using pipe characteristics, external characteristics, and hydraulic characteristics under social, economic, and environmental impact. Finally, to have a risk-based decision-making framework that consists of Comprehensive rating, POF, and COF. The developed risk-based model can be used to forecast future sewer conditions 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 corresponding to currently approved industry practices within the U.S. The following steps achieve this objective:

- Develop the CR model by using the AHP and *K*-NN method that considers a series of pipe characteristics, external pipe parameters, and structural, operational, and hydraulic conditions of the pipe.
- Based on CR, 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 COF of a given sewer segment.
- Risk-based decision-making framework based on Comprehensive rating, POF, and COF.

Figure 1-4 summarizes the proposed research work presented in this dissertation.

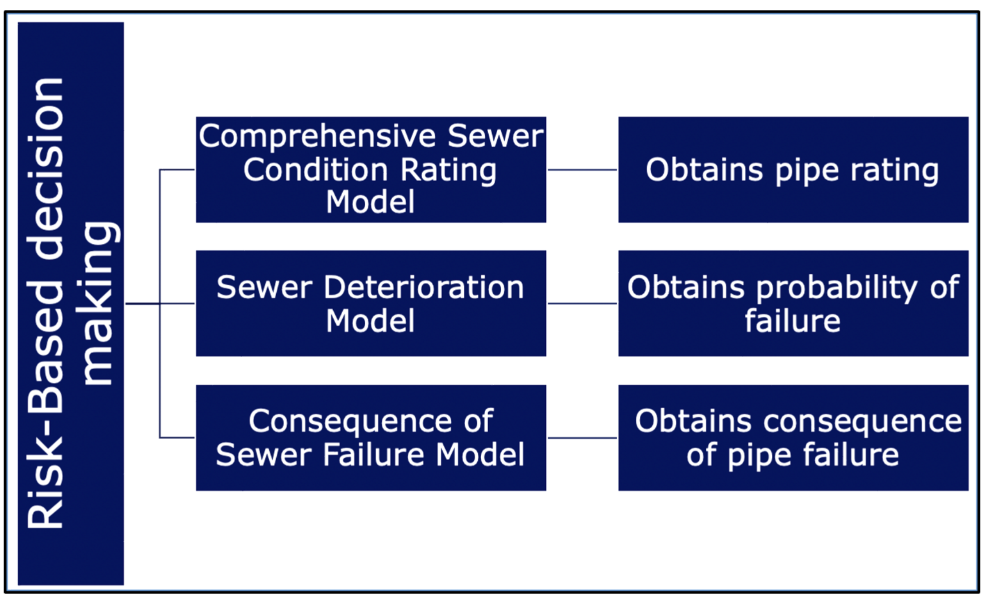

Figure 1-4: Proposed Research Work.

1.3 Dissertation Organization

This dissertation is organized into seven chapters: (1) Introduction; (2) Review of Relevant Literature; (3) Comprehensive Rating Model using AHP; (4) Comprehensive Rating Model using *K*-NN; (5) Sewer Pipe Deterioration Model Using Continuous Time Markov Chain Model; (6) Scenario Analysis; and (7) Conclusions and Recommendations.

Chapter 2 presents an overview of pipe failure and deterioration models and parameters used for their deterioration models.

Chapter 3 presents the comprehensive rating 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. Results of comprehensive rating model using AHP.

Chapter 4 presents the comprehensive rating development using the *K*-Nearest Neighbor *(K*-NN) method. Results of comprehensive rating model using *K*-NN.

Chapter 5 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 6 presents the consequence of failure model that determines the main factors which are responsible for pipe failure model.

Chapter 7 presents case study of pipe risk status for next year and different scenario analyses for 2 different yearly budgets for replacement, rehabilitation, and emergency repairs and suggests the best budget allocation for rehabilitation and replacement for our data and a risk matrix to find out the pipe risk failure and also budget planning comparison was also made.

Chapter 8 presents some concluding remarks on 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 using Analytic Hierarchy Process. To the best of the author's knowledge, this is the first attempt to prove Analytic Hierarchy Process is not a suitable model.

2. 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 with high accuracy.

3. 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 calculating transition probabilities between conditions. The author proposes a CTMC for the calculation of these probabilities. To the author's knowledge, CTMC deterioration models have been developed for bridge deterioration but not sewer deterioration.

4. The development of a TBL COF model that incorporates economic, social, and environmental impact factors to determine the COF. 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.

5. The developed model 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 renewal, rehabilitation, and replacement projects is a basic responsibility of water and wastewater utilities that must maximize the effectiveness of their yearly allotted funds to deliver the necessary level of service to their consumers. It is difficult for utilities to keep up with the maintenance and growth of their water and wastewater assets. However, due to the ongoing aging of the water and wastewater infrastructures and the underfunding of these systems in the US (ASCE, 2021). According to the Environmental Protection Agency, the wastewater infrastructure will need to be improved and expanded over the next 25 years in order to accommodate the demands of the population that is constantly rising (Selvakumar and Matthews, 2017).

Numerous prioritizing tools have been created and are now being utilized by utilities to identify pipelines that have the highest risk of failure to address the need for sewer pipe inspection, repair, and renewal. The chance of failure and the consequences of failure are the first two phases in calculating a pipe's risk of failure. Determine the likelihood that a pipe will fail at some point in the future by calculating its likelihood of failure. In the case of a sewer pipe, failure may be characterized as the condition rating of a pipe that is no longer structurally sound, the occurrence of a maintenance procedure, or in any other form that best serves the utility's needs. To make these predictions, statistical tools are employed that make use of existing historical pipe condition inspection data.

A consequence of pipe failure, however, is a more complicated component that involves several factors that need to be evaluated. The effects of a sudden sewer failure impact society, the environment, and the utility, more specifically the finances of the utility that looks after those assets. Ranking the most critical assets can be done to prioritize inspection and renewal plans by figuring out the likelihood that each sewer pipe in a system will fail.

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 et al., 2012)

Numerous complicated activities are involved in the decision-making process for trenchless sewer pipe rehabilitation, and none of them can be adequately represented by a single model or approach. A comprehensive decision-making tool that can capture the system's variability is needed to address the uncertainties connected to arbitrary pipe, economic, social, environmental, and technical aspects. Consequently, a thorough DSS was created with the aim of capturing the complexity of the procedure and assisting water utility management and stakeholders in their decision-making process for wastewater pipe replacement.

Figure 2-1 provides a summary of the decision-making procedure for pipe renewal. When a set of constraints are applied to a degradation model created from the input data, an effective DSS should produce the best result. The procedure should start with entering the data into the system, then move on to identifying the assets that are most at risk and providing, given several constraints, an optimal inspection and renewal schedule for those assets.

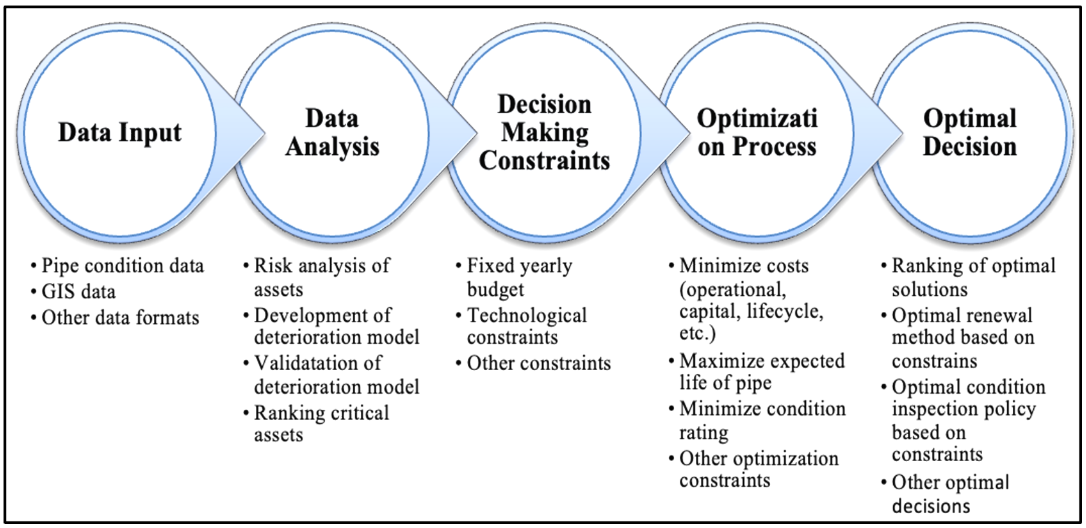

Figure 2-1: Decision-Making Procedure For Pipe Renewal.

2.2 Pipe Failure And Deterioration Modeling

There are many studies in the literature that examine the research on pipe failure and deterioration models seriously. Kleiner and Rajani (Kleiner and Rajani, 2001, Kleiner and Rajani, 2002), Liu, Kleiner, Rajani, Wang and Condit (Liu et al., 2012), Nishiyama and Filion (Nishiyama and Filion, 2013), and St. Clair and Sinha (St. Clair and Sinha, 2012) are a few of the evaluations that have had the most impact. The reviews above provide a thorough overview of the most significant models and techniques created over the past 35 years, focusing on statistical deterministic and probabilistic failure models as well as advanced models like artificial neural networks and heuristic models (St. Clair and Sinha, 2012). The review by Scheidegger, Leitao, and Scholten (Scheidegger et al., 2015) covers these models comprehensively. It offers model assumptions, explanations, data assumptions, the kinds of published probabilistic forecasts, and software implementations of the relevant published works.

When inspection data incorporates previous break events, pipe failure (or break) models are typically used to forecast water main breakdowns. Degradation models are useful for large-diameter transmission mains and wastewater pipes, where a condition rating system represents the current condition of a pipe. As a result, historical degradation data is gathered over time and utilized to create multiple deterioration curves that may be used to forecast future conditions for the evaluated assets as well as the likelihood that they would fail at a specific point in the future. The availability of past failure or deterioration data, as well as the type of data obtained, have a significant impact on the model type that is employed (i.e., either pipe breaks over time or condition deterioration of individual pipe segments over time).

2.3 Factors Affecting Wastewater Pipe Condition

There is no predictable pattern for how sewer pipe degeneration works, and several internal and external pipe variables can affect it (Najafi and Kulandaivel, 2005). The age, type of material, and diameter of the pipe are the three most common variables used to assess the quality of sewer pipes (Ennaouri and Fuamba, 2013). However, several additional elements also have an impact on the structural and functional state of the sewer; these variables have been extensively used to assess the present state of the sewer pipe and forecast future pipe conditions using deterioration models. According to Davies, Clarke, Whiter, Cunningham, and Leidl (Davies et al., 2001), the following categories best describe the most frequent causes of sewer pipe deterioration: (1) construction-related issues, (2) environmental variables, and (3) other factors. Information on the sewer pipe's diameter, pipe material, burial depth, pipe bedding, load transfer, pipe joint type and material, and sewer pipe connection are examples of construction factors (Wirahadikusumah et al., 2001, Ariaratnam et al., 2001, Gedam et al., 2016, Elsawah et al., 2016). External factors are considered, such as the root interface, ground conditions, groundwater level, and surface loading (Yan and Vairavamoorthy, 2003, Chughtai and Zayed, 2008, Elsawah et al., 2016). The type of waste transported, the age of the pipe, the degree of sediment, the surcharge, and bad maintenance are the final unrelated variables (Ennaouri and Fuamba, 2013).

A condition rating (or grading) system is used to indicate the current state of the sewer network when physical inspections are conducted for individual segments or the complete sewer network. To record the state of sewer pipes, a variety of techniques have been devised. To determine a structural and operational condition grade, many methods employ various input factors. The purpose of creating such a condition rating system is to have a process that utilities can readily use and apply swiftly and effectively. Pipes are often rated on a scale of 1 to 5, with 1 being in the best condition and 5 necessitating immediate renewal action, depending on the condition rating system that a municipality implements (DeBoda and Bayer, 2015, PACP, 2021, Version, 2021, Wirahadikusumah et al., 2001, Mcdonald and Zhao, 2001, Angkasuwansiri and Sinha, 2015);

Based on Rahman and Vanier (Rahman and Vanier, 2004), defect scores used to establish sewer condition ratings 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.

$$Mean\ Score = \frac{\sum(Deduct\ Values)}{Length\ of\ Pipe\ Segment} \qquad \textbf{Eq. 2-1}$$

$$Peak\ Score = Maximum\ Deduct\ Value \qquad \textbf{Eq. 2-2}$$

$$Total\ Score = \sum(Deduct\ Values) \qquad \textbf{Eq. 2-3}$$

The Water Research Center (Center, 2004) (WRc) procedure, which was created in the UK , served as the foundation for various other sewer condition assessment protocols, including the National Research Council (NRC) Guidelines for big sewers in Canada (Mcdonald and Zhao, 2001). The WRc recommendations are also the foundation of the PACP technique created by NASSCO. The PACP approach is described in depth in the next section. The reader is directed to Rahman and Vanier (Rahman and Vanier, 2004) and Kley, Kropp, Schmidt, and Caradot (Kley et al., 2013) for further details on those above and other widely used sewer condition evaluation approaches.

2.4 Sewer Pipe Condition Rating Systems In The United States

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.

2.4.1 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. 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.

2.5 Probability Of Failure

The possibility of pipe failure, the first element of a risk analysis framework, can be calculated by forecasting the asset's future condition rating using previous pipe condition data that is commonly gathered through pipe inspection. The condition rating of sewer pipes and the ensuing chance of failure are determined by several research in the literature using a range of statistical models and approaches. Regression analysis, Markov Chain models, artificial neural networks, survival functions, and Bayesian networks are some examples of these techniques. For more information, see Chughtai & Zayed (Chughtai and Zayed, 2008, Chughtai and Zayed, 2007), Salem, Salman, & Najafi (Salem et al., 2012), Micevski, Kuczera, & Coombes (Micevski et al., 2002), and Baik, Jeong, & Abraham (Baik et al., 2006). Anbari, Tabesh, & Roozbahani (Anbari et al., 2017). These models use a series of predictive variables, among which the most often used ones are the pipe's age, pipe material, pipe length, pipe depth, pipe 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 and Herz, 2002)	Pipe age, material, slope, category of street, sewer function, pipe shape, type of pipe.	Survival Functions
(Najafi and 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 Probity Method
(Chughtai and 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

2.6 Consequence Of Failure

It is challenging for utilities to quantify the impact of pipe failure that is external to the agency, such as social or environmental implications because there are not many studies in the literature that describe TBL consequences of failure (Raucher, 2017). (Gaewski and Blaha, 2007), (Grigg, 2007) , (Damodaran et al., 2005) authors who have studied the effects of water main breaks on TBL (2002). While the study by (Raucher, 2017) concentrated on the effects of water main failure, the same approach can be applied to evaluate the effects of sewer pipe failure. It has been demonstrated that TBL expenses can be up to four times greater than the utility's direct economic cost (Raucher, 2017, Gaewski and Blaha, 2007).

Another key finding of these studies is that the most important predictive element in determining the likelihood of a high consequence of failure is the position of the pipe and its closeness to significant receptors (Raucher, 2017). An overall consequence of failure was given to the examined sewers after the influence on the economy, society, and environment was considered. The authors Raucher, Gaewski and Blaha considered the pipe diameter, the distance from the groundwater level, the distance from the water well, the wastewater quality, the proximity to the river or lake, the type of road, the proximity to public areas, the number, and the significance of lateral connections when determining the consequences of failure. Fuzzy logic was used to calculate the risk of failure by combining the likelihood and consequences of the pipes' failure.

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 different measurement scales of these impacts.

For example, the economic impact is typically measured in monetary units, while social and environmental impact, although measurable in monetary units, 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.

The TBL is another approach suggested by NASSCO in the PACP program to calculate the COF of sewers for the consequences of failure of sewer pipes. The PACP approach offers a generic framework for determining the COF of a sewer pipe as part of the risk-based decision-making framework. Under economic, social, and environmental criteria, several variables are considered to determine a sewer segment's TBL COF, including pipe diameter, burial depth, location, relative network position, distance from environmentally sensitive features, customer type, and pipe accessibility. Each of the factors is given weight based on its contribution to the economic, social, and environmental impacts of failure. A weighted average of each element is used to determine the segment's overall COFs. However, utilities are recommended to either add or remove factors depending on their circumstances as this method is simply offered as a basic guideline for COF.

2.7 Risk Assessment Of Pipe Failure

Risk is a random factor that carries some uncertainty and may or may not follow a stochastic process. Utility companies cannot eliminate risks and uncertainties from their systems because doing so would be extremely expensive from an engineering standpoint. As a result, minimizing pipe failures and the costs associated with them is a component of all risk management strategies used by water and wastewater companies. Utilities have developed a few techniques that they employ effectively to calculate and evaluate the risk of a pipe failure. The most popular techniques are discussed here.

2.7.1 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 in Eq.2-1 presents the formula(Pietig, 2015, Hess, 2015).

$$ROF = POF * COF \qquad \textbf{Eq. 2-4}$$

Both the probability of failure and its consequences in this situation must be assessed. The accuracy of the multiplication prediction may not be as desired because to the uncertainties of the various factors that might affect the probability and consequences of failure of both sewer and water pipelines. This method gives a fast overview of the most susceptible assets within a system. Additionally, a disadvantage of this method is the fact that it cannot differentiate between pipe segments with a high probability of failure and low consequence of failure and those with a low probability of failure and high consequence of failure.

2.7.2 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 2-2.

Table 2-2: Risk Matrix.

Probability of Failure (POF)	**Consequence of Failure (COF)**				
	1 (Low)	**2 (Fair)**	**3 (Moderate)**	**4 (Moderate High)**	**5 (High)**
1 (Low)	Low	Low	Fair	Fair	Fair
2 (Fair)	Low	Fair	Fair	Moderate	Moderate
3 (Moderate)	Fair	Fair	Moderate	Moderate	Moderate High
4 (Moderate High)	Fair	Moderate	Moderate	Moderate High	High
5 (High)	Fair	Moderate	Moderate High	High	High

One 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.

2.8 Decision Support System For Risk Management

The establishment of a DSS to automate all or a portion of the process is usually the following step once the sewer deterioration model has been chosen, created, and validated. By combining the pipe failure/deterioration model with decision-making optimization based on the importance of rehabilitation, repair, or replacement of the evaluated assets, a DSS can be developed. Water utility managers and other stakeholders utilize DSSs to assist them in their decision-making process when deciding which aspects of their water and wastewater infrastructure should be prioritized for rehabilitation, repair, and replacement. A DSS is made up of five parts: users, a knowledge engine, a database management system, and a model management system field (Marakas, 2003).

(Zhang et al., 2013) claims that data gathering, archiving, and analysis all take place using the data management system. The model management system can use hybrid, data-driven, artificial intelligence, physical, mechanical, or mechanical models to enable a variety of modeling options within the DSS. An inference system that produces an output based on several input factors is part of the knowledge engine. A multi-criteria decision analysis tool, which can choose the best option out of numerous alternatives given several constraints, is the method most frequently employed in a DSS. It is best to utilize a geographical information system (GIS) to manage databases and models and to create a user-friendly environment. In (Zhang et al., 2013), the architecture of a DSS as well as its main elements are described in further detail. The decisions are based on previously established limitations, such as limiting the process's expenses and increasing the asset's estimated life while minimizing the system's average condition rating (Altarabsheh et al., 2016, Ward and Savić, 2012, Ward et al., 2014, Allouche et al., 2000). To do this, optimization algorithms are built into the DSS to look for and find the most efficient solution for any number of constraints.

DSSs are frequently used in buried infrastructure management to prioritize the most important assets (Loganathan et al., 2002, Sadiq et al., 2004, Giustolisi et al., 2008). Furthermore, DSSs are utilized to choose the best trenchless rehabilitation, repair, or replacement technology for an effective decision-making process (Kleiner and Rajani, 2001). For a thorough analysis of DSSs for risk management, see, for instance, Matthews (Matthews et al., 2012, Vladeanu and Matthews, 2018).

2.9 Summary

The sewer industry and academic literature have both produced a range of models, methodologies, and tools for calculating sewer pipe condition ratings for renewal decision-making, a consequence of failure scores, and failure likelihood for risk assessment. To calculate the risk of failure for a pipe, the work presented in this dissertation offers a novel and thorough framework for risk-based decision-making that considers several parameters related to the pipe's internal and external factors as well as information about the impact factors on the economy, society, and environment. With this data, proactive asset management may create capital improvement plans for impending renewal projects more quickly and affordable.

CHAPTER 3

COMPREHENSIVE RATING METHODOLOGY USING AHP

3.1 Background

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. Analytical Hierarchy Process (AHP) is used to develop a Comprehensive Rating (CR) 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 and to suggest AHP cannot be used in comprehensive rating.

3.2 AHP Process

Saaty is the creator of the AHP system (Saaty, 1980). A commonly used decision-making approach uses a hierarchical structure to analyze problems and issues. The decision-maker is led by a series of small decision blocks that make up the core question to be examined. AHP Process is used to determine weights of all factors and criteria based upon factor importance.

In the following sections, a stepwise description of the AHP is provided.

3.2.1 Hierarchical Structure

In the first step, the factor under each criterion is shown in Figure 3-1, the hierarchical structure of the model was developed, as shown in Figures 3-2, and factors that impact the worsening process of sewer pipes were selected and grouped under three main criteria: pipe characteristics, external characteristics, and hydraulic characteristics (Ennaouri and Fuamba, 2013).

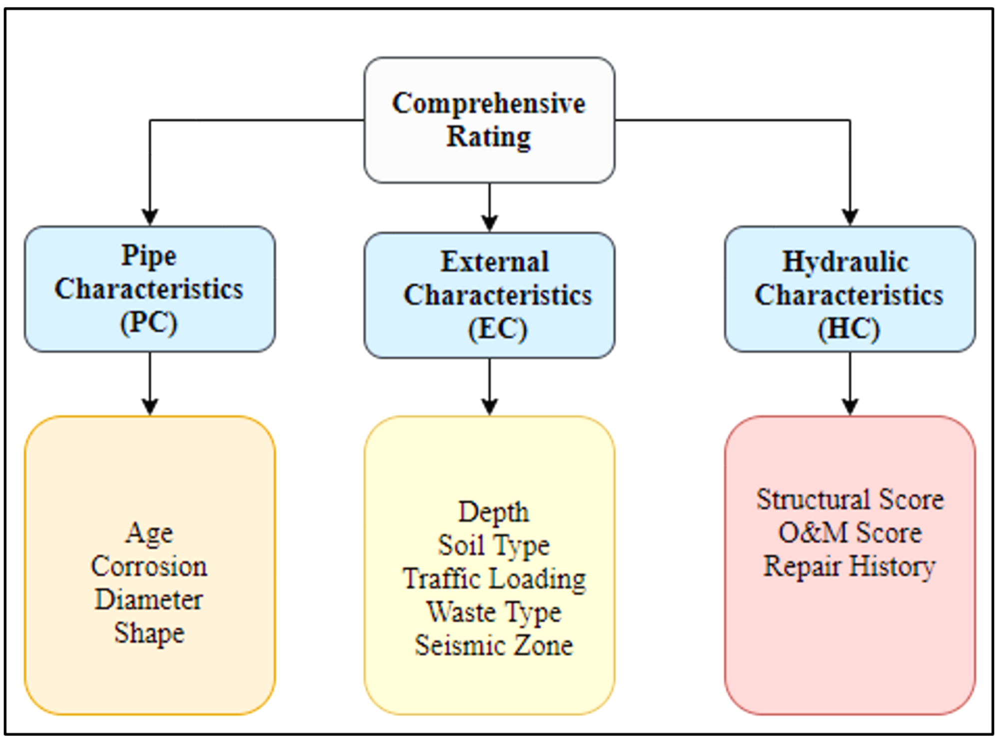

Figure 3-1: Factors Under Each Criterion for CR AHP Model.

The factors selected for external characteristics and hydraulic and other factors characteristics in Comprehensive Rating are different from external characteristics and hydraulic and other factors characteristic from POCR. Groundwater, Distribution of defects, flow/inflow, and pipe surcharge might affect the predicted comprehensive Rating in the POCR model because these factors were not considered in the actual comprehensive Rating. All the other Pipe Characteristics, External Characteristics, and Hydraulic Characteristics ratings were defined based on extensive information found in the literature. The factors summary is presented in Table 3-1. The rankings for the factors are presented in Table 3-2.

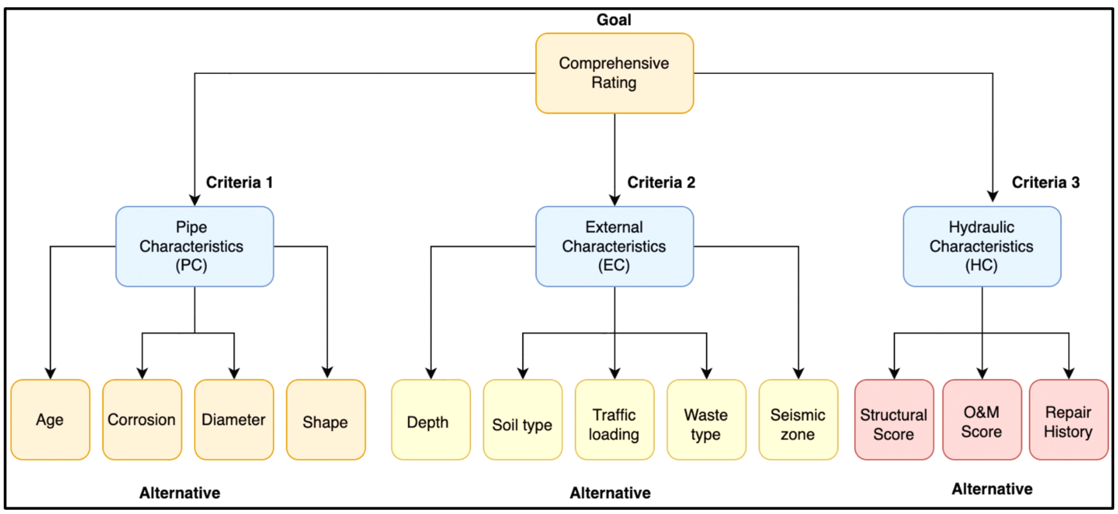

Figure 3-2: Hierarchical Structure of Characteristics.

Table 3-1: Factors and Description.

Criteria	Factor	Data Type	Description
Pipe Characteristics (PC)	Pipe age (years)	Numeric	The time between pipe installation and inspection year and aged pipes have more issues.
	Pipe material	String	The pipe material includes various types of material, such as ceramic, glass, fiberglass, many metals, concrete, and plastic.
	Diameter(mm)	Numeric	Nominal pipe diameter and smaller diameters are not easy to access.
	Shape	String	Typically pipe shapes are circular but depending upon the project, and shapes are changed. Circular shapes are easily accessed.
External Characteristics (EC)	Depth (feet)	Numeric	Higher-depth sewers are more challenging to access.
	Soil Type	String	Soil corrosiveness can impact the external pipe wall worsening mechanism.
	Traffic Loading	String	A pipe failure on or near a high traffic area can significantly increase delays and detour distances that negatively affect the social impact.
	Waste Type	String	Waste materials carried in a pipe can impact the pipe failure by blocking, corrosion, etc.
	Seismic Zone	String	Zones with higher seismic activities can negatively impact the structure.
Hydraulic Characteristics (HC)	Structural Score	Numeric	The score is given based upon the structure alignment.
	O & M Score	Numeric	The score is given based upon the operational and maintenance.
	Repair History	String	Pipes with more maintenance can impact the final Rating

Table 3-2: Ranking Value Descriptions For All Factors Under PC, EC And HC.

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

Under the pipe characteristics (PC) criteria, the following factors are defined: pipe age, material, diameter, length, and shape. Accordingly, as the pipe material ages, the degradation process becomes more significant (Hawari et al., 2017). In the present study, larger diameter pipes are considered more prone to worsening than smaller diameters (Balmer and Meers, 1981). Finally, different geometrical shapes will result in varying levels of deposits and degradation patterns (Ennaouri and Fuamba, 2013). The factors' attributes and the assigned rating of PC is presented in Table 3-3.

Table 3-3: Attributes Factors Rating For Pipe Characteristics.

Factor	Attribute	Ranking
Age (years)	<10	1
	≥10 and <25	2
	≥25 and <40	3
	≥40 and <50	4
	≥50 years	5
Corrosion	Plastic/GRP	1
	Clay	2
	NRCP/AC	3
	RCP	4
	Metallic	5
Diameter	>=49	1
	>31 and <=48	2
	>18 and <=30	3
	>11 and <= 18	4
	<=11	5
Shape	Circular	1
	Oval	2
	Horseshoe	3
	Semielliptical	4
	Arch	5

Under the external characteristics (EC) criteria, the following factors are defined: burial depth, soil type, traffic loading, waste carried, and seismic zone. The deep burial of the pipe results in increased soil overburden on the pipe. Next, the soil type refers to the surrounding soil that comes in direct contact with the pipe, which can impact the external pipe wall worsening mechanism, mainly corrosive materials, hydrocarbons, etc., present in the soil (Hawari et al., 2017). Traffic loads include all pedestrian and vehicle traffic above and in the proximity of the pipe, which impacts the overall integrity of the pipe. The type of waste carried can potentially erode the internal pipe wall if highly corrosive. Including the seismic zone factor ensures that any possible effects of seismic activities on the overall condition of the pipe are considered in the model. The factors' attributes and the assigned ratings of external characteristics (EC) is presented in Table 3-4.

Table 3-4: Attributes Factors Rating For External Characteristics.

Factor	Attribute	Ranking
Depth	<= 10 Feet	1
	> 10 and <= 15 Feet	2
	> 15 and <= 20 Feet	3
	> 20 and <= 25 Feet	4
	> 25 Feet	5
Soil Type	Low corrosivity	1
	Low to moderate corrosivity	2
	Moderate corrosivity	3
	Moderate-to-high corrosivity	4
	High corrosivity	5
Traffic Loading	No traffic to very light traffic	1
	Light traffic	2
	Medium traffic	3
	Moderate to heavy traffic	4
	Heavy traffic	5
Waste Type	Mildly corrosive	1
	Mildly to Moderate 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

Under the hydraulic characteristics (HC) criteria, the following factors are defined: PACP structural, PACP operations and maintenance (O&M) defects, and repair history. The PACP structural and O&M defect scores are on a scale of 1–5. PACP structural scores gives the defect rating for infrastructure with 1 being the least severe and 5 being the most severe defect. PACP operational scores gives the defect rating for maintenance with 1 being the least severe and 5 being the most severe defect. The repair history gives information about the maintenance of pipes in the previous years. The factors' attributes and the assigned ratings of Hydraulic characteristics (HC) is presented in Table 3-5.

Table 3-5: Attributes Factors Rating For Hydraulic Characteristics.

Factor	Attribute	Ranking
Structural Score	1	1
	2	2
	3	3
	4	4
	5	5
O & M Score	1	1
	2	2
	3	3
	4	4
	5	5
Repair History	No maintenance	1
	Minor maintenance	2
	Moderate maintenance	3
	Significant maintenance	4
	Extreme maintenance	5

3.2.2 Expert Judgement

Expert judgment is utilized for obtaining the relative importance weights of the factors close to the evaluation criteria. 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 answer of the scale is rated between 1-9 if the first factor is more important than the second or the reciprocal of the scale 1-9 if the second factor is more important than the first. The detailed description is shown in Table 3-6 (Saaty, 1980).

Table 3-6: AHP Importance Scale

Scale	Reciprocal Scale	Definition
1	1	Equally important
2	1/2	Slightly more important
3	1/3	Moderately more important
4	1/4	Moderately plus more important
5	1/5	Strongly more important
6	1/6	Strongly plus more important
7	1/7	Very strongly more important
8	1/8	Very very strongly more important
9	1/9	Extremely more important

3.2.3 Pairwise Comparison Matrix

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.

3.2.4 Factor Weights

Relative importance of the weights is average of each criterion of the normalized vector using the matrix multiplication.

3.2.5 Consistency Index

A Consistency Index (CI) is evaluated to test the consistency of the responses by experts. The comparisons must be re-examined when the CI does not reach the desired level. The CI is calculated as shown in Eq 3-1.

$$CI = \frac{(\lambda_{max} - n)}{(n-1)} \qquad \textbf{Eq. 3-1}$$

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

n is the order of the matrix.

3.2.6 Consistency Ratio

A Consistency Ratio (CR) is calculated by dividing CI by the value for the set of judgments corresponding to the order of the matrix, called the Random Consistency Index (RCI), as shown in Eq 3-2.

$$CR = \frac{CI}{RCI} \qquad \textbf{Eq. 3-2}$$

The values of RCI have been pre-determined by Saaty, who calculated these values for large samples of random matrices of varying orders, as shown in Table 3-7. If CR is > 0.1, we need to revisit the comparison.

Table 3-7: Random Consistency Index For Matrices Of Varying Order

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

3.3 Comprehensive Rating Score

The final step of the AHP is to determine utility. The utility is a numerical value providing information on how useful something is to you, and it will help you to select the best option The subject matter expert (SME) is PACP certified and has experience of 7 years. With the SME help, the relative weight of pipe characteristics (W_{PC}), the weight of external characteristics (W_{EC}), and the weight of hydraulic characteristics (W_{HC}) and the weight of each factor under this criterion has been determined.

Utility equation is developed using multi-linear regression equation without intercept. Regression analysis is a statistical tool used for the investigation of relationships between variables. Usually, it helps in seeking the effect of one variable upon another, the impact of grades on performance. To explore such issues, the data should be assembled on the underlying variables of interest, and regression should be employed to estimate the quantitative effect of the causal variables upon the variable that they influence. Typically, the 'statistical significance' of the estimated relationships is assessed, which is the degree of confidence.

Regression analysis utilizes the relationship between multiple quantitative or qualitative variables to predict dependent variables' behavior based on the independent variables' behavior(Gross and Groß, 2003). The simplified model can be created from the equation shown in Eq 3-3 that the true relationship is close to the estimated relationship.

$$\mathrm{Y}_i = \beta_0 + \beta_1 X_i + \varepsilon_i \qquad \textbf{Eq. 3-3}$$

Y_i represents the value of the response variable in the i^{th} trial.

β_0 and β_1 represents the regression parameters.

X_i represents the value of the predictor variable in the i^{th} trial.

ε_i represents the random Error.

Multiple variables are used to predict the behavior of the response variable in multiple regression models. As a result, Eq 3-3 can be converted into an Eq 3-4

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots.. + \beta_p X_{ip} + \varepsilon_i \qquad \textbf{Eq. 3-4}$$

The utility equation developed using multiple regression which is used in AHP is shown in Eq 3-5

$$U_{total} = U_1 W_1 + U_2 W_2 + \ldots.. + U_n W_n \qquad \textbf{Eq. 3-5}$$

$U_1, U_{2\,,} --- U_n$ criteria.

$W_1, W_{2,,} --- W_n$ weight of the criteria.

These weights, along with multi linear regression without intercept (β_0), are combined to obtain the final comprehensive rating scores (CRS), as shown from Eq 3-6 to Eq 3-9.

$$CRS = W_{PC}PC + W_{EC}cEC + W_{HC}HC \qquad \textbf{Eq. 3-6}$$

$$PC = \sum_{i\,=\,1}^{m}(w_i R_i) \qquad \textbf{Eq. 3-7}$$

$$EC = \sum_{j\,=\,1}^{n}(w_j R_j) \qquad \textbf{Eq. 3-8}$$

$$HC = \sum_{k\,=\,1}^{o}(w_k R_k) \qquad \textbf{Eq. 3-9}$$

W_{PC} is the factor weight for overall PC criteria.

W_{EC} is the factor weight for overall EC criteria.

W_{HC} is the factor weight for overall HC criteria.

w_i is each factor weights under the PC criteria.

w_j is each factor weights under the EC criteria.

w_k is each factor weights under the HC criteria.

R_i is the i^{th}category factor rating under the PC criteria.

R_j is the j^{th}category factor rating under the EC criteria.

R_k is the k^{th}category factor rating under the HC criteria.

m is number of factors under the PC criteria.

n is number of factors under the EC criteria.

o is number of factors under the HC criteria.

3.4 Data

Information such as diameter, depth, length of the pipes is given in pipe segment reports (i.e., pdf format), and the other information related to the pipes such as pipe age, corrosion, structural score, O&M score, traffic loading, waste type, shape and the seismic zone is given in MS Excel from the Dept. of Engineering & Environmental Services, Shreveport, Louisiana Phase 3. These Pipe Section reports contain different sections, as presented in Table 3-8. Each section contains text input by the inspector.

Table 3-8: Description Of Pipe Segment Reports

Section	Description
Pipe characteristics	information about the physical pipe properties (Ex: Diameter, Depth, Length)
Emergency Repair	Information about the Emergency Repair (Ex: Immediate Leakage Fixes)
Smoke Testing Assessment	Information about any smoke observed from pipes (Ex: Medium smoke observed emanating from cleanout)
CCTV Assessment	Information about the pipes using CCTV Camera (Ex: Multiple Defects)
Composite Assessment	Information about the Composite Material around the pipe
Criticality Assessment	Information about the risk value of the pipe (Ex: Medium)
Capacity	Information about the pipe Capacity

We used Python programming to process the records of all the sewer pipe reports to extract 12 specified variables from the pdf reports: Pipe ID, Pipe Diameter, Depth Category, Total Length (Feet), Existent Height (inches), Existent Material, Existent Lining Method, O&M score, Structural score, and Comprehensive Rating listed under Pipe characteristics section into a .csv file. For our final data, we have combined the .csv file and MS Excel from the Dept. of Engineering & Environmental Services. The flow diagram of the data cleaning process to obtain the final data is shown in Figure 3. We then randomly selected 200 reports and manually checked the data to verify if the same data was extracted using Python programming. The extraction and retrieval of information by the program were compared to the results of the manual review. Sample Data extracted using python programming into the .csv file. Final Data generated using Python programming and adding with excel is shown in Figure 3-3.

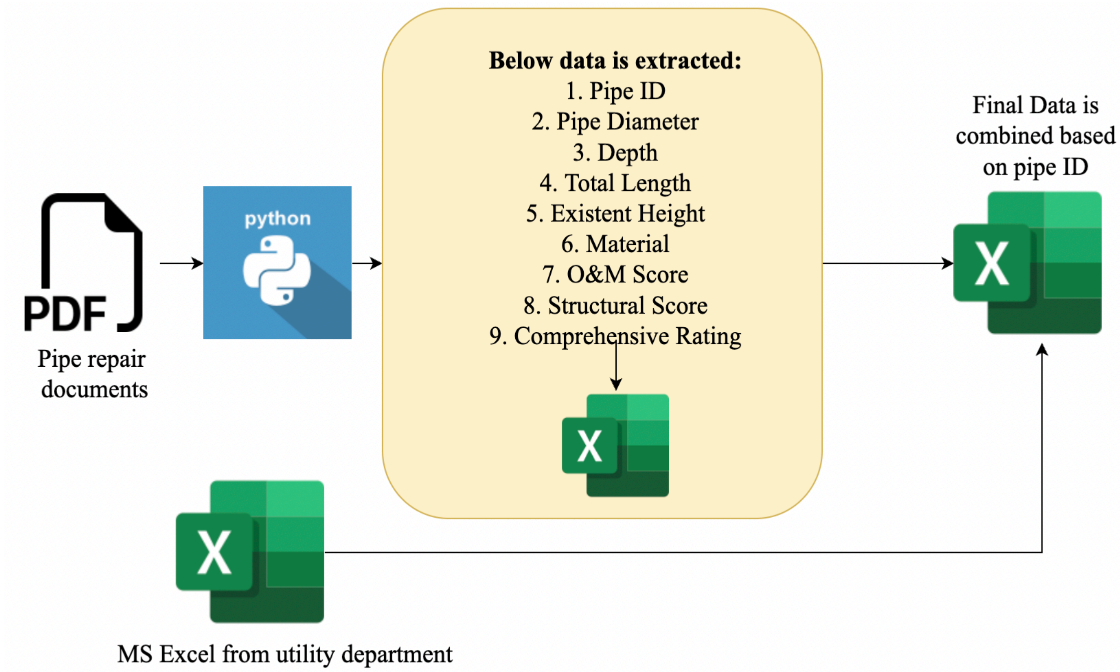

Figure 3-3: Final Data Generation

In this study, we included records with relevant data by removing 4.2% of records with inconsistent data, and 10% to 20% of missing information info per pipe for further analysis. This step makes the training dataset cleaner and error-free, which helps in improving the accuracy of the model.

Missing values: It is very usual to have missing values in our dataset. It may have happened during data collection by the CCTV inspector. We eliminated 60 reports related to the few missing information such as pipe material, depth, or structural score.

Inconsistent values: We know that data can contain inconsistent values. For instance, the unit mm is entered as cm, and feet in entered as inches. It may be due to human error, or maybe the information was misread while scanned from a handwritten form by the CCTV inspector. We have eliminated 70 reports related to inconsistent values.

After all these analyses and verification of data, the final data collection included 3100 pipe segment data with a total length of approximately 198.9 miles. The data contained information about pipes having an average age of 56 years. For this study, a pipe length of approximately 29.20 miles, totaling 1240 pipe segments using a stratified random sampling technique, were selected. For data analysis, a centralized spreadsheet was created with data for the 1240 pipe segments containing all factors listed. Final Data used is shown in Figure 3-4. Table 3-9 Table 3-10 Table 3-11 shows the sample data for few selected pipe data.

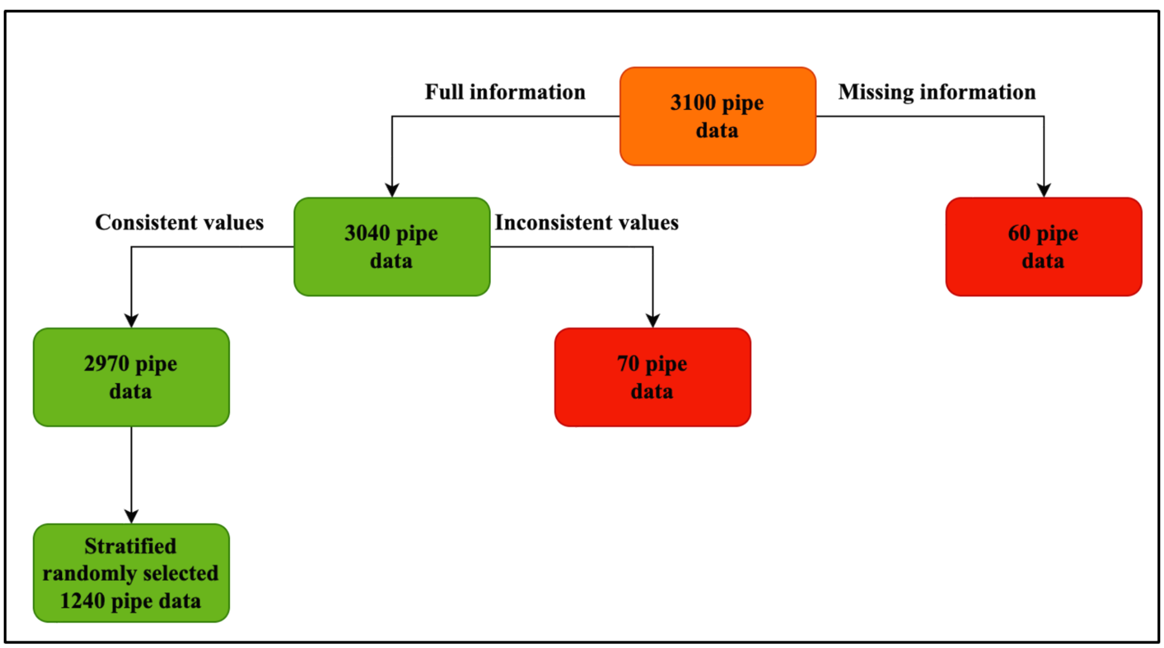

Figure 3-4: Process Of Finally Selected Pipe Data For Our Model.

Table 3-9: Pipe Characteristics For Selected Data.

Inspection ID	Year	Corrosion	Diameter(mm)	Shape
925	1965	Clay	8	Circular
197	1961	NRCP	8	Oval
213	1967	RCP	8	Circular
822	1969	Clay	8	Circular

Table 3-10: External Characteristics For Selected Data.

Inspection ID	Depth (Feet)	Soil Type	Traffic Loading	Waste Type	Seismic Zone
925	0-10	Low to moderate	Medium	Moderately	Zone 2
197	10-15	Low	Light	Mildly	Zone 2
213	15-20	Moderate	No traffic	Moderate	Zone 2
822	0-10	Low	Light	Highly	Zone 2

Table 3-11: Accuracy, Precision, Recall, And F1 Score For CR AHP.

Inspection ID	Structural Score	O&M Score	Repair History
925	3	3	Moderate
197	2	2	Minor
213	3	3	No
822	3	3	Moderate

3.5 AHP Results

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. Table 3-12 shows the pairwise comparison matrix of pipe characteristics, external characteristics, and hydraulic characteristics given by the expert.

Table 3-12: Pairwise Comparison Matrix Of PC, EC, and HC.

Criteria	Pipe Characteristics	External Characteristics	Hydraulic Characteristics
Pipe Characteristics	1	1/2	2
External Characteristics	2	1	2
Hydraulic Characteristics	1/2	1/2	1

Table 3-13 shows the pairwise comparison matrix of Age, Corrosion, Diameter and Shape of pipe characteristics given by the expert.

Table 3-13: Pairwise Comparison Matrix Of PC Criteria.

Criteria	Age	Corrosion	Diameter	Shape
Age	1	1/9	1	1
Corrosion	9	1	6	3
Diameter	1	1/6	1	1
Shape	1	1/3	1	1

Table 3-14 shows the pairwise comparison matrix of Depth, Soil Type, Traffic loading, Waste type and Seismic Zone of external characteristics given by the expert.

Table 3-14: Pairwise Comparison Matrix Of EC Criteria.

Criteria	Depth	Soil Type	Traffic Loading	Waste type	Seismic Zone
Depth	1	2	1/2	1/2	1/2
Soil Type	1/2	1	1/2	2	1/4
Traffic Loading	2	2	1	2	1/2
Waste type	2	1/2	1/2	1	1/4
Seismic Zone	2	4	2	4	1

Table 3-15 shows the pairwise comparison matrix of Structural Score, O&M Score and Repair history of hydraulic characteristics given by the expert.

Table 3-15: Pairwise Comparison Matrix Of HC Criteria.

Criteria	Structural Score	O&M Score	Repair History
Structural Score	1	2	2
O&M Score	1/2	1	2
Repair History	1/2	1/2	1

Once the expert judgment weights were determined using the AHP method, the relative importance weights of factors affecting sewer pipe conditions were calculated. The ranking of the factors is determined using global weights. The global weights are obtained by multiplying the individual factor's relative importance weight with the criterion's weight under which it falls. Table 3-16 will show the criteria weight, relative importance weight of each factor, global weights, and factors; the sum of all weights is 1. Global weights show the consequence of failure and Figure 3-5 shows the priority of factors.

Table 3-16: Resulting Weights Of Criteria And Factors Affecting Pipe Condition.

Criteria	**Factors**	**Criteria Weight**	**Relative Importance Weight of Factor**	**Global Weights**	**Rank**
Pipe Characteristics		**0.310814**			
	Age		0.103274	0.03209901	12
	Corrosion		0.646587	0.20096829	1
	Diameter		0.111992	0.03480868	11
	Shape		0.138146	0.04293771	9
			∑ = 1.0	**0.310814**	
External Characteristics		**0.493386**			
	Depth		0.139967	0.06905776	5
	Soil Type		0.121239	0.05981763	8
	Traffic Loading		0.221753	0.10940983	3
	Waste Type		0.125648	0.06199296	6
	Seismic Zone		0.391392	0.19310733	2
			∑ = 1.0	**0.493386**	
Hydraulic Characteristics		**0.195800**			
	Structural Score		0.493386	0.09660498	4
	O&M Score		0.310814	0.06085738	7
	Repair History		0.195800	0.03833764	10
			∑ = 1.0	**0.195800**	

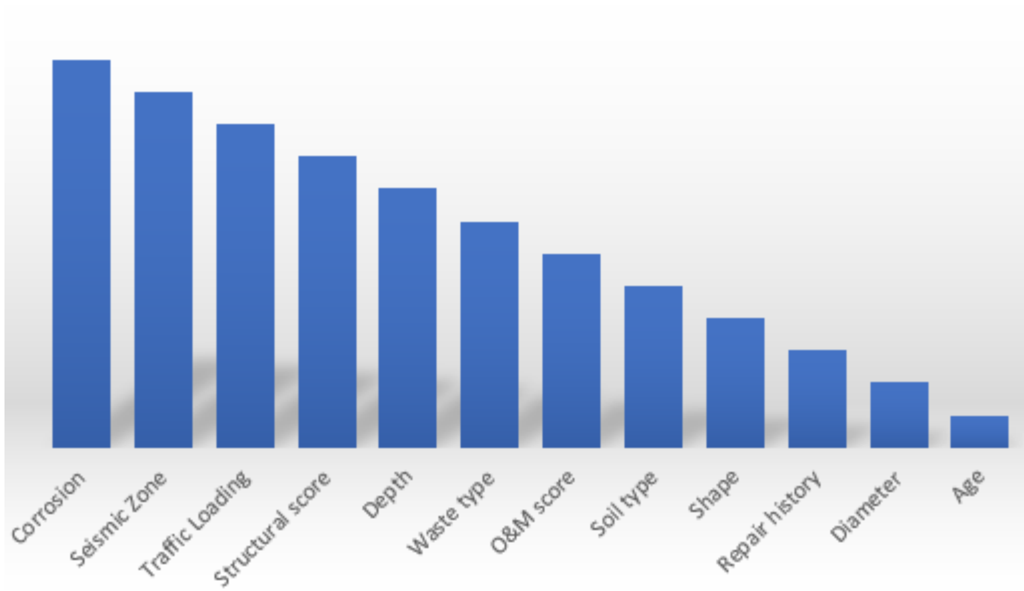

Figure 3-5: Consequence Of Failure Based On AHP.

Table 3-17 will show the consistency ratio for all the factors. The consistency ratio of all the factors was less than 0.1. The judgment of this decision-maker is acceptable.

Table 3-17: Consistency Index And Consistency Ratio

Criteria	λ_{max}	CI	CR	Factor	λ_{max}	CI	CR
Pipe Characteristics	3.05	0.026	0.046	Age	4.11	0.036	0.040
				Corrosion			
				Diameter			
				Shape			
External Characteristics				Depth	5.37	0.092	0.082
				Soil Type			
				Traffic Loading			
				Waste Type			
				Seismic Zone			
Hydraulic Characteristics				Structural Score	3.05	0.026	0.046
				O & M Score			
				Repair History			

3.6 Comprehensive Rating Results And Model Evaluation

The obtained Comprehensive rating scores for selected pipes calculated using Eq. 3-6 to Eq. 3-9 are presented in Table 3-18.

Table 3-18: Sample Comprehensive Rating Score

Pipe ID	PC Score	EC Score	HOF Score	CR Score
925	2.507650	2.207432	3	2.45592877
197	3.292383	1.753111	2	2.27987915
213	3.800824	2.165099	2.60840	2.76030357
822	2.507650	2.115736	3	2.41068725

The Comprehensive rating score (CRS) of a sewer pipe measures the overall deteriorated condition of the segment. Reaching a maximum score involves the fact that all the 12 factors have a rating of 5. Suppose the majority of the 12 factors have a rating of 5, and a few have intermediate values of 2, 3, and 4; in that case, the Comprehensive rating score will be in the maximum interval. Therefore, to categorize each segment into a condition based on the segment's Comprehensive Rating score, the following method was implemented.

The top-ranked factor based on the AHP analysis is the Corrosion factor. The second and third factor based on the AHP analysis is seismic zone and traffic loading. 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 factors were given the same Rating. First, all factors were set to 1; then all were provided a rating of 2, then a rating of 3, 4, and finally, all factors' ratings were set to 5.

This process aimed to obtain an approximate interval variability of the Comprehensive rating score based on the value of the factor ratings. The results are summarized in Table 3-19.

Table 3-19: Ratings Based On Comprehensive Rating Score For Different Materials.

Pipe Material	All 1's	All 2's	All 3's	All 4's	All 5's
Plastic/GRP	1.990323	2.180020	2.369717	2.559414	2.749111
Clay	2.103344	2.293041	2.482738	2.672435	2.862132
NRCP/AC	2.216366	2.406063	2.559414	2.749111	2.938808
RCP	2.329388	2.519085	2.708782	2.898479	3.088176
Metallic	2.442409	2.632106	2.821803	3.011500	3.201197

Table 3-20 shows the average rating of comprehensive rating 1, comprehensive rating 2, comprehensive rating 3, comprehensive rating 4 and comprehensive rating 5.

Table 3-20: Average Ratings Of Comprehensive Rating Score.

All 1's	All 2's	All 3's	All 4's	All 5's
2.216366	2.406063	2.5884908	2.7781878	2.9678848

Final ratings of comprehensive ratings based on the average are summarized in Table 3-21.

Table 3-21: Final Ratings Based On Comprehensive Score For Our Data

Comprehensive Score Ranges	Comprehensive Rating
>= 2.216366 and < 2.406063	1
>= 2.406063 and < 2.5884908	2
>= 2.5884908 and < 2.7781878	3
>= 2.7781878 and < 2.9678848	4
>= 2.9678848	5

As a general guideline, pipes in comprehensive rating 1 do not require any further consideration as these pipes are in excellent condition and can be reassessed in ten years. These pipes in comprehensive rating 2 are in good condition and can be rehabilitated or replaced in six to ten years. These pipes are in fair condition for pipes in comprehensive rating 3 and can be rehabilitated or replaced in three to five years. These pipes are in poor condition for pipes in comprehensive rating 4 and can be rehabilitated or replaced in zero to two years. Finally, pipes in condition 5 are in the worst condition and require immediate attention. The overall comprehensive rating Framework is shown in Figure 3-6.

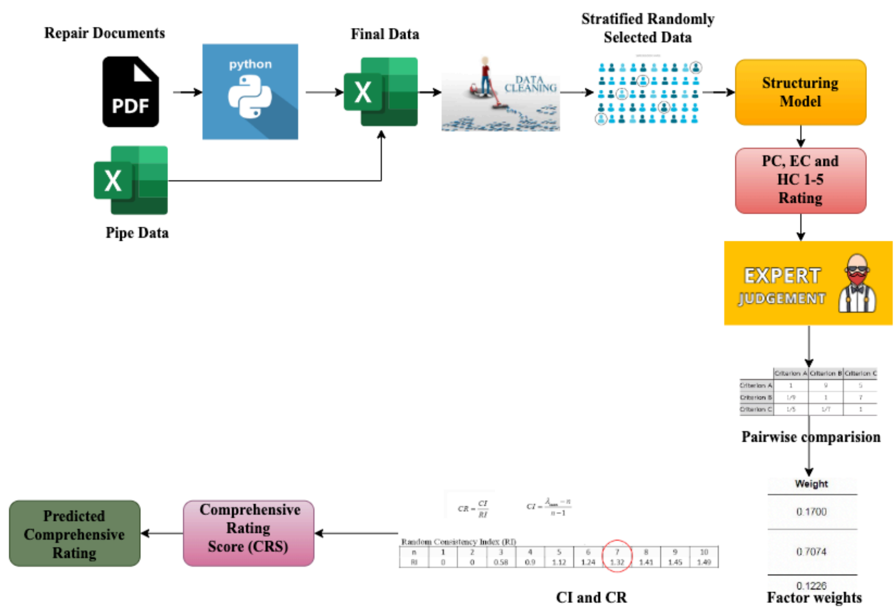

Figure 3-6: Overall Comprehensive Rating Framework For AHP.

Model evaluation is an essential step in the creation of a model to calculate the overall performance of the developed CR model. It helps in showing how well the chosen model performed for our data using the confusion matrix. A confusion matrix is used for evaluating the performance of the developed model by comparing the actual comprehensive ratings with the predicted comprehensive ratings.

There are four types of outcomes that are represented in the confusion matrix that occur there are True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Accuracy, Precision, Recall, and F1 scores are calculated using Eq 3-10 to Eq 3-13. TP, TN, FP, FN, Accuracy, Precision, Recall, and F1 scores are defined below.

TP - Predict an observation that belongs to one specific comprehensive rating given that belongs to this specific comprehensive rating. (Actual comprehensive rating is 1, and it predicts the predicted comprehensive rating as 1).

TN - Predict an observation that does not belong to one specific comprehensive rating. (Actual comprehensive rating is 1, and it predicts the predicted comprehensive rating as 2, 3, 4, or 5).

FP - Predict an observation that belongs to one specific comprehensive rating, and it does belong to another comprehensive rating. (Actual comprehensive rating is 2 or 3 or 4 or 5, but it predicts the predicted comprehensive rating as 1)

FN - Predict an observation that does not belong to one specific comprehensive rating. (Actual comprehensive rating is 1, and it predicts the predicted comprehensive rating not as 1).

Accuracy - Percentage of correct predictions for the test data.

Precision - Ratio of correctly predicted positive observations to the predicted positive observations.

Recall - the ratio of correctly predicted positive observations to all observations in the actual class.

F1 score - Weighted average of Precision and Recall.

$$Accuracy = \left(\frac{TP + TN}{TP + TN + FP + FN}\right) * 100\% \qquad \textbf{Eq. 3-10}$$

$$Precision = \frac{TP}{TP + FP} \qquad \textbf{Eq. 3-11}$$

$$Recall = \frac{TP}{TP + FN} \qquad \textbf{Eq. 3-12}$$

$$F1\,Score = \frac{2TP}{2TP + FP + FN} \qquad \textbf{Eq. 3-13}$$

These True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN) outcomes are often plotted on a confusion matrix. A confusion matrix is a summary of prediction results on a classification problem. The correct and incorrect predictions are summarized with count values and broken down by each class using AHP for comprehensive rating model is shown in Table 3-22. Table 3-23 shows the confusion matrix for POCR using AHP.

Table 3-22: Confusion Matrix For Comprehensive Rating AHP.

Predicted Comprehensive Rating	Actual Comprehensive Rating Count				
	1	2	3	4	5
1	22	44	50	68	30
2	39	36	58	81	46
3	46	66	38	95	24
4	33	75	66	44	32
5	30	54	65	78	20

Table 3-23: Confusion Matrix For POCR AHP.

Predicted Comprehensive Rating	Actual Comprehensive Rating Count				
	1	2	3	4	5
1	15	46	54	72	32
2	43	25	63	85	49
3	42	63	29	98	31
4	36	79	72	34	33
5	29	53	67	77	13

Overall, the accuracy of our model predicted Comprehensive Rating with the actual Comprehensive Rating of the pipe segment reports was 12.90%. Since linear regression assumes a linear relationship between the input and output variables, it failed to fit the dataset properly because the relationship between response and the predictor is not linear. All the conclusions we drew became null and void and led towards the very low accuracy of the model. The achieved overall accuracy of all the models is shown in Table 3-24 and Figure 3-7.

Table 3-24: Overall Accuracy Between POCR AHP And CR AHP.

Comprehensive Rating	POCR model using AHP	CR model using AHP
Accuracy	9.35%	12.90%

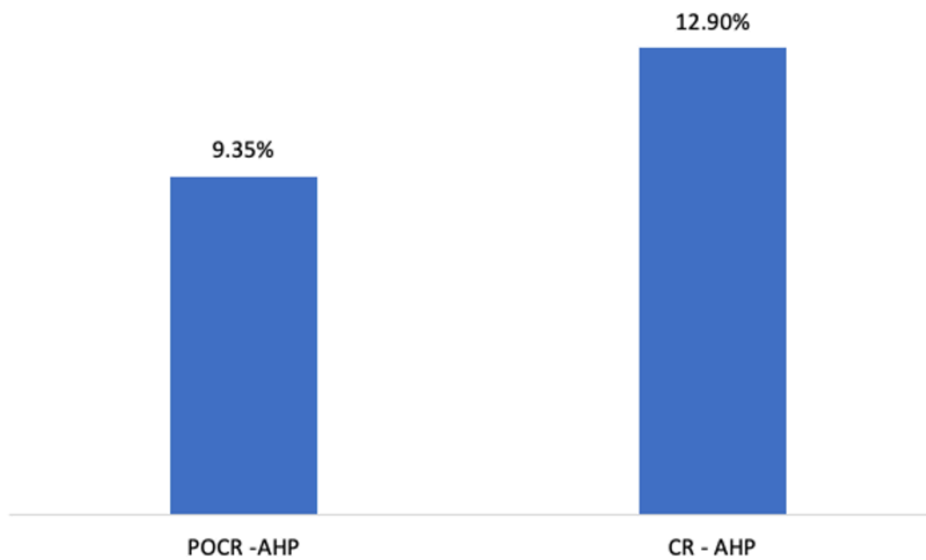

Figure 3-7: Overall Accuracy Comparison Between POCR AHP And CR AHP.

Table 3-25 shows the accuracy, precision, recall, and F1 score for 5 predicted Comprehensive ratings compared with the Actual Comprehensive Rating given by the inspector for comprehensive rating AHP and Table 3-26 shows the accuracy, precision, recall, and F1 score for 5 predicted Comprehensive ratings compared with the Actual Comprehensive Rating given by the inspector for POCR AHP.

Table 3-25: Accuracy, Precision, Recall, And F1 Score For CR AHP.

Comprehensive Rating	Accuracy	Precision	Recall	F1 Score
1	72.58%	0.10	0.13	0.11
2	62.66%	0.14	0.13	0.13
3	62.10%	0.14	0.14	0.14
4	57.42%	0.18	0.12	0.14
5	71.05%	0.081	0.13	0.10

Table 3-26: Accuracy, Precision, Recall, And F1 Score For POCR AHP

Comprehensive Rating	Accuracy	Precision	Recall	F1 Score
1	71.45%	0.068	0.091	0.078
2	61.21%	0.094	0.094	0.094
3	60.48%	0.11	0.10	0.11
4	55.48%	0.13	0.093	0.11
5	70.08%	0.054	0.082	0.065

The comprehensive ratings vs. predicted comprehensive ratings for few random pipes were plotted in Figure 3-8 to evaluate better the difference of both the ratings.

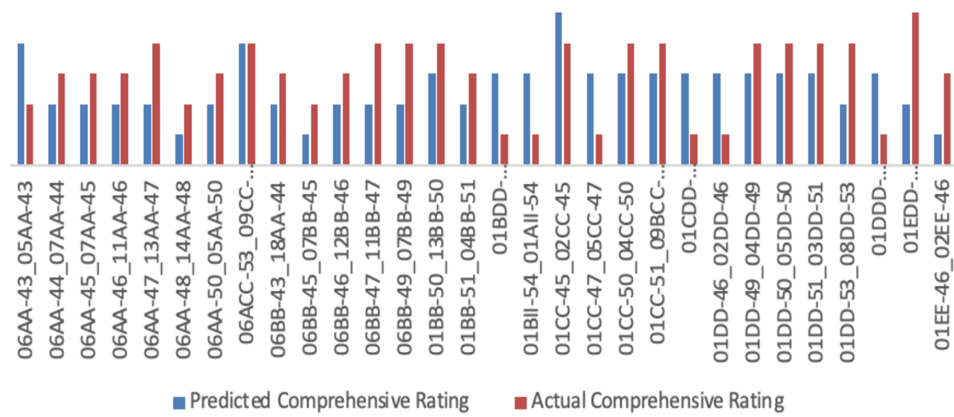

Figure 3-8: Comparison Between Actual And Predicted For Selected Pipe ID's.

3.7 Summary

AHP modeling has been used extensively to develop a model to predict the failure of sewer pipes. This study developed an AHP model for sewer pipe failure prediction models and calculated the overall pipe rating based on the pipe characteristics, external factors, and hydraulic and other factors in the sewer pipes in Shreveport in Louisiana, the United States. The comprehensive score was determined using a linear combination between the relative importance weights of all factors and their respective ratings. AHP was used to obtain the relative importance weights of all criteria. The predicted comprehensive Rating is compared with the actual comprehensive Rating, and this model showed us an accuracy of 12.90%, which is not satisfactory. Since the actual relation between the response and the predictor is not linear, the accuracy of the model is very low. SME judgment can vary among different utilities. Because the CRS score is determined using a linear combination, any change in any of the factors will result in an obvious change of the outcome, a change that cannot be determined if it is statistically significant or not. Therefore, this model is not suggested as it requires manual effort from the inspectors to calculate the importance of factors for better accuracy, which might lead to human errors again. We have developed a Comprehensive Rating model using *K*-NN.

CHAPTER 4

COMPREHENSIVE RATING METHODOLOGY USING *K*-NN

4.1 Background

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. *K*-Nearest Neighbor (*K*-NN) is used to develop a Comprehensive Rating (CR) 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, which is more accurate than Comprehensive rating than AHP and to reduce the manual efforts of the inspector. The present model developed is still applied to Shreveport Phase 3 data for validation.

4.2 Introduction

In the first step, the factors under criteria of the model developed using AHP, as shown in Figure 3-1 are still used. Data used for AHP is still used. The overall framework is shown in Figure 4-1.

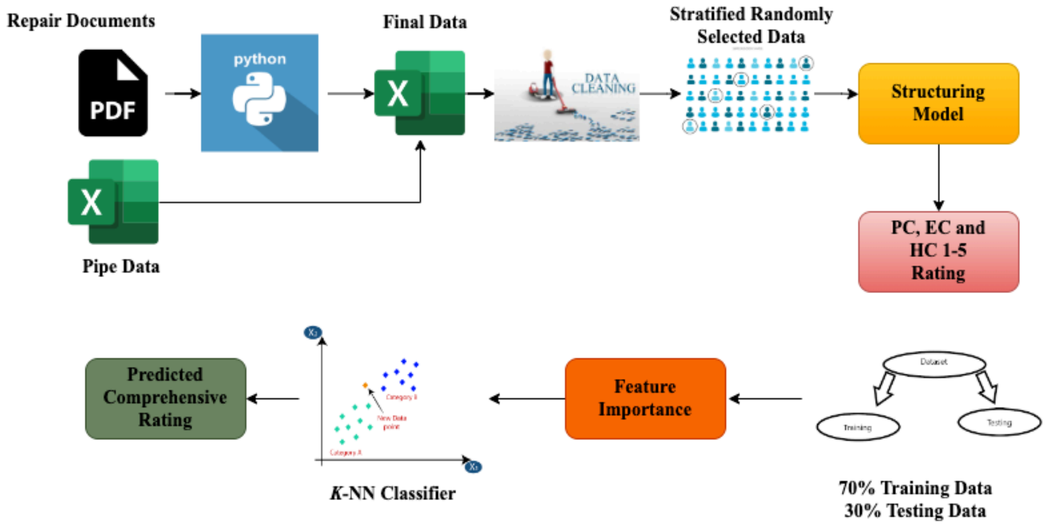

Figure 4-1: Overall Comprehensive Rating Framework For *K*-NN.

4.3 Feature Importance

Feature Importance refers to techniques that calculate a score for all the input features for a given model and the scores simply represent the "importance" of each feature. A higher score means that the specific feature will have a larger effect on the model that is being used to predict a certain variable. The feature importance which is used is Permutation Feature Importance. The feature importance is calculated by noticing the increase or decrease in error when we permute the values of a feature. If permuting the values causes a huge change in the error, it means the feature is important for our model. The best thing about this method is that it can be applied to every machine learning model. Its approach is model agnostic which gives you much freedom. There are no complex mathematical formulas behind it. The permutation feature importance is based on an algorithm that works as follows.

- Calculate the mean squared error with the original values.

- Shuffle the values for the features and make predictions.

- Calculate the error rate with the shuffled values.
- Compare the difference between them.
- Sort the differences in descending order to get features with most to least importance.

4.4 *K*-Nearest Neighbor

The next step is to build our model using $K -$ Nearest Neighbor (*K*-NN) (Peterson, 2009) classifier. The *K*-nearest neighbor's algorithm was first described in early 1950. This method did not gain popularity until 1960, when increased computing power became available. The *K*-nearest neighbor's algorithm is a non-parametric, supervised learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual data point. *K*-NN classifies the new data points based on the similarity measure of the earlier stored data points. To select the *K* value, we need to estimate the error rate of the classifier for different *K* values and select the *K* value which have a minimum error rate.

Compared to other algorithms, *K*-NN is called Lazy Learner (Instance-based learning). It does not learn anything in the training period. It does not derive any discriminative function from the training data. It stores the training dataset and learns from it only when making real-time predictions. This makes the *K*-NN algorithm much faster than other algorithms that require training e.g., SVM, Linear Regression, etc. New data can be added seamlessly at any point in time, which will not impact the algorithm's accuracy. Finally, it is very easy to implement because it only requires two parameters *K* and the Euclidean distance function.

Algorithm:

Input: E: All factors, K: Chosen Number of Neighbors

Output: C: Mode of K labels

Begin:

- Load the data.
- Initialize K to your chosen number of neighbors.
- For each testing data:
    - Calculate the distance between 30% of testing data (x, y) with all 70% of the training data. (a, b) using Euclidean distance (ED) as shown in Eq 4-1.

$$ED = \sqrt{(x-a)^2 + (y-b)^2)} \qquad \textbf{Eq. 4-1}$$

    - Add the distance and the index of testing data to the ordered collection.
- Sort the ordered collection of distances and indices in ascending order by distances.
- Pick the first *K* entries from the sorted collection.
- Get the labels of selected entries.
- Return the mode of *K* labels.

  End

4.5 Results and Model Evaluation

We have divided the data into 70% training and 30% testing data. Permutation Feature importance is performed for our algorithm. Base line error is 0.27 with all the 12 factors. Figure 4-2 shows the Shuffled error rate minus Base line error rate of all factors. 10 factors except the seismic zone and diameter are important in predicting the target variable.

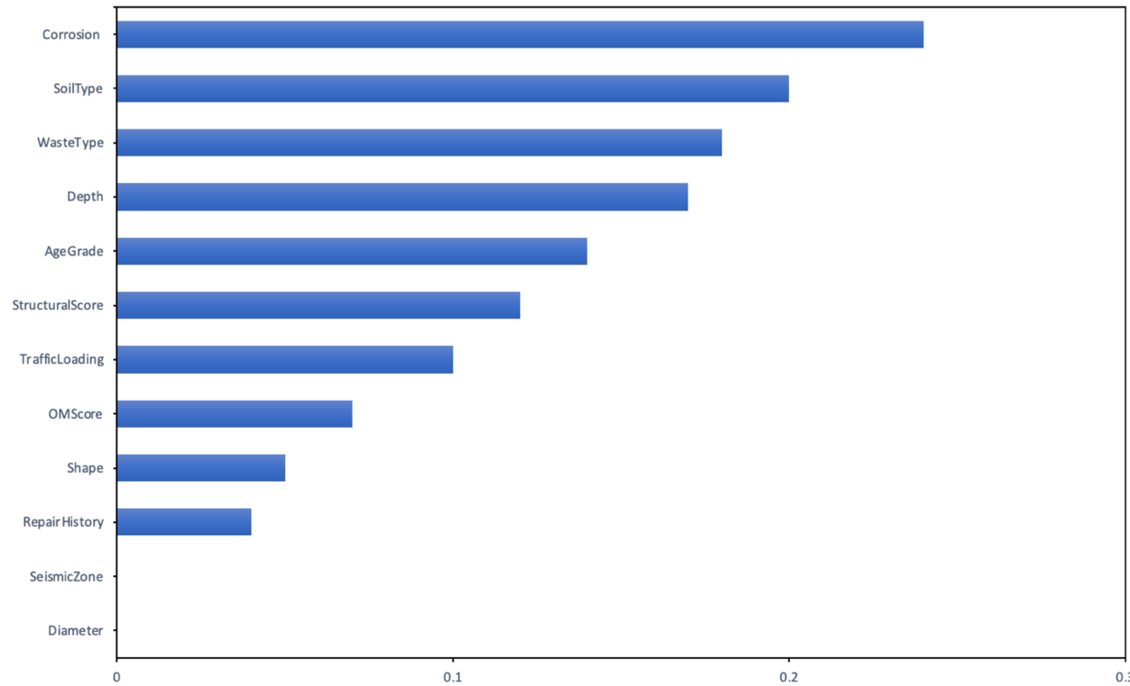

Figure 4-2: Feature Importance Of The Factors.

We have eliminated seismic zone and diameter in our data, and the process is repeated several times with different values of *K* to reduce errors and to make accurate predictions. We have finally chosen the value as *K* = 9. As the value of *K* is increased, our predictions become more stable and will have more accurate predictions up to a certain point. Figure 4-3 shows the graph of the misclassification rate as a function of *K* for 25 and 30, and from both graphs, we see the lowest error is found at *K* = 9 with a value of 0.27290. We also checked for different values of *K,* such as 15 and 20*,* and we found the lowest value of the misclassification rate at 7. So, we have used the value as *K* = 9 for better accuracy. Table 4-1 shows the count and misclassification rate for training and testing data for different *K* values. Misclassification is slightly higher because of less training data for comprehensive ratings 1 and slightly fewer training data for comprehensive ratings 2 and 3 compared to comprehensive ratings 4. This can be reduced when the model is trained with a broader variety of data with different comprehensive ratings. In our scenario, we didn't consider the entire dataset because we have more comprehensive ratings related to 3 and 4 than others.

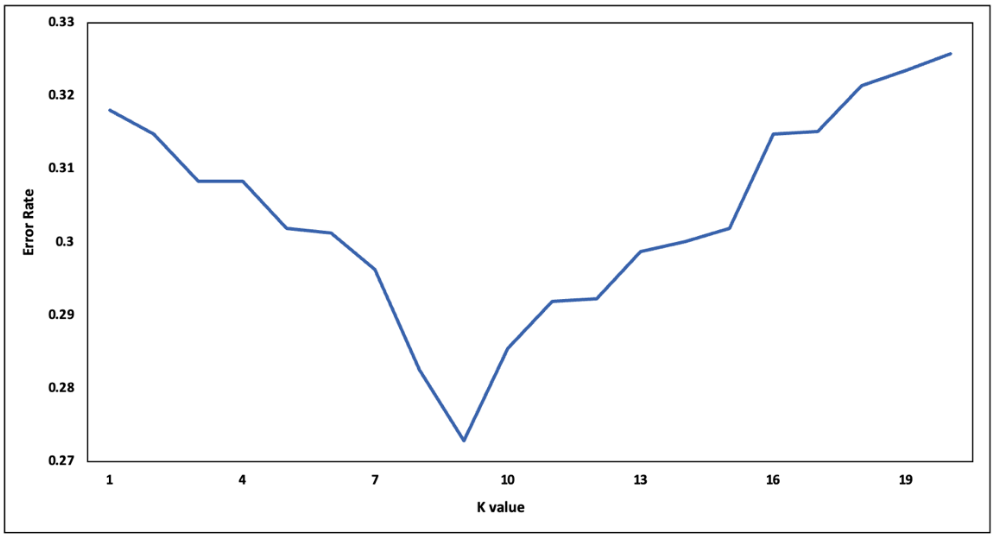

Figure 4-3: Misclassification Error For Function Of K.

Table 4-1: Misclassification Rate For Each *K*.

K	Training Count	Misclassification Error	Validation Count	Misclassification Error
1	868	0.31602	372	0.31806
2	868	0.31215	372	0.31484
3	868	0.30984	372	0.30839
4	868	0.30414	372	0.30839
5	868	0.30054	372	0.30194
6	868	0.29594	372	0.30127
7	868	0.29176	372	0.29627
8	868	0.28978	372	0.28258
9	868	0.27796	372	0.27290
10	868	0.27883	372	0.28548
11	868	0.27935	372	0.29194
12	868	0.28011	372	0.29226
13	868	0.28656	372	0.29871
14	868	0.28978	372	0.30012
15	868	0.29012	372	0.30194
16	868	0.30102	372	0.31484
17	868	0.30996	372	0.31516
18	868	0.31125	372	0.32145
19	868	0.31179	372	0.32349
20	868	0.32245	372	0.32574

To proceed with the *K*-NN calculation process, Euclidian distance is used to find the distance between each testing data to training data as shown in Eq 4-1. Table 4-2 shows the confusion matrix of validation data compared with the actual comprehensive ratings given by the inspector.

Table 4-2: Confusion Matrix For *K*-NN.

Predicted Comprehensive Rating	Actual Comprehensive Rating Count				
	1	2	3	4	5
1	33	12	0	0	0
2	6	58	7	6	0
3	0	7	79	15	5
4	0	0	11	61	9
5	0	2	10	13	38

We have compared our same data set for Pipe overall conditional rating (POCR) model developed (Vladeanu and Matthews, 2019a) using multicriteria decision analysis and Comprehensive Rating (CR) model using Analytical Hierarchy Process (AHP) (Betgeri, 2022) a with the actual comprehensive ratings given by the inspector. Table 4-3 shows the confusion matrix of the POCR model, and Table 4-4 shows the confusion matrix of the Comprehensive Rating model using AHP. The achieved overall accuracy of all the models is shown in Table 4-5 and Figure 4-4.

Table 4-3: Confusion Matrix For Comprehensive Rating Model Using AHP.

Predicted Comprehensive Rating	Actual Comprehensive Rating Count				
	1	2	3	4	5
1	5	17	23	20	6
2	10	2	20	31	14
3	7	22	20	27	18
4	9	20	19	8	13
5	8	18	25	9	1

Table 4-4: Confusion Matrix For POCR Model Using AHP.

Predicted Comprehensive Rating	Actual Comprehensive Rating Count				
	1	2	3	4	5
1	4	15	24	21	8
2	12	3	22	23	17
3	7	21	11	26	19
4	8	27	21	5	12
5	6	14	27	17	2

Table 4-5: Overall Accuracy Comparison Between *K*-NN, CR AHP And POCR AHP.

Comprehensive Rating	CR model *K*-NN	CR model using AHP	POCR model using AHP
Accuracy	72.31%	9.68%	6.72%

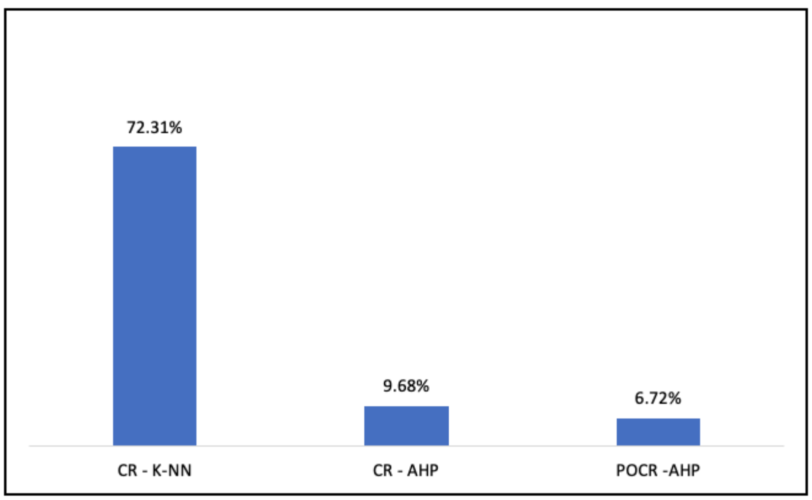

Figure 4-4: Overall Accuracy Comparison Between *K*-NN, POCR AHP And CR AHP.

Table 4-6 Table 4-7 and Table 4-8 shows the accuracy, precision, recall, and F1 score for all 5 predicted comprehensive ratings for *K*-NN CR, AHP CR and POCR. For Classification predictions, four types of outcomes occur there are True Positive (TP), True

Negative (TN), False Positive (FP), False Negative (FN), and Accuracy, Precision, Recall and F1 score are calculated using Eq 3-10 to Eq 3-13.

Table 4-6: Accuracy, Precision, Recall, And F1 Score Of *K*-NN CR.

Comprehensive Rating	Accuracy	Precision	Recall	F1 Score
1	95.16%	0.73	0.85	0.79
2	89.25%	0.75	0.73	0.74
3	85.22%	0.75	0.74	0.74
4	85.48%	0.75	0.64	0.69
5	89.52%	0.60	0.73	0.66

Table 4-7: Accuracy, Precision, Recall, And F1 Score Of AHP CR.

Comprehensive Rating	Accuracy	Precision	Recall	F1 Score
1	73.12%	0.070	0.13	0.091
2	59.14%	0.026	0.025	0.026
3	56.72%	0.210	0.190	0.200
4	60.22%	0.120	0.084	0.098
5	70.16%	0.016	0.019	0.018

Table 4-8: Accuracy, Precision, Recall, And F1 Score Of AHP POCR.

Comprehensive Rating	Accuracy	Precision	Recall	F1 Score
1	72.85%	0.056	0.11	0.073
2	59.41%	0.039	0.037	0.039
3	55.11%	0.130	0.100	0.120
4	58.33%	0.068	0.054	0.061
5	67.74%	0.030	0.034	0.032

In summary, *K*-NN classifier is superior to the AHP POCR and AHP CR for classifying defect ratings based on the 10 factors and reducing the manual efforts of the inspector. In general, we have used other Machine Learning classifiers to check the accuracy of the classification of comprehensive rating. Fortunately, *K*-NN performed well compared to other classifiers. Table 4-9 shows the accuracy of the other Machine Learning classifier algorithms.

Table 4-9: Accuracy Of The Other Classifier Algorithms.

Algorithm	Accuracy
Naïve Bayes	55.38%
Decision Tree	63.25%
Random Forest	67.72%

4.6 Summary

The proposed condition rating model assesses the overall state of degradation of the sewer pipe, combining a series of pipe characteristics, external characteristics, and hydraulic characteristics. A *K*-Nearest Neighbor (*K*-NN) model was used to find the pipe rating based on existing training data. To validate the model, the predicted Comprehensive ratings of our model were compared with actual comprehensive ratings, and our accuracy was 72.31% which is satisfactory. We also compared the predicted comprehensive rating Pipe overall conditional rating (POCR) model using AHP and the Comprehensive Rating model AHP with actual comprehensive ratings. The accuracy was 6.72%, and 9.68%, which shows the *K*-NN model is more accurate in predicting the comprehensive rating. In general, we have used other Machine Learning classifiers to check the accuracy of the classification of comprehensive rating. Fortunately, *K*-NN performed well compared to another classifier.

CHAPTER 5

DETERIORATION MODEL USING MARKOV CHAIN

5.1 Background

A comprehensive model for rating the condition of sewer pipes has so far been created. The likelihood that the pipe will fail is necessary for a full decision framework (POF). To assess a POF's risk of failure at any given time, knowledge about it is essential. Decision-makers can more effectively plan for and allocate funds for present and upcoming rehabilitation and replacement projects with the use of this information. This chapter's objective is to show a sewer deterioration model that calculates the likelihood that any given age of the pipe will be in one of the five states previously established with the model developed in chapter 4. 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 produces several results. First, a transition rate matrix is created, which is then used to compute the probabilities of transitioning from one condition to another at any given time. Next, deterioration curves are created to provide a visual representation of the pipe's conditions over time.

[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.

For decision-making reasons, several studies developed sewer pipe deterioration models using the Markov Chain technique. The degradation process is typically believed to occur on a discrete timescale in research studies that focus on deterioration modeling, indicating that condition changes happened at distinct time steps (such as yearly, bi-yearly, or every five years). (Wirahadikusumah et al., 2001, Kleiner and Rajani, 2001, Baik et al., 2006, Micevski et al., 2002, Wirahadikusumah et al., 1998, Abraham et al., 1998), are some of the most well-known studies (2006).

For large, combined sewers, for instance, Wirahadikusumah (Wirahadikusumah et al., 2001) created a discrete time markov chain (DTMC) model on the presumption that only one condition change can take place during a one-year transition period. The transition probabilities between the five condition states were predicted using a nonlinear optimization, and different deterioration models were created for various combinations of pipe material, backfill material, groundwater table elevation, and depth of cover. The study's conclusion was that to confirm the Markovian property, at least three successive data sets containing inspection data from various observation periods were required. 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 (Babu, 1998, Kulkarni, 1995).

The condition changes in a wastewater pipe deterioration process modeled with Continuous Time Markov Chain (CTMC) occur on a continuous time scale as opposed to a discrete one like a DTMC process. To simulate the degradation of large diameter water and wastewater systems, Kleiner and Rajani (Kleiner and Rajani, 2001) used a semi-Markov approach. A semi-Markov model is a Markovian process in which the time spent in each state has an independent distribution in duration. This work used a two-parameter Weibull probability distribution to model the duration of time as a random variable. It was thought that degradation happened one state transition at a time. Since there were no inspection data available for the investigation, data were generated using a Monte Carlo simulation to determine the duration periods in each state. However, due to a lack of actual data, the study still only serves as a theoretical foundation. Additionally, no other variables, such as pipe material, diameter, soil type, or any other parameters, were employed to evaluate the impact of these variables on the asset's degradation other than the asset's age as a factor determining deterioration (Baik et al., 2006).

For stormwater pipelines, Micevski (Micevski et al., 2002) created a Markov model. In contrast to earlier studies, this one considered various state changes within the one-year transition period. With the help of the Metropolis-Hastings algorithm, the transition probabilities were calculated. According to the study's findings, separate Markov deterioration models are needed for pipes belonging to different categories depending on the pipe's diameter, material, type of soil, and proximity to a coastline.

For the deterioration of wastewater systems, (Baik et al., 2006) created a Markov chain model. For each of the five condition states under consideration, the transition probabilities were calculated separately using an ordered probity model. Their research revealed that older pipes in better condition are more likely to decay at a faster rate than pipelines that are shorter or newer. More specifically, a pipe with a steeper slope has a larger chance of degradation. The absence of data integrity resulted in a lower goodness of fit for the ordered probity model of conditions 4 and 5, and the subjectivity of certified inspectors' interpretation of the CCTV inspection data are two limitations of the model that the authors mention. Additional shortcomings of the application of the ordered probity model in estimating transition probabilities of Markov chain models (Baik et al., 2006, Madanat et al., 1995) has been presented by Kallen (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. Kallen has detailed other drawbacks of using the ordered probity model to estimate the transition probabilities of Markov chain models (Madanat et al., 1995, Baik et al., 2006, Kallen, 2009). The fact that these probabilities should be calculated directly using inspection data for all the assets rather than by averaging the transition probabilities of individual assets is one of the most notable disadvantages of estimating the transition probabilities for groups of assets using the ordered probity method.

5.2 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 (Babu, 1998, 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 Discrete Time Markov Chain (DTMC) model is useful in modeling the deterioration process of infrastructure systems such as bridges (Kallen and Van Noortwijk, 2006, Madanat et al., 1995) and wastewater pipes

(Abraham et al., 1998, Wirahadikusumah et al., 2001, Wirahadikusumah et al., 1998, Micevski et al., 2002, Kleiner and Rajani, 2001, Kleiner and Rajani, 2002, Baik et al., 2006, Angkasuwansiri and Sinha, 2015) 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. 5-1. 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.

$$P\{X_{t+1} = j | X_t = i, X_{t-1} = i_{n-1}, \ldots, X_1 = i_1, X_0 = i_0\} = p_{ij} \qquad \textbf{Eq. 5-1}$$

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. 5-2:

$$\begin{aligned} P\{X_{n+1} = j | X_n = i, X_{n-1} = i_{n-1}, \ldots, X_1 = i_1, X_0 = i_0\} \\ = P\{X_{n+1} = j | X_n = i\} = p_{ij} \end{aligned} \qquad \textbf{Eq. 5-2}$$

Wastewater pipes are assumed to be installed in an excellent condition that is worsening as the pipe ages. The Comprehensive rating, previously determined in Chapter 4, describes this overall condition. So, a wastewater pipe will deteriorate from condition 1 at the time of installation, to a worse condition, condition 5 as time passes, assuming no maintenance or rehabilitation actions are taken. Figure 5-1 presents the DTMC of a wastewater deterioration process where there are five conditions the pipe can be in at any given time. The probabilities of moving from a good condition to a worse condition are shown as p_{ij}.

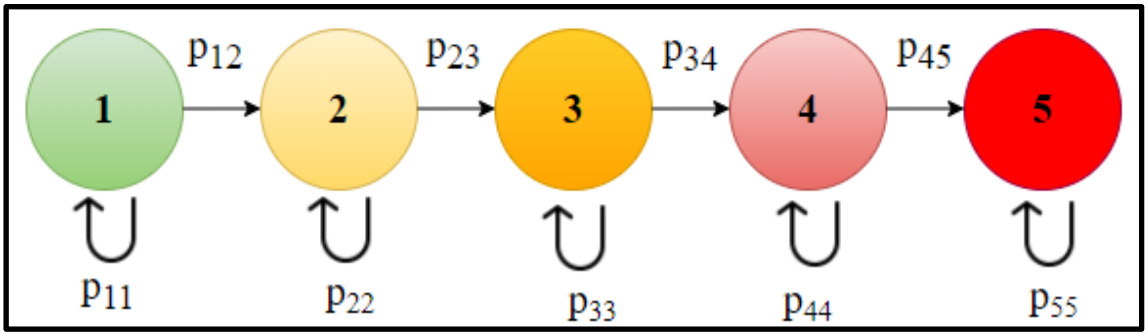

Figure 5-1: DTMC Process Of Wastewater Pipe Deterioration In Five Conditions.

Considering the DTMC model and Eq. 5-3, the transition probabilities can be presented in a 5 x 5 transition probability matrix, P, where deterioration occurs entropically, which means that the pipe 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. 5-3:

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} & p_{15} \\ 0 & p_{22} & p_{23} & p_{24} & p_{25} \\ 0 & 0 & p_{33} & p_{34} & p_{35} \\ 0 & 0 & 0 & p_{45} & p_{55} \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \qquad \textbf{Eq. 5-3}$$

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. 5-4 are applicable:

$$p_{ij} \geq 0 \qquad i, j \geq 0; \qquad \sum_{j=0}^{\infty} p_{ij} = 1 \qquad i = 0, 1, \dots, m \qquad \textbf{Eq. 5-4}$$

The element in the last row of matrix P represents the absorbing state; therefore, the probability is 1, meaning that once a wastewater pipe enters condition state 5, it will remain there with probability 1 until it is rehabilitated or replaced. Once a wastewater that is in condition 5 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 and Van Noortwijk, 2006). According to Kallen and Van Noortwijk (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.

5.3 Continuous-Time Markov Chain Process

5.3.1 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 wastewater 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. 5-5 (Kulkarni, 1995):

$$P\{X_{n+1} = j, Y_{n+1} > y, |X_n = i, Y_{n,} X_{n-1}, Y_{n-1}, \ldots, X_1, Y_1, X_0, Y_0\} = p_{ij}e^{-q_i y} \qquad \textbf{Eq. 5-5}$$

where

- $Y_n = S_n - S_{n-1}$ ($n \geq 1$) is the n^th^ sojourn time
- S_n is the time of the n^th^ ($n \geq 1$) 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.5-5 (Kulkarni, 1995).

5.3.2 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 a time t. According to Kulkarni (Kulkarni, 1995), the sojourn time and the new state depend only on the current state, that is state i, and not on any past states prior to time t. Thus, the 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. 5-6 (forward Kolmogorov equation) must be solved:

$$\frac{\partial}{\partial \mathrm{t}} P(s,t) = P(s,t)Q(t) \qquad \textbf{Eq. 5-6}$$

---

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

In Equation (5-6), 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 wastewater. For a finite state space, computing the transition probability matrix $P(t)$ associated with a CTMC is done using Eq.5-7:

$$P(t) = \exp\,(Qt) \qquad \textbf{Eq. 5-7}$$

The generator matrix, Q, is defined as per Eq. 5-8.

$$Q = [q_{ij}] \qquad i, j \in S \qquad \textbf{Eq. 5-8}$$

For the generator matrix, Q, the sum of all elements in a row adds up to 1, as shown in Eq.5-9:

$$\sum_{j \in S} q_{ij} = 0, \quad q_{ii} = -\sum_{j \neq i} q_{ij} = -q_i, \qquad i = 0, 1, \ldots, J \qquad \textbf{Eq. 5-9}$$

The matrix of transition rates $Q = [q_{ij}]$ column values should be zero and the diagonal elements are the negative sum of the off-diagonal elements in the column.

The CTMC that describes the wastewater deterioration model in this study is shown in Figure 5-2.

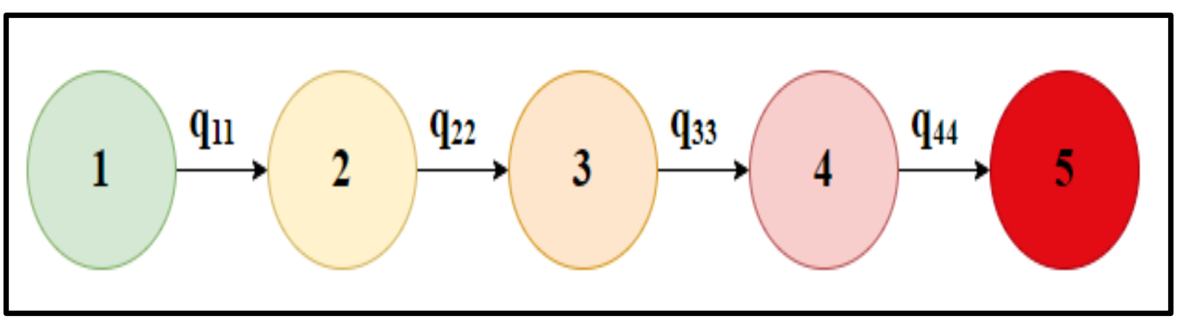

Figure 5-2: CTMC Process Of Wastewater Deterioration Considered In This Study.

The time spent in a state before moving to a next state, the sojourn time *(Y_{ij})*, can be computed from the transition rates. As a result, the time spent in rating 1 before moving to rating 2 is calculated using the rate q_{11}, while the sojourn time in rating 2 is calculated using rate q_{22} and similarly the sojourn time for other ratings is calculated as shown in Eq. 5-10:

$$Y_{ij} = \frac{1}{q_{ij}}\ , i = j \qquad \textbf{Eq. 5-10}$$

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 5-2, a is a row vector of five elements, each element representing the probability of being in any of the five states, at time 0, that is the time of installation of the pipes. Since it is assumed that the pipes were installed in perfect conditions and installed at same year, so the initial distribution of the CTMC in this study is the row vector shown in Eq. 5-11:

$$a = [1\ 0\ 0\ 0\ 0] \qquad \textbf{Eq. 5-11}$$

To find the transition probabilities at any age of the wastewater pipe, the desired age must be inserted into Eq. 5-7. 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 because our CTMC model will only be in the present state or will move to worst state but will not improve its condition. The method to computationally find generator matrix Q is described in next Section 5.4.

5.4 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 and Sørensen, 2005, Bladt and Sørensen, 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 wastewater 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 (Bladt and Sørensen, 2005, Bladt and Sørensen, 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 et al., 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 (Yildirim, 2012) presented the generic algorithm of the Gibbs sampling method.

Algorithm 1 for Gibbs Sampler generalized by Yildirim:

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

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

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

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

$$\dots$$

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

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 many iterations and early iterations are generally discarded. The discarded samples, or iterations, are called the burn-in period (Yildirim, 2012, Bladt and Sørensen, 2005, Bladt and Sørensen, 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 $x = \{x_i^k | i = 1,2, \dots, n_k, k = 1,2, \dots, N\}$. 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 are represented by $X = \{X_t^k | 0 \leq t \leq \tau, k = 1,2, \dots, N\}$. 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 (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 5.5 has this type of data as well.

Bladt and Sørensen (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. (5-12):

$$
\begin{aligned}
& f(Q|\{s(0), s(T)\}) \\
& \qquad \propto L(Q|\{s(0), s(T)\}) \prod_{i=1}^{I} \prod_{j \neq i} q_{ij}^{\phi_{ij}-1} \exp\left(-q_{ij}\psi_i\right) \\
& \qquad \propto \prod_{i=1}^{I} \prod_{j \neq i} q_{ij}^{N_{ij}(T)+\phi_{ij}-1} \exp\left(-q_{ij}(R_i(T) + \psi_i)\right)
\end{aligned}
\qquad \textbf{Eq. 5-12}
$$

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. (5-12), Bladt and Sørensen (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 (Bladt and Sørensen, 2005, Bladt and Sørensen, 2009).

Based on Eq. 5-12, 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 each 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 iterations, the first 1,000 being discarded. After the 10,000 iterations, each element of the generator matrix is sampled.

5.5 Data Preparation and Implementation

The selected pipe cohort for developing the CTMC and subsequent deterioration model is Vitrified Clay (VC) sanitary wastewater 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*) which is 1965, and the second row of information contains data from the inspection year which is 2021. 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 reported available inspection. For each pipe segment, the Comprehensive Rating was computed using *K*-NN, as presented in Chapter 4. We have considered that during the installation all the pipes are installed in the best condition, so the comprehensive rating of 1 is assigned for all the pipes installed in the year 1965. Part of the data file which is given as input to R environment is shown in Table 5-1.

Table 5-1: Input Data In R Environment For Computing Generator Matrix Q.

Pipe ID	Inspection Year	Age [Year]	CR
1	1965	0	1
1	2021	56	3
2	1965	0	1
2	2021	56	3
3	1965	0	1
3	2021	56	3
4	1965	0	1
4	2021	56	4
5	1965	0	1
5	2021	56	2
6	1965	0	1
6	2021	56	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 = 56, 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)
- the method stands for Gibbs sampler
- prior is the prior distribution defined in a list form
- burning is the first 1000 iterations that are removed from the method
- Q is the 5x5 generator matrix obtained 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 and Sørensen, 2005, Bladt and Sørensen, 2009). The results are discussed in the next section.

5.6 Results

5.6.1 Generator Matrix

The R programming code for obtaining the generator matrix of the CTMC is in Appendix H. 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 below.

$$Q = \begin{bmatrix} -1.870230 & 0.794333 & 0.533956 & 0.485380 & 0.056558 \\ 0.000000 & -2.507080 & 1.449363 & 0.854130 & 0.203587 \\ 0.000000 & 0.000000 & -2.870152 & 1.439711 & 1.430441 \\ 0.000000 & 0.000000 & 0.000000 & -3.971936 & 3.971936 \\ 0.000000 & 0.000000 & 0.000000 & 0.000000 & 0.000000 \end{bmatrix}$$

From the generator matrix, the sojourn times were calculated using Eq. 5-10. The results show that the time spent in rating 1, before moving to rating 2, is on average 29.94 years. The time spent in rating 2, before moving to the rating condition 3, is 22.33 years. The time spent in rating 3, before moving to the rating condition 4, is 19.51 years. The time spent in rating 4, before moving to the rating condition 5, is 14.09 years. Based on the sojourn times, a VC pipe of 8-inch diameter from the analyzed cohort moves to the worst rating 5 is after 85.87 years. Figure 5-3 presents these results.

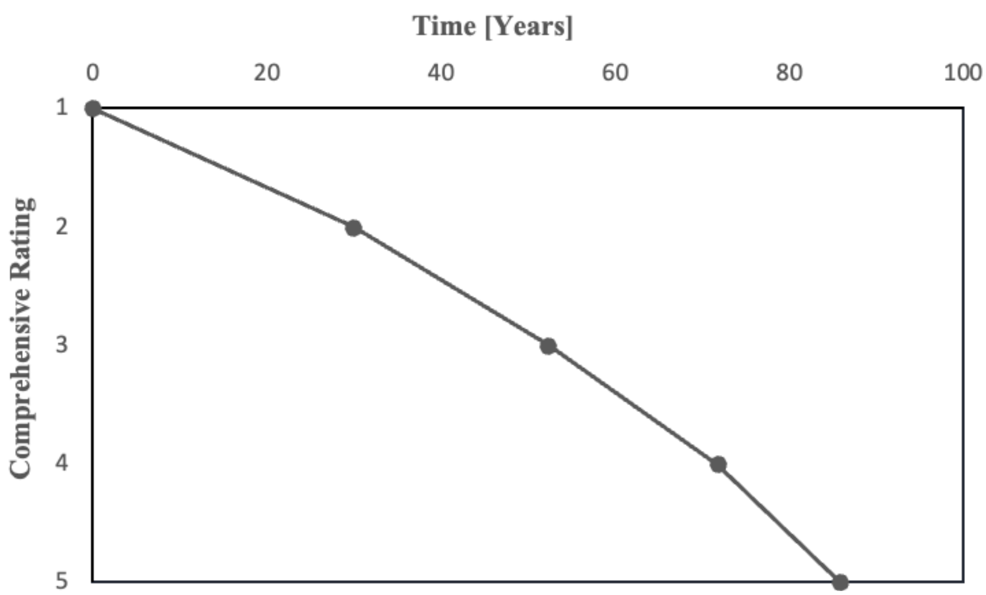

Figure 5-3: Sojourn Times VC Pipes Of 8-Inch.

5.6.2 Transition Probabilities

Once the generator matrix is found, transition probabilities for given age of pipe are easily found using Eq. 5-7. Note that the time interval between the observations is 56 years; therefore, a factor of (*t/56*) 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 below:

$$P(1) = \exp\left(\left(\frac{1}{56}\right)Q\right) =$$

$$\begin{bmatrix} 0.96715460 & 0.013640910 & 0.009315716 & 0.008448261 & 0.001440503 \\ 0.00000000 & 0.956218070 & 0.024668287 & 0.014710140 & 0.004403507 \\ 0.00000000 & 0.000000000 & 0.950038552 & 0.024185950 & 0.025775494 \\ 0.00000000 & 0.000000000 & 0.000000000 & 0.931529490 & 0.068470508 \\ 0.00000000 & 0.000000000 & 0.000000000 & 0.00000000 & 1.000000000 \end{bmatrix}$$

Thus, Equation 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 rating 5 from any of the rating 1 is 0.001440503. The probability of failure is defined as the probability of entering the worst state that is rating 5 from any of the rating 2 is 0.004403507. The probability of failure is defined as the probability of entering the worst state that is rating 5 from any of the rating 3 is 0.025775494. The probability of failure is defined as the probability of entering the worst state that is rating 5 from any of the rating 4 is 0.068470508.

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. Figure 5-4 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. 5-7, and knowing the initial distribution, Eq. 5-10.

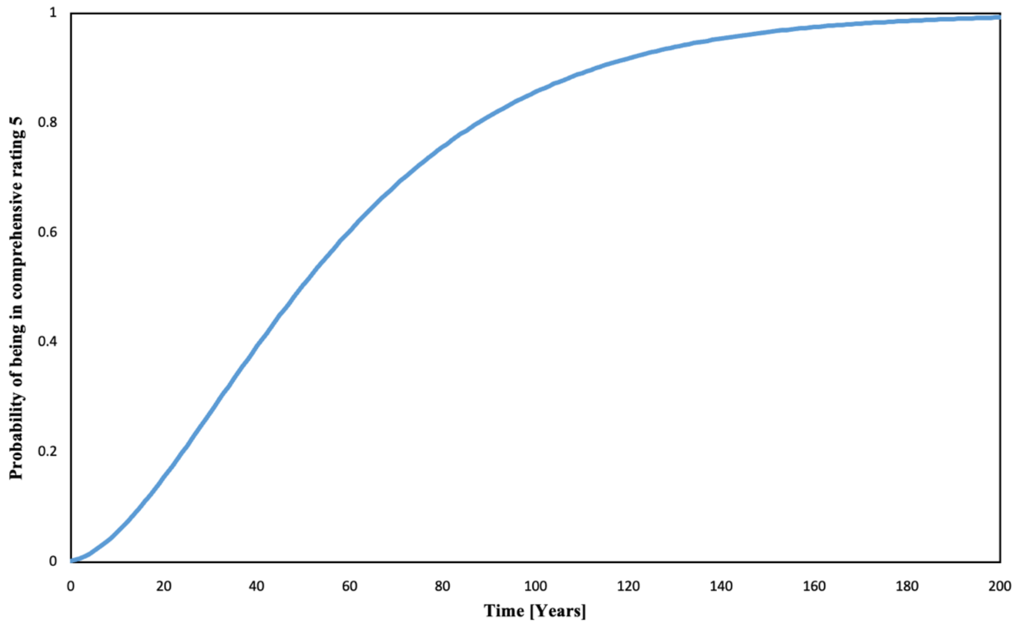

Figure 5-4: Probability Failure Of VC Pipes Of 8-Inch For 200 Years.

From Figure 5-4 the probability of being in the worst condition state of rating 5 is seen. The probability is almost 0.85 for the pipe at the age of 85 years for comprehensive rating 5. 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 56 years is not desirable and might lead to inaccurate estimations of the generator matrix that subsequently may lead to unreliable probability estimates.

5.7 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 wastewater 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 56 years in 2021 ($t = 56$). It was assumed that at time

0, almost all wastewaters were in excellent condition, rating 1. It was also assumed that a small percentage of the installed wastewaters reached condition rating 2, rating 3, rating 4 and rating 5 very shortly after installation due to unforeseen problems, such as structural defects when installed, or poor workmanship during pipe installation.

To find the generator matrix Q the R programming package “ctmcd” was used which describes the pipes’ deterioration process. To find the generator matrix Q the Gibbs sampling method was implemented. Once the generator matrix Q was found using R programming package, transition probabilities were determined based on Eq. 5-7 starting from the observation time in 2021 to any desired future time. More importantly, POF values from any observed condition in 2021 can be determined as the probability of transitioning from any rating to rating 5 during the analyzed time. The main limitation of our developed CTMC model is the fact that the available observation data has a large gap of 56 years because it makes the results of the elements of *Q* matrix obtained from the implementation of the Gibbs sampling uncertain. If more observation data at shorter time intervals were available, the accuracy of the generator matrix Q matrix could be improved. Additionally, a larger data with multiple 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 6

CONSEQUENCE OF FAILURE OF WASTEWATER PIPE

6.1 Background

This chapter presents the second critical component of the decision-making framework for wastewater pipe rehabilitation and renewal planning, a comprehensive Consequence of Failure of wastewater pipe (COF) model. The COF model is built using the TBL methodology and includes a total of 12 factors. The model is developed using weightage ranking. Having the COF, Comprehensive Rating value obtained as previously presented in Chapter 4 and POF obtained in Chapter 5 allows for determining the risk of failure of the analyzed wastewaters for risk-based decision-making purposes.

6.2 Consequence Of Failure Of Wastewater Pipe (COF) Model

Water Research Foundation report on the COF for buried assets 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 stressed the importance of assessing the COF 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 customers and the affected community due to travel delays, rerouting, service outages, and property damages; and (3) environmental impacts that might arise due to percent land lost upon an unforeseen wastewater failure, contamination of groundwater and wildlife habitats, and other environmental impacts. A total of 12 factors have been identified and used from the PACP COF guidelines and extensive literature review as shown in Chapter 3. The 12 factors are arranged under the three main criteria (economic, social, and environmental) hierarchically. Previously there were a developed model for consequence of failure for wastewater (COF) (Vladeanu and Matthews, 2019b) using weightage average and AHP. COF model built using the Analytical Hierarchy Process consists of pipe characteristics, external characteristics, and hydraulic characteristics under social, economic, and environmental impact. The relative importance of COF model is calculated using expert advice which is like the POCR model. The COF score are determined using the Equation 6-1 to 6-4.

$$\mathrm{COF} = w_{EI} \times \mathrm{EI} + w_{SI} \times \mathrm{SI} + w_{ENVI} \times \mathrm{ENVI} \qquad \textbf{Eq. 6-1}$$

$$\mathrm{EI} = \sum_{i=1}^{n} (w_i R_i) \qquad \textbf{Eq. 6-2}$$

$$\mathrm{SI} = \sum_{j=1}^{m} \left(w_j R_j\right) \qquad \textbf{Eq. 6-3}$$

$$\mathrm{ENVI} = \sum_{k=1}^{o} (w_k R_k) \qquad \textbf{Eq. 6-4}$$

W_{EI} is the factor weight for overall EI criteria.

W_{SI} is the factor weight for overall SI criteria.

W_{ENVI} is the factor weight for overall ENVI criteria.

w_i is each factor weights under the EI criteria.

w_j is each factor weights under the SI criteria.

w_k is each factor weights under the ENVI criteria.

R_i is the i^{th}category factor rating under the EI criteria.

R_j is the j^{th}category factor rating under the SI criteria.

R_k is the k^{th}category factor rating under the ENVI criteria.

m is number of factors under the EI criteria.

n is number of factors under the SI criteria.

o is number of factors under the ENVI criteria.

Since AHP involves subject matter expert (SME), whenever SME opinion is varying consequence of failure is changing. COF model built using weightage average consists of only 5 factors related to pipe characteristics under social, economic, and environmental impact. Weighted rating based on weightage average with only pipe characteristics was used to find the consequence of failure by giving them low, medium, and high values(Anbari et al., 2017). The Hierarchical structure of COF model is shown in Figure 6-1. Description of factors of COF model are shown in Table 6-1, list of factors of economic, social and environmental factors are shown from Table 6-2 Table 6-3 and Table 6-4 and Ranking description is shown in Table 6-5. For wastewater pipe COF, the TBL was also the method proposed by National Association of Wastewater Service Companies (NASSCO) in the Pipeline Assessment and Certification Program (PACP) program to quantify the COF of wastewaters. In the United States, PACP is the accepted industry standard for wastewater pipe condition evaluation, developed by NASSCO (2001). As part of the risk-based decision-making framework, the PACP methodology provides a general guideline on determining the COF of a wastewater pipe. To determine a wastewater segment's TBL COF, a series of factors are considered under economic, social, and environmental criteria. An overall COF score of the analyzed segment is calculated as a weighted average of all individual factors.

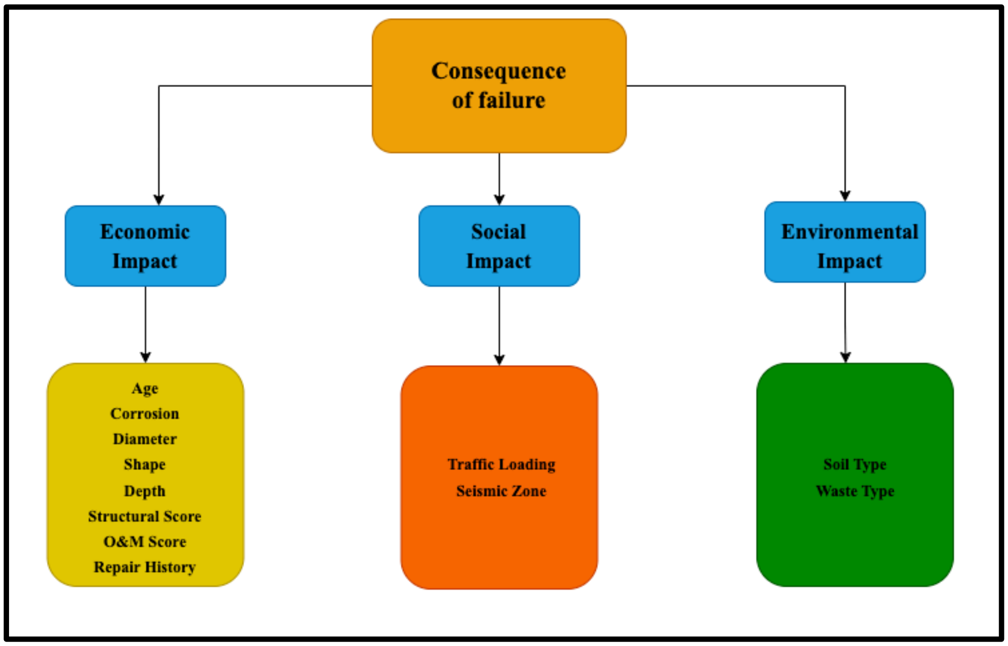

Figure 6-1: Hierarchical Structure Of COF Model.

Table 6-1: Factors And Description Of Consequence Of Failure Model.

Criteria	Factor	Data Type	Description
Economic Impact	Pipe age (years)	Numeric	The time between pipe installation and inspection year and aged pipes have more issues.
	Pipe material	String	The pipe material includes various types of material, such as ceramic, glass, fiberglass, many metals, concrete, and plastic.
	Diameter (mm)	Numeric	Nominal pipe diameter and smaller diameters are not easy to access.
	Shape	String	Typically pipe shapes are circular but depending upon the project, and shapes are changed. Circular shapes are easily accessed.
	Depth (feet)	Numeric	Higher-depth wastewaters are more challenging to access.
	Repair History	String	Pipes with more maintenance can impact the final Rating
	Structural Score	Numeric	The score is given based upon the structure alignment.
	O & M Score	Numeric	The score is given based upon the operational and maintenance.
Social Impact	Traffic Loading	String	A pipe failure on or near a high traffic area can significantly increase delays and detour distances that negatively affect the social impact.
	Seismic Zone	String	Zones with higher seismic activities can negatively impact the structure. Zone 1, Zone 2, Zone 3, Zone 4, Zone 5.
Environmental Impact	Waste Type	String	Waste materials carried in a pipe can impact the pipe failure by blocking, corrosion, etc.
	Soil Type	String	Soil corrosiveness can impact the external pipe wall worsening mechanism.

* 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 6-2: Attributes Factors Rating For Economic Impact (EI).

Factor	Attribute	Ranking
Age (years)	<10	1
	≥10 and <25	2
	≥25 and <40	3
	≥40 and <50	4
	≥50 years	5
Corrosion	Plastic/GRP	1
	Clay	2
	NRCP/AC	3
	RCP	4
	Metallic	5
Diameter	>=49	1
	>31 and <=48	2
	>18 and <=30	3
	>11 and <= 18	4
	<=11	5
Shape	Circular	1
	Oval	2
	Horseshoe	3
	Semielliptical	4
	Arch	5
Depth	<= 10 Feet	1
	> 10 and <= 15 Feet	2
	> 15 and <= 20 Feet	3
	> 20 and <= 25 Feet	4
	> 25 Feet	5
Structural Score	1	1
	2	2
	3	3
	4	4
	5	5

Table 6-2 (Cont..): Attributes Factors Rating For Economic Impact.

Factor	Attribute	Ranking
O & M Score	1	1
	2	2
	3	3
	4	4
	5	5
Repair History	No maintenance	1
	Minor maintenance	2
	Moderate maintenance	3
	Significant maintenance	4
	Extreme maintenance	5

Table 6-3: Attributes Factors Rating For Social Impact (SI).

Factor	Attribute	Ranking
Traffic Loading	No traffic to very light traffic	1
	Light traffic	2
	Medium traffic	3
	Moderate to heavy traffic	4
	Heavy traffic	5
Seismic Zone	Zone 1	1
	Zone 2	2
	Zone 3	3
	Zone 4	4
	Zone 5	5

Table 6-4: Attributes Factors Rating For Environmental Impact (ENVI).

Factor	Attribute	Ranking
Soil Type	Low corrosivity	1
	Low to moderate corrosivity	2
	Moderate corrosivity	3
	Moderate-to-high corrosivity	4
	High corrosivity	5
Waste Type	Mildly corrosive	1
	Mildly to Moderate corrosive	2
	Moderately corrosive	3
	Moderately to highly corrosive	4
	Highly corrosive	5

Table 6-5: Ranking Value Descriptions For All Factors Under EI, SI And ENVI.

Ranking	Description
1	Very low
2	Low
3	Moderate
4	Moderate to High
5	High

6.2.1 Weighted Average

The weighted average is a calculation considering the varying degrees of importance of the numbers in a data set. In calculating a weighted average, each number in the data set is multiplied by a predetermined weight before the final calculation is made. Weighted Average is calculated using the Eq. 6-5. Weights given to the quantities can be a percentage, whole number, or decimal.

$$Weighted\ Average = \frac{\sum(Weigths * Quantities)}{\sum Weigths} \quad \textbf{Eq. 6-5}$$

The weighted average is calculated using following steps:

1. Determining the weight of each data point.
2. Find the sum of all weights.
3. Calculate the sum of each number multiplied by its weight.
4. Divide the results of step two by the sum of all weights.

6.2.2 Weighted Ranking

Weighting the criteria by ranks in either ascending or descending order. Ascending means factors which are least responsible for consequence of failure are given rank 1, the second criterion rank 2 etc. When ranking in descending order, rank 1 the factors are responsible for consequence of failure are given rank 1, the second criterion rank 2 etc. In our scenario we have considered descending order for weighted ranking.

6.2.3 Standard Competition Ranking

Standard Competition Ranking is a ranking system where ranking positions, are given by taking the possibility of ties occurring into account. It indicates that data items that are equal in value receive the same ranking.

6.3 Results

To apply the developed COF model, the same VCP 8-inch cohort was selected as in the case of the Comprehensive Rating model application. The same process as for the Comprehensive Rating model was followed for all 1240 wastewater pipes. Information such as diameter, depth, length of the pipes is given in pipe segment reports (i.e., pdf format), and the other information related to the pipes such as pipe age, corrosion, and the seismic zone is given in MS Excel from the Dept. of Engineering & Environmental Services, Shreveport, Louisiana Phase 3. Final spreadsheet is created using combining MS Excel and pdf reports. The sample data which is used to calculate weightage average is shown in Table 6-6.

Table 6-6: Sample Data To Calculate Weigtage Average.

Factor	Pipe Data 1	Pipe Data 2	Pipe Data 3	Pipe Data 4	Pipe Data 5	Pipe Data 6
Age	5	5	1	4	4	4
Corrosion	4	2	4	4	2	1
Shape	2	3	1	1	1	1
Depth	3	4	1	1	3	3
Soil Type	4	5	3	3	1	1
Traffic Loading	2	2	3	3	2	3
Waste type	3	3	3	3	1	1
Structural Score	1	3	1	1	3	5
O&M Score	3	1	1	5	3	3
Repair History	2	2	1	3	1	3
Diameter	2	2	2	2	2	2
Seismic Zone	2	2	2	2	2	2

The calculate weightage average results calculated using Eq 6-5 are shown in Table 6-7, and the weightage ranking calculated using standard competition ranking are shown in Table 6-8.

Table 6-7: Weigtage Average.

Factor	1	2	3	4	5	Weighted Average
Age	175	0	0	97	100	2.86
Corrosion	72	69	70	84	77	3.07
Shape	176	123	55	18	0	1.77
Depth	75	78	73	79	67	2.96
Soil Type	72	81	76	67	76	2.98
Traffic Loading	68	105	149	15	35	2.58
Waste type	57	79	121	49	66	2.97
Structural Score	254	19	35	29	35	1.85
O&M Score	205	46	32	45	44	2.13
Repair History	189	41	51	42	49	2.25
Diameter	0	372	0	0	0	2.00
Seismic Zone	0	372	0	0	0	2.00

Table 6-8: Weigtage Ranking Using Standard Competition Ranking.

Factor	Weighted Average
Age	5
Corrosion	1
Shape	12
Depth	4
Soil Type	2
Traffic Loading	6
Waste type	3
Structural Score	11
O&M Score	8
Repair History	7
Diameter	9
Seismic Zone	9

Based on values presented in Table 6-8, the corrosion is ranked 1, soil type is ranked 2, waste type is ranked 3, depth is ranked 4, age grade is ranked 5, loading is ranked 6, repair history is ranked 7, diameter and the seismic zone is ranked 8 according to standard competition ranking, O & M score is ranked 10, the shape is ranked 11, and the structural score is ranked 12. According to the rankings assigned to the factor corrosion plays an important role in pipe consequence failure, followed by soil type and waste type. The weightage average is shown in Figure 6-2 and factors for the consequence of failure based on its responsibility to pipe failure is shown in Figure 6-3 and percentage of consequence of failure is shown in Figure 6-4.

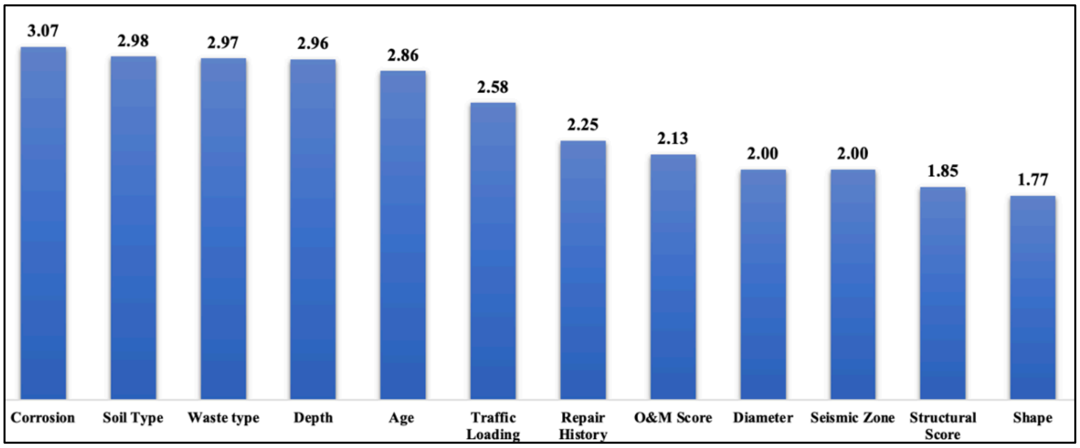

Figure 6-2: Weightage Average.

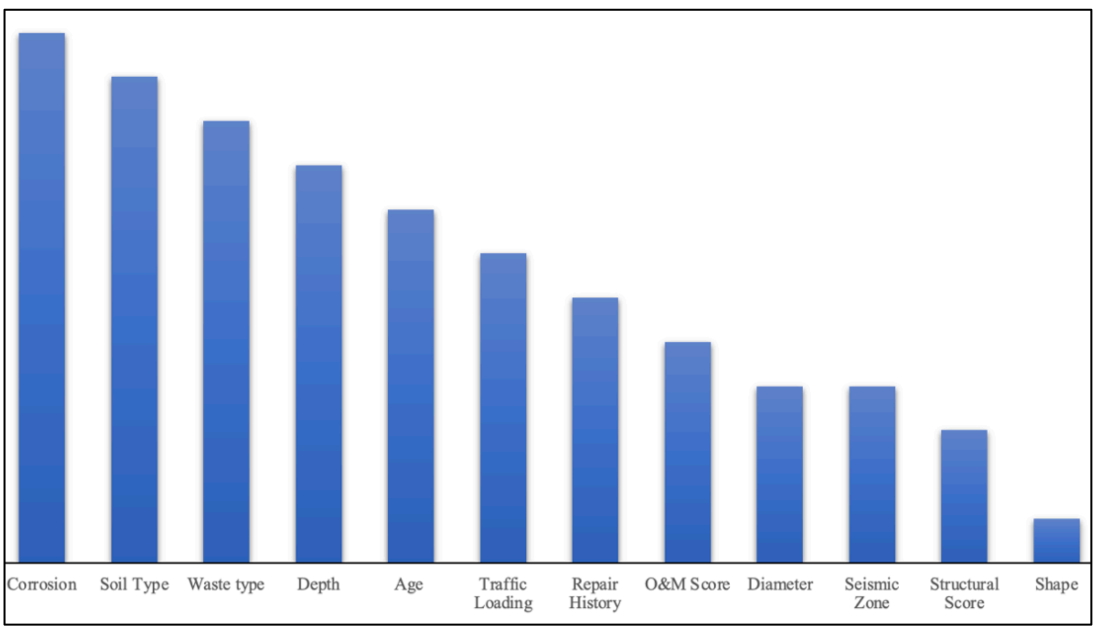

Figure 6-3: Consequence Of Failure Based On Its Responsibility To Pipe Failure.

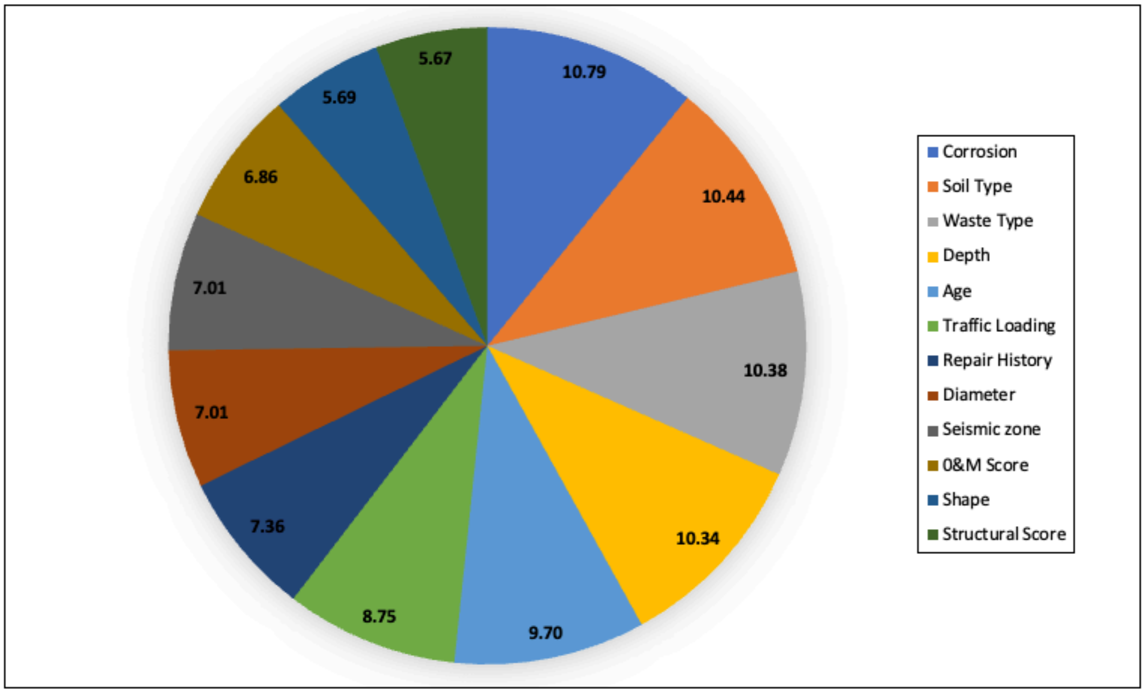

Figure 6-4: Consequence Of Failure In Percentage.

From Figure 6-2 and Figure 6-3 we can see that corrosion is the main reason for pipe consequence failure. Under the economic factor corrosion plays an important consequence for pipe failure, traffic loading plays an important consequence for pipe failure under social factor and waste type plays an important consequence for pipe failure under environmental factor. The developed model could not be verified because the main factors determining the consequence of failure is not mentioned in the data or the by the contractor or the inspector.

To determine a wastewater segment's TBL COF for each wastewater, a series of factors considered under economic, social, and environmental criteria is applied to each wastewater pipe. An overall CoF score of the analyzed segment is calculated as a weighted average of all individual factors. Weightage average for each pipe is for a sample data is shown in Table 6-9.

Table 6-9: Weigtage Average Calculation For Sample Data.

Factor	Pipe Data 1	Pipe Data 2	Pipe Data 3	Pipe Data 4	Pipe Data 5	Pipe Data 6
Age	5	5	1	4	4	4
Corrosion	4	2	4	4	2	1
Shape	2	3	1	1	1	1
Depth	3	4	1	1	3	3
Soil Type	4	5	3	3	1	1
Traffic Loading	2	2	3	3	2	3
Waste type	3	3	3	3	1	1
Structural Score	1	3	1	1	3	5
O&M Score	3	1	1	5	3	3
Repair History	2	2	1	3	1	3
Diameter	2	2	2	2	2	2
Seismic Zone	2	2	2	2	2	2
Weighted Average	3.1818	3.3529	2.4783	3.2500	2.5200	3.0690

This process aimed to obtain an approximate interval variability of the weighted average score based on the value. The results are summarized in Table 6-10 to determine the pipes consequence of failure.

Table 6-10: Final Ratings Based On Weighted Average For Our Data.

COF Ranges	COF	Costs Involved
>= 1.65145 and < 2.1812	1	Very low
>= 2.1812 and < 2.7471	2	Low
>= 2.7471 and < 3.313	3	Moderate
>= 3.313 and < 3.8778	4	Moderate to High
>= 3.8778	5	High

Figure 6-5 shows the percentage of pipes with consequence of pipe failure rating 1 to 5.

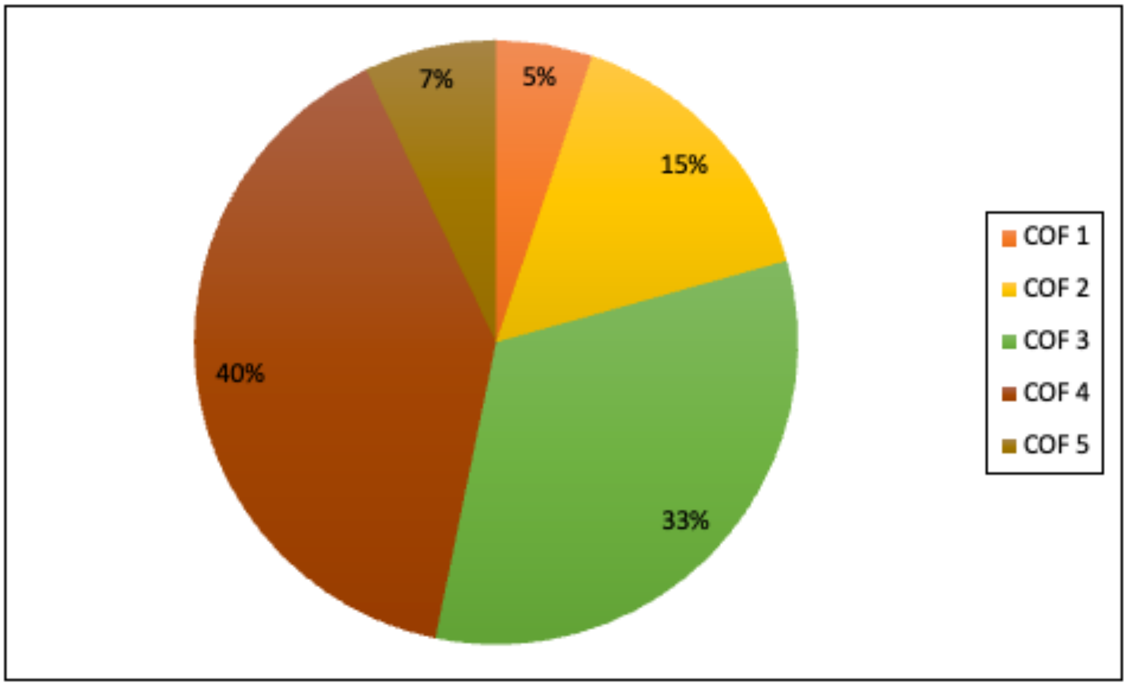

Figure 6-5: Pipe Consequence Of Failure In Percentage.

6.4 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 weightage average and weighted ranking using standard competition ranking is used to find the consequence of pipe failure.

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 corrosion plays an important consequence for pipe failure from the selected VC pipe segments under economic factor, traffic loading under social factor and waste type under environmental factor. By considering all the economic, social, and environmental cost 40%

of pipes have failure rating 4. The developed model could not be verified because the main factors determining the consequence of failure is not mentioned in the data.

CHAPTER 7

RISK OF FAILURE, BUDGET PLANNING FOR OUR CASE STUDY

7.1 Assessment Of Risk Of Failure

Risk is an uncertain quantity that may or may not follow a stochastic process since it involves some degree of uncertainty. Utility companies are unable to totally eliminate risks and uncertainties from their systems because doing so would be extremely expensive from an engineering standpoint. As a result, minimizing pipe failures and the costs associated with them is a component of all risk management strategies used by water and wastewater companies. Utilities have developed a number of techniques that they employ effectively to calculate and evaluate the risk of a pipe failure. The most popular techniques is outlined here.

7.1.1 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 in Eq.7-1 presents the formula (Pietig, 2015, Hess, 2015).

$$ROF = POF * COF \qquad \textbf{Eq. 7-1}$$

The Risk of Failure (ROF) is determined as the multiplication between the POF (Chapter 5) and COF (Chapter 6) scores. POF can be determined at any desired time in the future using the developed CTMC model. Since most of the criteria have a consistent rating, the COFS score is likely to remain stable as the pipe matures. All factor ratings remain constant, except for age, unless there are significant changes in the area around the sewer (such as the development of a new road, highway, or building that might affect any of the variables). The age rating, however, remains constant at 5 once the pipe has been in service for more than 50 years. As a result, by considering the POF and COF values, the ROF may likewise be calculated for any age of the pipe. The 56-year probabilities must be employed, multiplied by the COF score established in the preceding section, in order to compute the ROF of the pipe at the moment of observation. The most important assets are ranked and then given the highest priority using the ROF values for each individual segment. A risk matrix designed specifically for the key POF and COF score values discovered in this investigation is shown in Figure 7-1.

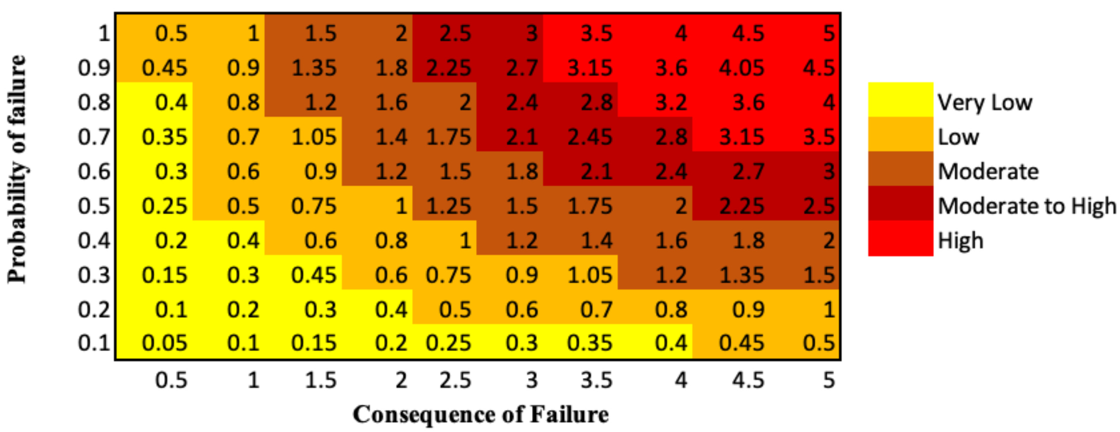

Figure 7-1: Risk Of Failure.

From the risk matrix presented in Figure 7-1, the Very Low, Low, Moderate, Moderate to High and High regions of ROF are clearly differentiated. Generally, to determine a wastewater ROF, Table 7-1 summarizes the critical values.

Table 7-1: ROF Based On POF And COF

Risk of Failure	Probability of Failure	Consequence of Failure Score	Risk of Failure Value
Very Low	<= 0.2	<=2.18	<=0.4
Low	>0.2 and <= 0.4	>2.18 and <=2.75	>0.4 and <=1.1
Moderate	>0.4 and <= 0.6	>2.75 and <=3.31	>1.1 and <=2
Moderate to High	>0.6 and <= 0.8	>3.31 and <=3.87	>2 and <=3.1
High	>0.8 and <= 1.0	>3.87	>3.1

Having the POF values and the COF score of each individual pipe segment, the ROF for 2023 is determined by multiplying these values. From the total length of VC pipe 8-inch pipes, 1.29% have a low risk of failure, while 64.52% have a moderate risk of failure and 34.19% have a moderate to high risk of failure. None of the segments fell into the moderate ROF category. Figure 7-2 shows the distribution of pipes, of the ROF of the analyzed sewer cohort.

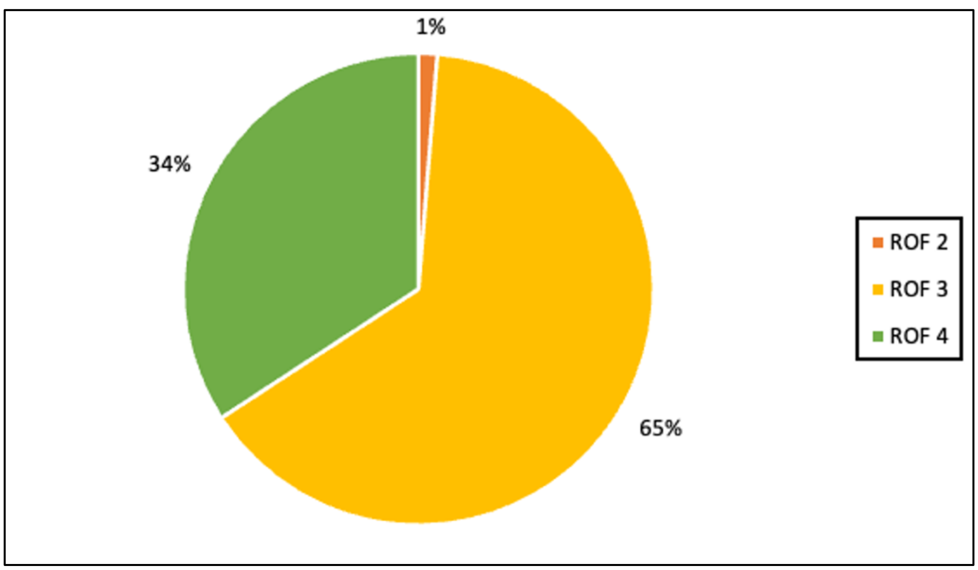

Figure 7-2: Risk Of Failure Distribution.

7.2 Cost Considerations For VC Pipe Renewal

Cost information about VC pipe renewal (pipe rehabilitation and replacement) was obtained from the report by Simicevic and Sterling (Simicevic and Sterling, 2000). For pipe rehabilitation, the Cured-In-Place-Pipe (CIPP) technology and for replacement, the open-cut method was considered. CIPP pipe lining is one of several methods used to repair existing pipelines that don't require digging up the pipes, which is results in low pipe rehabilitation cost and minimum social impact. Open cut method is the most common method for pipe replacement, and it is less expensive compared to other trenchless methods. Accordingly, Eq. (7-2) presents the equation for the best curve fit for CIPP technology, where D is the diameter of the pipe:

$$Cost_{CIPP} = 0.77 \times D^{3/2} + 25.90 \quad \textbf{Eq. 7-2}$$

Similarly, Eq. (7-3) presents the best fit curve for CIPP technology, where *D* is the diameter of the pipe

$$Cost_{open\ cut} = 0.60 \times D^{3/2} + 76.24 \quad \textbf{Eq. 7-3}$$

Both costs are in $/foot of pipe. As a result, using Eq. (7-1) and (7-2), rehabilitation using CIPP for an 8-inch VC pipe cost pipe costs $ 43.32/ft and for the open-cut replacement of an 8-inch VC pipe cost was $ 89.82 /ft., while. It is important to note that these costs are for 2000 data. Therefore, the value of both the rehabilitation and replacement costs need to be determined for the current observation year 2021, using Eq. (7-4):

$$FV = P_0(1 + r)^n \quad \textbf{Eq. 7-4}$$

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 15 November 2021 was 0.25%[3]

As a result, the 2021 value of the cost items were determined to be \$45.65/ft. for CIPP rehabilitation technology and \$94.65/ft. for open-cut replacement and. For both costs, future value will be determined starting from 2022 until the year 2040. Additionally, emergency replacement costs are considered double the amount of scheduled replacement costs, i.e., \$189.31/ft. in 2021. This information is summarized in Table 7-2.

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[3] Information was retrieved from https://ycharts.com/indicators/us_discount_rate on 15th November 2021.

Table 7-2: Future Value Of Scheduled And Emergency Renewal Costs Of VCP 8-Inch.

Year	Future Value of CIPP Rehabilitation Technology [$/ft.]	Future Value of Open-Cut Replacement [$/ft.]	Future Value of Emergency Replacement [$/ft.]
2022	45.76	94.89	189.78
2023	45.88	95.12	190.24
2024	45.99	95.36	190.72
2025	46.11	95.60	191.2
2026	46.22	95.84	191.68
2027	46.34	96.08	192.16
2028	46.45	96.32	192.64
2029	46.57	96.56	193.12
2030	46.68	96.80	193.6
2031	46.80	97.04	194.08
2032	46.92	97.29	194.58
2033	47.04	97.53	195.06
2034	47.15	97.77	195.54
2035	47.27	98.02	196.04
2036	47.39	98.26	196.52
2037	47.51	98.51	197.02
2038	47.63	98.75	197.5
2039	47.75	99.00	198
2040	47.87	99.25	198.5

7.3 800,000 US Dollars Yearly Cost Condition-Based Rehabilitation And Replacement Scenario

For this, all wastewater segments with a Comprehensive rating of 5 were selected with 22,774 ft. of total length. This is the total length of the pipes that are in condition 5 in 2021. A fixed budget of $800,000 can 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. The $800,000 yearly budget must cover the scheduled replacement of as many feet of wastewater as possible while addressing all emergency repairs first. It was assumed that emergency repairs would cover one percent of the total length (116,634 ft) of the system each year. This equals to roughly 1,166 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 or rehabilitate as many feet of pipe as possible.

7.3.1 $800,000 Yearly Rehabilitation Analysis

Table 7-3 summarizes the results of the $800,000 yearly rehabilitation scenario analysis for all wastewater pipes with a Comprehensive Rating of 5. Remaining Length are calculated using Eq. (7-5)

$$\begin{aligned} &Remaining\ Length \\ &= Initial\ Length \\ &- Scheduled\ Repalcement\ (or)\ Rehabilitation\ Length \end{aligned} \qquad \textbf{Eq. 7-5}$$

Table 7-3: $800,000 Yearly rehabilitation scenario analysis of VCP 8-inch

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Remaining Length
2022	800,000	22,774.00	1,166	221,283.00	578,717.00	12,583.53	10,190.47
2023	800,000	10,190.47	1,166	221,819.84	578,180.16	10190.47	0

7.3.2 $800,000 Yearly Rehabilitation Analysis

Table 7-4 summarizes the results of the $800,000 yearly replacement scenario analysis for all wastewater pipes with a Comprehensive Rating of 5. Remaining Length are calculated using Eq. (7-5)

Table 7-4: $800,000 Yearly Replacement Scenario Analysis Of VCP 8-Inch.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Replacement Length	Remaining Length
2022	800,000	22,774.00	1,166	221,283.00	578,717.00	6,098.81	16,675.19
2023	800,000	16,675.19	1,166	221,819.84	578,180.16	6,078.42	10,596.77
2024	800,000	10,596.77	1,166	222,379.52	577,620.48	6,057.26	4,539.51
2025	800,000	4,539.51	1,166	222,939.20	577,060.80	4,539.51	0.00

7.3.3 $800,000 Yearly 20% Rehabilitation And 80% Replacement Analysis

Dept. of Engineering & Environmental Services, Shreveport, Louisiana initial recommendation is to consider 20% remaining budget for rehabilitation and 80% remaining budget for replacement and these results are summarized in Table 7-5

Table 7-5: $800,000 Yearly 20% Rehabilitation And 80% Replacement Scenario Analysis.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Scheduled Replacement Length	Remaining Length
2022	800,000	22,774.00	1,166	221,283.00	578,717.00	2,516.71	4,855.01	15,402.28
2023	800,000	15,402.28	1,166	221,819.84	578,180.16	2,507.83	4,838.33	8,056.13
2024	800,000	8,056.13	1,166	222,379.52	577,620.48	2,499.44	4,821.54	735.15
2025	800,000	735.15	1,166	222,939.20	577,060.80	147.03	588.12	0.00

As seen from Table 7-3, in two years, all wastewater pipes that are in comprehensive rating 5, will be rehabilitated using CIPP and from Table 7-4, With in four years, all wastewater pipes that are in comprehensive rating 5 are replaced using Open cut. From Table 7-5, with in 4 years all the wastewater pipes can be rehabilitated or replaced when 20% and 80% budget is allocated is allocated. For the next years comprehensive pipe ratings 4 and 3 are reassessed and the next budgets can be used to rehabilitate or replace those pipes. Figure 7-3 shows the number of years required for rehabilitation and replacement for 100% rehabilitation, 100% replacement and 20% rehabilitation and 80% replacement of a yearly budget of $800,000.

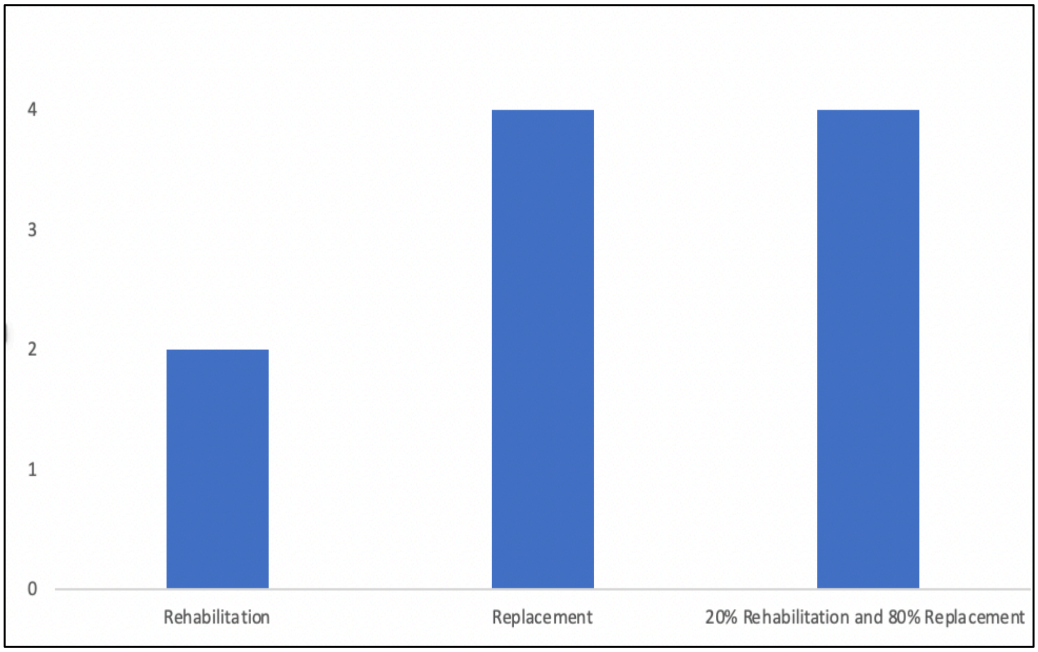

Figure 7-3: Years Required For Few Case Study With A Yearly Budget Of $800,000.

7.4 800,000 US Dollars Yearly Cost Condition-Based Rehabilitation And Replacement Scenario With Different Budget Ratio's

It is still assumed that emergency repairs would cover one percent of the total length (116,634 ft) of the system each year. This equals to roughly 1,166 ft. of pipe length requiring emergency repairs. We have considered different budget ratios for pipe rehabilitate and replacement and the results are shown in different case studies below.

7.4.1 $800,000 Yearly 10% Rehabilitation And 90% Replacement Analysis

Table 7-6 summarizes the results of the yearly replacement and rehabilitation scenario analysis for all wastewater pipes with a Comprehensive Rating of 5 with 10% budget for rehabilitation and 90% budget for replacement.

Table 7-6: $800,000 Yearly 10% Rehabilitation And 90% Replacement Analysis.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Scheduled Replacement Length	Remaining Length
2022	800,000	22,774.00	1,166	221,283.00	578,717.00	1,258.35	5,461.88	16,053.76
2023	800,000	16,053.76	1,166	221,819.84	578,180.16	1,253.91	5,443.12	9,356.73
2024	800,000	9,356.73	1,166	222,379.52	577,620.48	1,249.72	5,424.23	2,682.78
2025	800,000	2,682.78	1,166	222,939.20	577,060.80	268.27	2,414.51	0.00

7.4.2 $800,000 Yearly 30% Rehabilitation And 70% Replacement Analysis

Table 7-7 summarizes the results of the yearly replacement and rehabilitation scenario analysis for all wastewater pipes with a Comprehensive Rating of 5 with 30% budget for rehabilitation and 70% budget for replacement.

Table 7-7: $800,000 Yearly 30% Rehabilitation And 70% Replacement Analysis.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Scheduled Replacement Length	Remaining Length
2022	800,000	22,774.00	1,166	221,283.00	578,717.00	3,775.06	4,248.13	14,750.81
2023	800,000	14,750.81	1,166	221,819.84	578,180.16	3,761.74	4,233.54	6,755.52
2024	800,000	6,755.52	1,166	222,379.52	577,620.48	2,026.66	4,728.87	0.00

7.4.3 $800,000 Yearly 40% Rehabilitation And 60% Replacement Analysis

Table 7-8 summarizes the results of the yearly replacement and rehabilitation scenario analysis for all wastewater pipes with a Comprehensive Rating of 5 with 40% budget for rehabilitation and 60% budget for replacement.

Table 7-8: $800,000 Yearly 40% Rehabilitation And 60% Replacement Analysis.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Scheduled Replacement Length	Remaining Length
2022	800,000	22,774.00	1,166	221,283.00	578,717.00	5,033.42	3,641.26	14,099.33
2023	800,000	14,099.33	1,166	221,819.84	578,180.16	5,015.66	3,628.75	5,454.92
2024	800,000	5,454.92	1,166	222,379.52	577,620.48	2,181.97	3,272.95	0.00

7.4.4 $800,000 Yearly 50% Rehabilitation And 50% Replacement Analysis

Table 7-9 summarizes the results of the yearly replacement and rehabilitation scenario analysis for all wastewater pipes with a Comprehensive Rating of 5 with half remaining budget for rehabilitation and half remaining budget for replacement.

Table 7-9: $800,000 Yearly 50% Rehabilitation And 50% Replacement Analysis.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Scheduled Replacement Length	Remaining Length
2022	800,000	22,774.00	1,166	221,283.00	578,717.00	6,323.39	3,049.41	13,401.20
2023	800,000	13,401.20	1,166	221,819.84	578,180.16	6,301.00	3,039.21	4,060.98
2024	800,000	4,060.98	1,166	222,379.52	577,620.48	2,030.49	2,030.49	0.00

7.4.5 $800,000 Yearly 60% Rehabilitation And 40% Replacement Analysis

Table 7-10 summarizes the results of the yearly replacement and rehabilitation scenario analysis for all wastewater pipes with a Comprehensive Rating of 5 with 60% budget for rehabilitation and 40% budget for replacement.

Table 7-10: $800,000 Yearly 60% Rehabilitation And 40% Replacement Analysis.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Scheduled Replacement Length	Remaining Length
2022	800,000	22,774.00	1,166	221,283.00	578,717.00	7,550.12	2,427.50	12,796.37
2023	800,000	12,796.37	1,166	221,819.84	578,180.16	7,523.49	2,419.16	2,853.72
2024	800,000	2,853.72	1,166	222,379.52	577,620.48	1,712.23	1,141.49	0.00

7.4.6 $800,000 Yearly 70% Rehabilitation And 30% Replacement Analysis

Table 7-11 summarizes the results of the yearly replacement and rehabilitation scenario analysis for all wastewater pipes with a Comprehensive Rating of 5 with 70% budget for rehabilitation and 30% budget for replacement.

Table 7-11: $800,000 Yearly 70% Rehabilitation And 30% Replacement Analysis.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Scheduled Replacement Length	Remaining Length
2022	800,000	22,774.00	1,166	221,283.00	578,717.00	8,808.48	1,820.63	12,144.89
2023	800,000	12,144.89	1,166	221,819.84	578,180.16	8,777.40	1,814.37	1,553.12
2024	800,000	1,553.12	1,166	222,379.52	577,620.48	1,087.18	465.94	0.00

7.4.7 $800,000 Yearly 80% Rehabilitation And 20% Replacement Analysis

Table 7-12 summarizes the results of the yearly replacement and rehabilitation scenario analysis for all wastewater pipes with a Comprehensive Rating of 5 with 80% budget for rehabilitation and 20% budget for replacement.

Table 7-12: $800,000 Yearly 80% Rehabilitation And 20% Replacement Analysis.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Scheduled Replacement Length	Remaining Length
2022	800,000	22,774.00	1,166	221,283.00	578,717.00	10,066.83	1,213.75	11,493.42
2023	800,000	11,493.42	1,166	221,819.84	578,180.16	10,031.32	1,209.58	252.51
2024	800,000	252.51	1,166	222,379.52	577,620.48	202.01	50.50	0.00

7.4.8 $800,000 Yearly 90% Rehabilitation And 10% Replacement Analysis

Table 7-13 summarizes the results of the yearly replacement and rehabilitation scenario analysis for all wastewater pipes with a Comprehensive Rating of 5 with 90% budget for rehabilitation and 10% budget for replacement.

Table 7-13. $800,000 Yearly 90% Rehabilitation And 10% Replacement Analysis.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Scheduled Replacement Length	Remaining Length
2022	800,000	22,774.00	1,166	221,283.00	578,717.00	11,325.19	606.88	10,841.94
2023	800,000	10,841.94	1,166	221,819.84	578,180.16	9,757.74	1,084.19	0.00

Figure 7-4 shows the number of years required for rehabilitation and replacement for the above-mentioned cases of a yearly budget of $800,000.

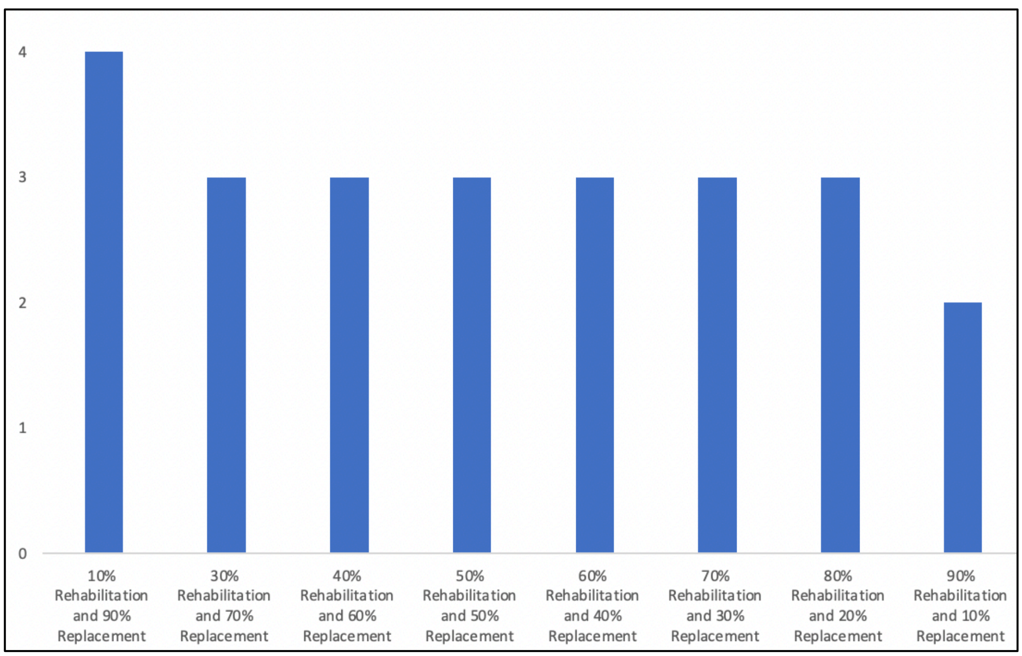

Figure 7-4: Years Required For 8 Cases With Yearly Budget Of $800,000.

7.5 400,000 US Dollars Yearly Cost Condition-Based Rehabilitation And Replacement Scenario

For this scenario also, we considered wastewater segments with a Comprehensive rating of 5 with 22,774 ft. of total length. A fixed budget of $400,000 can also 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. The $400,000 yearly budget must cover the scheduled replacement of as many feet of wastewater as possible while addressing all emergency repairs first. It is still assumed that emergency repairs would cover one percent of the total length (116,634 ft) of the system each year. This equals to roughly 1,166 ft. of pipe length requiring emergency repairs.

7.5.1 <u>$400,000 Yearly Rehabilitation Analysis</u>

Table 7-14 summarizes the results of the $400,000 yearly rehabilitation scenario analysis for all wastewater pipes with a Comprehensive Rating of 5. The remaining Length was calculated using Eq. (7-5).

Table 7-14. $400,000 Yearly Rehabilitation Analysis Of VCP 8-Inch.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Remaining Length
2022	400,000	22,774.00	1,166	221,283.00	178,716.52	3,905.52	18,868.48
2023	400,000	18,868.48	1,166	221,819.84	178,180.16	3,883.61	14,984.87
2024	400,000	14,984.87	1,166	222,379.52	177,620.48	3,862.15	11,122.71
2025	400,000	11,122.71	1,166	222,939.20	177,060.80	3,839.97	7,282.75
2026	400,000	7,282.75	1,166	223,498.88	176,501.12	3,818.72	3,464.03
2027	400,000	3,464.03	1,166	224,058.56	175,941.44	3,464.03	0.00

7.5.2 $400,000 Yearly Replacement Analysis

Table 7-15 summarizes the results of the $400,000 yearly replacement scenario analysis for all wastewater pipes with a Comprehensive Rating of 5.

Table 7-15. $400,000 Yearly Replacement Analysis Of VCP 8-Inch.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Remaining Length
2022	400,000	22,774.00	1,166	221,283.48	178,716.52	1,883.41	20,890.59
2023	400,000	20,890.59	1,166	221,819.84	178,180.16	1,873.21	19,017.38
2024	400,000	19,017.38	1,166	222,379.52	177,620.48	1,862.63	17,154.75
2025	400,000	17,154.75	1,166	222,939.20	177,060.80	1,852.10	15,302.65
2026	400,000	15,302.65	1,166	223,498.88	176,501.12	1,841.62	13,461.02
2027	400,000	13,461.02	1,166	224,058.56	175,941.44	1,831.20	11,629.83
2028	400,000	11,629.83	1,166	224,618.24	175,381.76	1,820.82	9,809.00
2029	400,000	9,809.00	1,166	225,177.92	174,822.08	1,810.50	7,998.50
2030	400,000	7,998.50	1,166	225,737.60	174,262.40	1,800.23	6,198.27
2031	400,000	6,198.27	1,166	226,297.28	173,702.72	1,790.01	4,408.26
2032	400,000	4,408.26	1,166	226,880.28	173,119.72	1,779.42	2,628.84
2033	400,000	2,628.84	1,166	227,439.96	172,560.04	1,769.30	859.54
2034	400,000	859.54	1,166	227,999.64	172,000.36	859.54	0.00

7.5.3 $400,000 Yearly 20% Rehabilitation And 80% Replacement Analysis

Table 7-16 summarizes the results of the 20% remaining budget for rehabilitation and 80% remaining budget for a replacement for all wastewater pipes with a Comprehensive Rating of 5.

Table 7-16. $400,000 Yearly 20% Rehabilitation And 80% Replacement Analysis.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Scheduled Replacement Length	Remaining Length
2022	400,000	22,774.00	1,166	221,283.48	178,716.52	781.10	1,506.73	20,486.17
2023	400,000	20,486.17	1,166	221,819.84	178,180.16	776.72	1,498.57	18,210.88
2024	400,000	18,210.88	1,166	222,379.52	177,620.48	772.43	1,490.10	15,948.34
2025	400,000	15,948.34	1,166	222,939.20	177,060.80	767.99	1,481.68	13,698.67
2026	400,000	13,698.67	1,166	223,498.88	176,501.12	763.74	1,473.30	11,461.63
2027	400,000	11,461.63	1,166	224,058.56	175,941.44	759.35	1,464.96	9,237.32
2028	400,000	9,237.32	1,166	224,618.24	175,381.76	755.14	1,456.66	7,025.52
2029	400,000	7,025.52	1,166	225,177.92	174,822.08	750.79	1,448.40	4,826.32
2030	400,000	4,826.32	1,166	225,737.60	174,262.40	746.63	1,440.19	2,639.51
2031	400,000	2,639.51	1,166	226,297.28	173,702.72	742.32	1,432.01	465.18
2032	400,000	465.18	1,166	226,880.28	173,119.72	93.03	372.15	0.00

As seen from Table 7-14, in six years, all wastewater pipes that are in comprehensive rating 5, will be rehabilitated using CIPP and from Table 7-15, Within thirteen years, all wastewater pipes that are in comprehensive rating 5 are replaced using Open cut. From Table 7-16, within 11 years all the wastewater pipes can be rehabilitated or replaced when 20% and 80% budget is allocated. For the next years, comprehensive pipe ratings 4 and 3 are reassessed and the next budgets can be used to rehabilitate or replace those pipes. Figure 7-5 shows the number of years required for rehabilitation and replacement for 100% rehabilitation, 100% replacement and 20% rehabilitation, and 80% replacement of a yearly budget of $400,000.

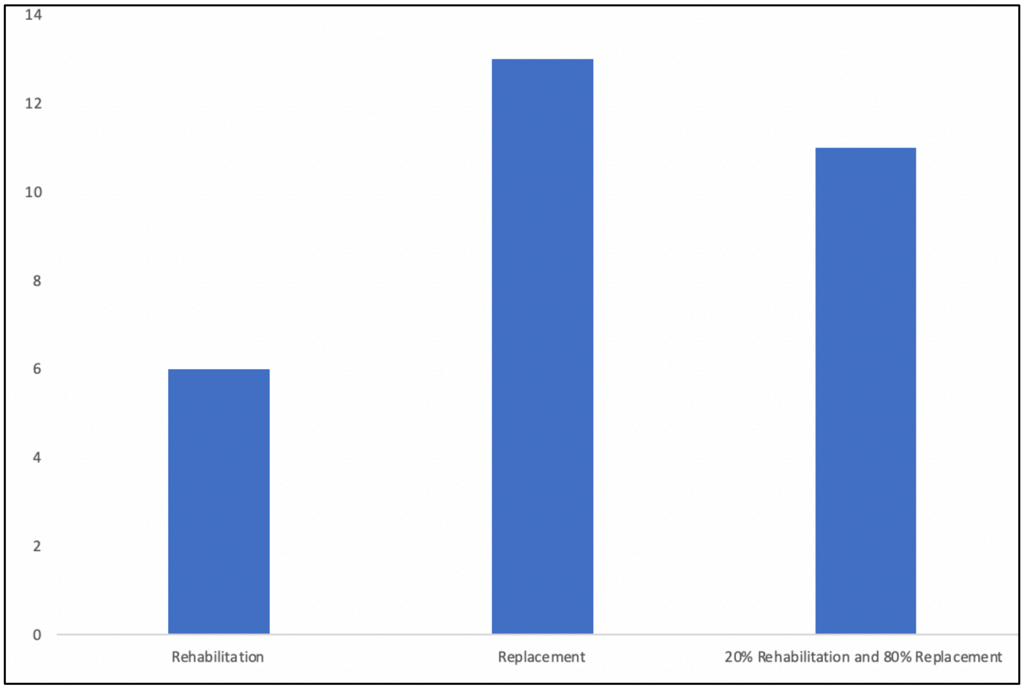

Figure 7-5: Years Required For Few Case Study With A Yearly Budget Of $400,000.

7.6 400,000 US Dollars Yearly Cost Condition-Based Rehabilitation and Replacement Scenario with different budget ratio's

It is still assumed that emergency repairs would cover one percent of the total length (116,634 ft) of the system each year. This equals to roughly 1,166 ft. of pipe length requiring emergency repairs. We have considered different budget ratios for pipe rehabilitation and replacement and the results are shown in different case studies below.

7.6.1 $400,000 Yearly 10% Rehabilitation And 90% Replacement Analysis

Table 7-17 summarizes the results of the yearly replacement and rehabilitation scenario analysis for all wastewater pipes with a Comprehensive Rating of 5 with a 10% budget for rehabilitation and a 90% budget for replacement.

Table 7-17. $400,000 Yearly 10% Rehabilitation And 90% Replacement Analysis.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Scheduled Replacement Length	Remaining Length
2022	400,000	22,774.00	1,166	221,283.48	178,716.52	390.55	1,695.07	20,688.38
2023	400,000	20,688.38	1,166	221,819.84	178,180.16	388.36	1,685.89	18,614.13
2024	400,000	18,614.13	1,166	222,379.52	177,620.48	386.22	1,676.37	16,551.54
2025	400,000	16,551.54	1,166	222,939.20	177,060.80	384.00	1,666.89	14,500.66
2026	400,000	14,500.66	1,166	223,498.88	176,501.12	381.87	1,657.46	12,461.32
2027	400,000	12,461.32	1,166	224,058.56	175,941.44	379.68	1,648.08	10,433.57
2028	400,000	10,433.57	1,166	224,618.24	175,381.76	377.57	1,638.74	8,417.26
2029	400,000	8,417.26	1,166	225,177.92	174,822.08	375.40	1,629.45	6,412.41
2030	400,000	6,412.41	1,166	225,737.60	174,262.40	373.31	1,620.21	4,418.89
2031	400,000	4,418.89	1,166	226,297.28	173,702.72	371.16	1,611.01	2,436.72
2032	400,000	2,436.72	1,166	226,880.28	173,119.72	368.97	1,601.48	466.27
2033	400,000	466.27	1,166	227,439.96	172,560.04	46.27	420.00	0.00

7.6.2 $400,000 Yearly 30% Rehabilitation And 70% Replacement Analysis

Table 7-18 summarizes the results of the yearly replacement and rehabilitation scenario analysis for all wastewater pipes with a Comprehensive Rating of 5 with 30% budget for rehabilitation and 70% budget for replacement.

Table 7-18. $400,000 30% Yearly Rehabilitation And 70% Replacement Analysis.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Scheduled Replacement Length	Remaining Length
2022	400,000	22,774.00	1,166	221,283.48	178,716.52	1,171.66	1,318.39	20,283.96
2023	400,000	20,283.96	1,166	221,819.84	178,180.16	1,165.08	1,311.25	17,807.63
2024	400,000	17,807.63	1,166	222,379.52	177,620.48	1,158.65	1,303.84	15,345.14
2025	400,000	15,345.14	1,166	222,939.20	177,060.80	1,151.99	1,296.47	12,896.68
2026	400,000	12,896.68	1,166	223,498.88	176,501.12	1,145.62	1,289.14	10,461.93
2027	400,000	10,461.93	1,166	224,058.56	175,941.44	1,139.03	1,281.84	8,041.06
2028	400,000	8,041.06	1,166	224,618.24	175,381.76	1,132.71	1,274.58	5,633.77
2029	400,000	5,633.77	1,166	225,177.92	174,822.08	1,126.19	1,267.35	3,240.23
2030	400,000	3,240.23	1,166	225,737.60	174,262.40	1,119.94	1,260.16	860.13
2031	400,000	860.13	1,166	226,297.28	173,702.72	258.03	602.10	0.00

7.6.3 $400,000 Yearly 40% Rehabilitation And 60% Replacement Analysis

Table 7-19 summarizes the results of the yearly replacement and rehabilitation scenario analysis for all wastewater pipes with a Comprehensive Rating of 5 with 40% budget for rehabilitation and 60% budget for replacement.

Table 7-19. $400,000 Yearly 40% Rehabilitation And 60% Replacement Analysis.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Scheduled Replacement Length	Remaining Length
2022	400,000	22,774.00	1,166	221,283.48	178,716.52	1,562.21	1,130.04	20,081.75
2023	400,000	20,081.75	1,166	221,819.84	178,180.16	1,553.45	1,123.93	17,404.37
2024	400,000	17,404.37	1,166	222,379.52	177,620.48	1,544.86	1,117.58	14,741.93
2025	400,000	14,741.93	1,166	222,939.20	177,060.80	1,535.99	1,111.26	12,094.69
2026	400,000	12,094.69	1,166	223,498.88	176,501.12	1,527.49	1,104.97	9,462.23
2027	400,000	9,462.23	1,166	224,058.56	175,941.44	1,518.70	1,098.72	6,844.81
2028	400,000	6,844.81	1,166	224,618.24	175,381.76	1,510.28	1,092.49	4,242.03
2029	400,000	4,242.03	1,166	225,177.92	174,822.08	1,501.59	1,086.30	1,654.14
2030	400,000	1,654.14	1,166	225,737.60	174,262.40	661.65	992.49	0.00

7.6.4 $400,000 Yearly 50% Rehabilitation And 50% Replacement Analysis

Table 7-20 summarizes the results of the yearly replacement and rehabilitation scenario analysis for all wastewater pipes with a Comprehensive Rating of 5 with half the remaining budget for rehabilitation and half the remaining budget for replacement.

Table 7-20. $400,000 Yearly 50% Rehabilitation And 50% Replacement Analysis.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Scheduled Replacement Length	Remaining Length
2022	400,000	22,774.00	1,166	221,283.48	178,716.52	1,952.76	941.70	19,879.54
2023	400,000	19,879.54	1,166	221,819.84	178,180.16	1,941.81	936.61	17,001.12
2024	400,000	17,001.12	1,166	222,379.52	177,620.48	1,931.08	931.32	14,138.73
2025	400,000	14,138.73	1,166	222,939.20	177,060.80	1,919.98	926.05	11,292.70
2026	400,000	11,292.70	1,166	223,498.88	176,501.12	1,909.36	920.81	8,462.53
2027	400,000	8,462.53	1,166	224,058.56	175,941.44	1,898.38	915.60	5,648.55
2028	400,000	5,648.55	1,166	224,618.24	175,381.76	1,887.86	910.41	2,850.29
2029	400,000	2,850.29	1,166	225,177.92	174,822.08	1,876.98	905.25	68.05
2030	400,000	68.05	1,166	225,737.60	174,262.40	34.02	34.03	0.00

7.6.5 $400,000 Yearly 60% Rehabilitation And 40% Replacement Analysis

Table 7-21 summarizes the results of the yearly replacement and rehabilitation scenario analysis for all wastewater pipes with a Comprehensive Rating of 5 with 60% budget for rehabilitation and 40% budget for replacement.

Table 7-21. $400,000 Yearly 60% Rehabilitation And 40% Replacement Analysis.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Scheduled Replacement Length	Remaining Length
2022	400,000	22,774.00	1,166	221,283.48	178,716.52	2,343.31	753.36	19,677.33
2023	400,000	19,677.33	1,166	221,819.84	178,180.16	2,330.17	749.29	16,597.87
2024	400,000	16,597.87	1,166	222,379.52	177,620.48	2,317.29	745.05	13,535.53
2025	400,000	13,535.53	1,166	222,939.20	177,060.80	2,303.98	740.84	10,490.71
2026	400,000	10,490.71	1,166	223,498.88	176,501.12	2,291.23	736.65	7,462.83
2027	400,000	7,462.83	1,166	224,058.56	175,941.44	2,278.05	732.48	4,452.30
2028	400,000	4,452.30	1,166	224,618.24	175,381.76	2,265.43	728.33	1,458.54
2029	400,000	1,458.54	1,166	225,177.92	174,822.08	875.12	583.42	0.00

7.6.6 $400,000 Yearly 70% Rehabilitation And 30% Replacement Analysis

Table 7-22 summarizes the results of the yearly replacement and rehabilitation scenario analysis for all wastewater pipes with a Comprehensive Rating of 5 with a 70% budget for rehabilitation and a 30% budget for replacement.

Table 7-22. $400,000 Yearly 70% Rehabilitation And 30% Replacement Analysis.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Scheduled Replacement Length	Remaining Length
2022	400,000	22,774.00	1,166	221,283.48	178,716.52	2,733.86	565.02	19,475.11
2023	400,000	19,475.11	1,166	221,819.84	178,180.16	2,718.53	561.96	16,194.62
2024	400,000	16,194.62	1,166	222,379.52	177,620.48	2,703.51	558.79	12,932.32
2025	400,000	12,932.32	1,166	222,939.20	177,060.80	2,687.98	555.63	9,688.72
2026	400,000	9,688.72	1,166	223,498.88	176,501.12	2,673.10	552.49	6,463.13
2027	400,000	6,463.13	1,166	224,058.56	175,941.44	2,657.73	549.36	3,256.04
2028	400,000	3,256.04	1,166	224,618.24	175,381.76	2,643.00	546.25	66.80
2029	400,000	66.80	1,166	225,177.92	174,822.08	46.76	20.04	0.00

7.6.7 <u>$400,000 Yearly 80% Rehabilitation And 20% Replacement Analysis</u>

Table 7-23 summarizes the results of the yearly replacement and rehabilitation scenario analysis for all wastewater pipes with a Comprehensive Rating of 5 with 80% budget for rehabilitation and 20% budget for replacement.

Table 7-23. $400,000 Yearly 80% Rehabilitation And 20% Replacement Analysis.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Scheduled Replacement Length	Remaining Length
2022	400,000	22,774.00	1,166	221,283.48	178,716.52	3,124.41	376.68	19,272.90
2023	400,000	19,272.90	1,166	221,819.84	178,180.16	3,106.89	374.64	15,791.37
2024	400,000	15,791.37	1,166	222,379.52	177,620.48	3,089.72	372.53	12,329.12
2025	400,000	12,329.12	1,166	222,939.20	177,060.80	3,071.97	370.42	8,886.73
2026	400,000	8,886.73	1,166	223,498.88	176,501.12	3,054.97	368.32	5,463.43
2027	400,000	5,463.43	1,166	224,058.56	175,941.44	3,037.40	366.24	2,059.79
2028	400,000	2,059.79	1,166	224,618.24	175,381.76	1,647.83	411.96	0.00

7.6.8 <u>$400,000 Yearly 90% Rehabilitation And 10% Replacement Analysis</u>

Table 7-24 summarizes the results of the yearly replacement and rehabilitation scenario analysis for all wastewater pipes with a Comprehensive Rating of 5 with 90% budget for rehabilitation and 10% budget for replacement.

Table 7-24. $400,000 Yearly 90% Rehabilitation And 10% Replacement Analysis.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Scheduled Replacement Length	Remaining Length
2022	400,000	22,774.00	1,166	221,283.48	178,716.52	3,514.97	188.34	19,070.69
2023	400,000	19,070.69	1,166	221,819.84	178,180.16	3,495.25	87.32	15,388.12
2024	400,000	15,388.12	1,166	222,379.52	177,620.48	3,475.94	86.26	11,725.92
2025	400,000	11,725.92	1,166	222,939.20	177,060.80	3,455.97	85.21	8,084.74
2026	400,000	8,084.74	1,166	223,498.88	176,501.12	3,436.85	84.16	4,463.73
2027	400,000	4,463.73	1,166	224,058.56	175,941.44	3,417.08	83.12	863.54
2028	400,000	863.54	1,166	224,618.24	175,381.76	777.18	6.35	0.00

Figure 7-6 shows the number of years required to rehabilitate and replacement for above mentioned 8 cases of a yearly budget of 400,000 US dollars.

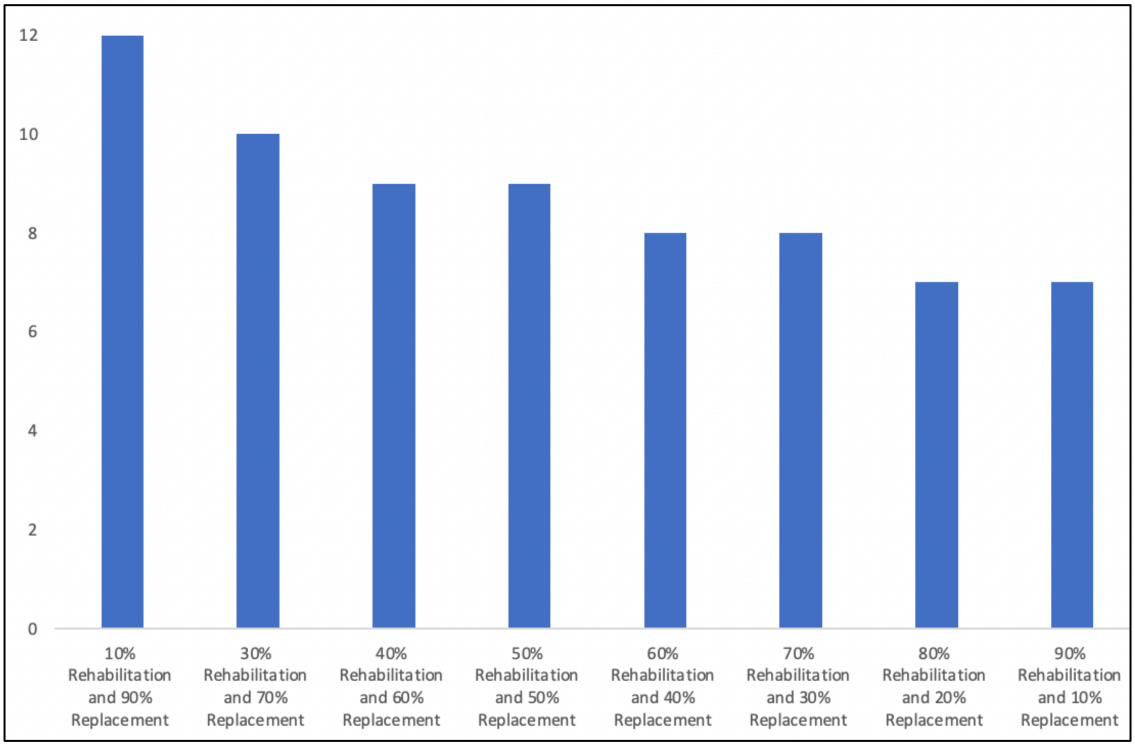

Figure 7-6: Years Required For 8 Cases With Yearly Budget Of $400,000.

After our entire analysis, we have considered we suggest 800,000 US dollars budget with 90% for rehabilitation and 10% for replacement which is going to complete in 2 years. Even though 800,000 US dollars budget with 100% for rehabilitation, there might be a few pipes that cannot be rehabilitated and needs only replacement. According to comprehensive rating 4 pipes needs to be reassessed within 2 years so by allocating the scenario mentioned above pipes with comprehensive rating 5 replacement and rehabilitation will be complete and pipe of comprehensive rating 4 which move to 5 replacement and rehabilitation and can be assessed.

7.7 800,000 US Dollars Yearly Cost Condition-Based 90% Rehabilitation And 10% Replacement Scenario For CR-AHP And POCR

For this scenario also, we considered wastewater segments with a Comprehensive rating of 5 with 29,231 ft. of total length for CR-AHP and 34,367 ft. of total length for POCR-AHP. A fixed budget of $800,000 with 90% rehabilitation and 10% replacement for comparative study with *K*-NN CR. The $800,000 yearly budget must cover the scheduled replacement and rehabilitation of as many feet of the wastewater as possible while addressing all emergency repairs first. It is still assumed that emergency repairs would cover one percent of the total length (116,634 ft) of the system each year. This equals to roughly 1,166 ft. of pipe length requiring emergency repairs. Table 7-25 summarizes the results of the yearly replacement and rehabilitation scenario analysis for all wastewater pipes with a Comprehensive Rating of 5 with 90% budget for rehabilitation and 10% budget for replacement for CR-AHP.

Table 7-25. $800,000 Yearly 90% Rehabilitation And 10% Replacement For CR-AHP.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Scheduled Replacement Length	Remaining Length
2022	800,000	29,231.30	1,166	221,283.00	578,717.00	11,325.19	606.88	17,299.23
2023	800,000	17,299.23	1,166	221,819.84	578,180.16	11,341.80	607.84	5,349.59
2024	800,000	5,349.59	1,166	222,379.52	577,620.48	4,814.63	534.96	0.00

Table 7-26 summarizes the results of the yearly replacement and rehabilitation scenario analysis for all wastewater pipes with a Comprehensive Rating of 5 with a 90% budget for rehabilitation and a 10% budget for a replacement for POCR-AHP.

Table 7-26. $800,000 Yearly 90% Rehabilitation And 10% Replacement Analysis For POCR.

Year	Yearly Budget [$]	Initial Length [ft.]]	Emergency Replacement Length [ft.]]	Emergency Cost [$]	Remaining Budget	Scheduled Rehabilitation Length	Scheduled Replacement Length	Remaining Length
2022	800,000	34,367.00	1,166	221,283.00	578,717.00	11,325.19	606.88	22,434.93
2023	800,000	22,434.93	1,166	221,819.84	578,180.16	11,341.80	607.84	10,485.29
2024	800,000	10,485.29	1,166	222,379.52	577,620.48	9,877.01	608.28	0.00

Figure 7-7 shows the number of years required to rehabilitate and replacement for CR - *K*-NN, CR-AHP and POCR-AHP.

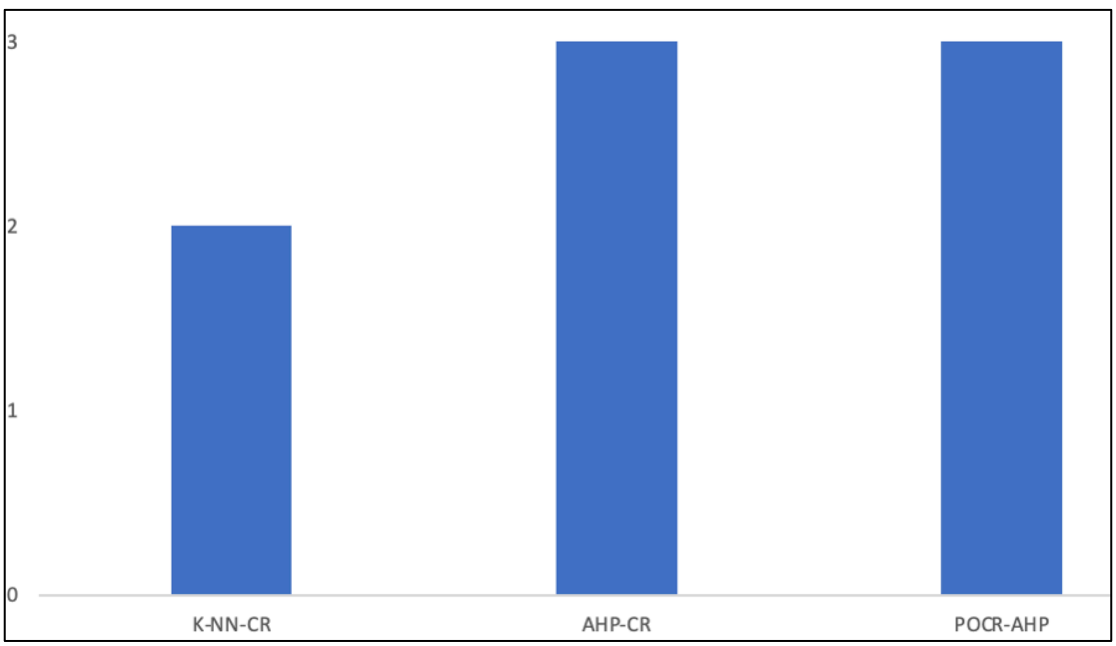

Figure 7-7: Number Of Years Required For *K*-NN CR, CR-AHP, POCR-AHP.

After the comparative study we suggest *K*-NN CR with more accurate rating is preventing the saving of the budget for one year which can be used for other pipe replacement or rehabilitation.

7.8 Summary

This chapter presented the cost analysis and budget planning for 22,774.00 Feet total length using $400,000 and $800,000 budgets. Cost analysis and budget planning for both budgets are considered for different scenarios of pipe rehabilitation and pipe replacement. For pipe rehabilitation, the Cured-In-Place-Pipe (CIPP) technology and for replacement, the open-cut method was considered. CIPP pipe lining is one of several methods is used to repair existing pipelines that don't require digging up the pipes, which is results in low pipe rehabilitation cost and minimum social impact. Open cut method is the most common method for pipe replacement, and it is less expensive compared to other trenchless methods. We suggest by the best budget allocation is 800,000 US dollars budget with 90% for rehabilitation and 10% for replacement. Finally, we have compared our same data budget analysis for CR-AHP and POCR-AHP.

CHAPTER 8

CONCLUSIONS LIMITATIONS AND FUTURE WORK

8.1 Summary

A review of the relevant literature on risk-based decision-making for wastewater pipe renewal, including a review of condition rating methods and models allowed for the development of the Comprehensive rating model using Analytic Hierarchy Process and *K*-NN. The suggested Comprehensive rating model using Analytic Hierarchy Process is not a suitable method. A CTMC model was developed to determine the POF at any given age of the pipe, using the Comprehensive Rating conditions as states of the Markov chain at two separate observation times. A consequence of failure COF model was developed to find out the main consequence of failure. Finally cost analysis and budget planning for 2 different budgets is considered to find out time required to rehabilitate and replace pipe segments and suggested the best budget for pipe replacement and rehabilitation.

8.2 Conclusions

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

1. The proposed condition rating model assesses the overall state of degradation of the wastewater pipe, combining a series of pipe characteristics, external characteristics, and hydraulic characteristics. The model considered 12 initial factors that contribute to the wastewater pipe degradation. Analytic Hierarchy

Process is used for model building. Finally, we suggested that Comprehensive rating model using Analytic Hierarchy Process is not a suitable method.

2. The proposed condition rating model assesses the overall state of degradation of the wastewater pipe, combining a series of pipe characteristics, external characteristics, and hydraulic characteristics. The model considered 12 initial factors that contribute to wastewater pipe degradation. A K-Nearest Neighbor (*K*-NN) model was used to find the pipe rating. To validate the model, the predicted Comprehensive ratings of our model were compared with actual comprehensive ratings, and our accuracy was 73.31% which is satisfactory.
3. We compared the predicted comprehensive rating Pipe overall conditional rating (POCR) model and the Comprehensive Rating model of AHP with actual comprehensive ratings, and the accuracy was 6.72% and 9.14% which shows the *K*-NN model is more accurate in predicting the comprehensive rating.
4. A CTMC deterioration model was developed using the CR of VC pipe of 8-inch diameter to determine the POF at any age of the pipe. Pipe moves to the worst rating 5, after 85.87 years.
5. A COF model was developed to determine the main consequence of pipe failure corrosion plays an important consequence for pipe failure from the selected VC pipe segments under economic factor, traffic loading under social factor and waste type under environmental factor. By considering all the economic, social, and environmental cost 40% of pipes have failure rating 4. The developed model could not be verified because the main factors determining the consequence of failure is not mentioned in the data.

6. Finally cost analysis and budget planning for 2 different budgets is considered to find out the time required to rehabilitate and replace pipe segments and compared with CR-AHP and POCR-AHP and a risk matrix is developed and pipe risk of failure for next year is calculated.

8.3 Limitations

This section presents limitations in this work:

1. One of the main limitations of the study was the data. All the pipes' data had the same diameter and seismic zone. Therefore, more pipe from different geographic locations is needed to improve and convey more robustness to the obtained results.
2. The other limitation was the execution time because *K*-NN Classifiers are real-time execution, so their execution is slow compared to other classifier algorithms.
3. CCTV inspection data at closer time intervals is needed more to have a more accurate CTMC deterioration model and to validate the model.
4. We did not find the main consequence of failure reason in our data to validate the COF model.

8.4 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 suggested for refining and improving the number of structural, operational, and hydraulic factors used in the model by considering more variety of data. By adding more factors, this method could be applied to any wastewater pipes to recognize the worst condition of

wastewater pipes that need to be replaced immediately. In significantly less time by reducing many manual efforts.

2. 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.

APPENDIX A

AHP CALCULATION

A.1 AHP Questionnaire

The purpose of this questionnaire is to ask you, as a subject matter expert in wastewater 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 pipe characteristics, external characteristics, and hydraulic characteristics related to the worsening of wastewater pipe conditions. Questions 1 through 4 are connected to establishing priorities among various factors and sub-factors as they relate to the condition of the wastewater pipe. The scores presented in Table A-1 must be used for the pairwise comparison.

Table A-1: AHP Importance Scale

Scale	Definition
1	Equally important
2	Slightly more important
3	Moderately more important
4	Moderately plus more important
5	Strongly more important
6	Strongly plus more important
7	Very strongly more important
8	Very very strongly more important
9	Extremely more important

When performing the pairwise comparisons, compare the row component to the column component. For example, (Ex. 1), if Pipe characteristics are extremely more important than External characteristics with respect to the condition of a wastewater pipe, the importance for the Pipe characteristics row would be a strong Importance of 5. Alternatively, if External characteristics are strongly more important than Pipe characteristics with respect to the condition of a wastewater pipe, the importance for the Pipe characteristics would be the inverse of Strong Importance or 1/5 (see example in Table A-2 below).

Table A-2: Example pairwise comparison between two factors

Condition of Wastewater Pipe	Pipe characteristics	External characteristics
Ex. 1: Pipe characteristics	1	5
Ex. 2: External characteristics	1	1/5

The following figures are presented as a reference for the questions. (see Figures A-1) for reference only.

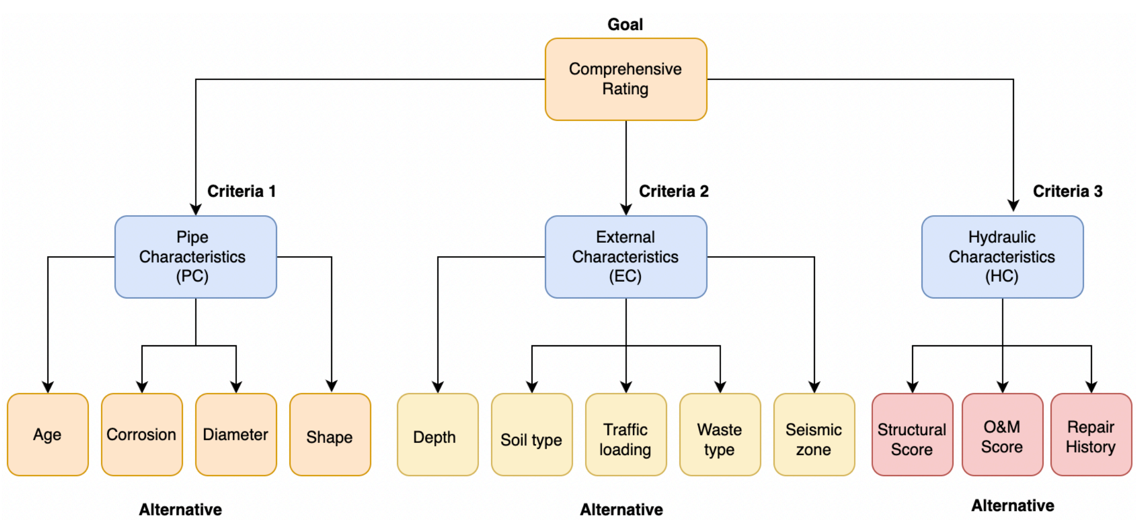

Figure A-1: Hierarchical structure

S E C T I O N: C O N D I T I O N OF P I P E S E G M E N T S

1. What are the relative importance of pipe characteristics, external conditions, and other factors relative to the overall condition of the wastewater pipe?

Table A-3: Relative Importance Of PC, EC And HC

Condition	Pipe Characteristics	External Characteristics	Hydraulic Characteristics
Pipe characteristics	1		
External Characteristic		1	
Hydraulic Characteristic			1

2. What is the relative importance of the age, Corrosion, diameter, and pipe shape relative to other pipe characteristics?

Table A-4: Relative Importance Of PC Characteristics

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

3. The relative importance of depth, soil type, loading, waste type, seismic zone, and groundwater relative to the other external characteristics?

Table A-5: Relative Importance Of EC Characteristics

External Characteristics	Depth	Soil Type	Traffic Loading	Waste Type	Seismic Zone
Depth	1				
Soil Type		1			
Traffic Loading			1		
Waste Type				1	
Seismic Zone					1

4. What is the relative importance of the PACP structural score, PACP O&M score, and repair history relative to other Hydraulic Characteristics?

Table A-6: Relative Importance Of HC Characteristics

Hydraulic Characteristics	Structural Score	O&M Score	Repair History
Structural Score	1		
O&M Score		1	
Repair History			1

SUPPORTING INFORMATION FOR OVERALL CONDITION OF WASTEWATER PIPE

Table A-7: Supporting Information Of PC Characteristics

FACTOR SCORE	PIPE CHARACTERISTICS			
	Pipe Age [yrs]	**Corrosion**	**Diameter [inch]**	**Shape**
1	< 10 yrs	Reinforced Plastic Pipe, Polyvinyl Chloride, Vitrified clay pipe, Polyethylene	>=49	Circular
2	≥ 10 yrs and < 25 yrs	Cast Iron, Ductile Iron Pipe	>31 and <=48	Oval
3	≥ 25 yrs & < 40 yrs	Reinforced Concrete Pipe, concrete pipe (non-reinforcement), Concrete Segments	>18 and <=30	Horseshoe
4	≥ 40 yrs & < 50 yrs	Not Known	>11 and <= 18	Semi-elliptic
5	≥ 50 yrs	Other	<=11	Arch

Table A-8: Supporting Information Of EC Characteristics

FACTOR SCORE	EXTERNAL CHARACTERISTICS					
	Depth [feet]	**Soil Type**	**Traffic Loading**	**Waste Type**	**Seismic Zone***	**Groundwater**
1	<10 Feet	Granular (Crushed Stone/Gravel)	No/Very Light Traffic	Mildly Corrosive	Zone 1	Low
2	> 10 and <= 15 Feet	Coarse Grained (Gravelly	Light Traffic	Mildly to Moderately Corrosive	Zone 2	Low to Moderate
3	> 15 and <= 20 Feet	Silty/Clayey Gravels	Medium Traffic	Moderately Corrosive	Zone 3	Moderate
4	> 20 and <= 25 Feet	Fine Grained (Sands/Silts)	Moderate to Heavy Traffic	Moderately to Highly Corrosive	Zone 4	Moderate to High
5	> 25 Feet	Inorganic Silts/Clays	Heavy Traffic	Highly Corrosive	Zone 5	High

Table A-9: Supporting Information Of HC Characteristics

FACTOR SCORE	HYDRAULIC CHARACTERISTICS		
	Structural Score	**O&M Score**	**Repair History**
1	1	1	No maintenance
2	2	2	Minor maintenance
3	3	3	Moderate maintenance
4	4	4	Significant maintenance
5	5	5	Extreme maintenance

*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

A.2 Example Calculation Of Relative Weights And Consistency Ratio

This appendix presents an example calculation of the Relative weights and Consistency Ratio (CR) with random values.

Step 1. Pairwise comparison

Each entry of the upper diagonal is based on 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 wastewater pipe? As shown in Table A-3

Table A-10: Example pairwise comparison between two factors

	Pipe Characteristics	External Characteristics	Hydraulic Characteristics
Pipe Characteristics	**1**	3	9
External Characteristics	0.333	**1**	6
Hydraulic Characteristics	0.111	0.167	**1**
Σ	**1.444**	**4.167**	**16**

Step 2. Normalization and Relative weight calculation

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 and calculating the normalized eigenvectors which is the relative weight. As a result, a new matrix is obtained. For example, the first component of the first row is obtained as $\frac{1}{1.444} = 0.6923$. For this matrix, the sum of all rows is calculated, and normalized eigenvector also computed, as shown in Table A-4. The sum of eigen vector is 1.

Table A-11: Normalized matrix

	Pipe Characteristics	External Characteristics	Hydraulic Characteristics	Normalized Eigen Vector
Pipe Characteristics	0.6923	0.7200	0.5625	**0.6583**
External Characteristics	0.2308	0.2400	0.3750	**0.2819**
Hydraulic Characteristics	0.0769	0.0400	0.0625	**0.0598**
Σ	**1**	**1**	**1**	**1**

Relative weight is the average of the normalized matrix

$$W = \begin{bmatrix} 0.6583 \\ 0.2819 \\ 0.0598 \end{bmatrix}$$

Step 3: $\boldsymbol{\lambda_{max}}$ calculation

The Next step is to calculate λ_{max}

λ_{max} = (0.6583*1.444) + (0.2819*4.617) + (0.0598*16) = 3.20888

Step 4. Consistency Index (CI) calculation

The next step is to calculate the consistency index.

The Consistency Index is calculated as the next step as presented in Eq. A-1.

$$CI = \frac{(\lambda_{max} - n)}{(n-1)} \qquad \textbf{Eq. A-1}$$

Then

$$CI = \frac{3.20888 - 3}{2} = 0.10444$$

Step 5. Calculation of the Consistency Ratio (CR.)

The *CR* is calculated as presented in.

$$CR = \frac{CI}{RCI} \qquad \textbf{Eq. A-2}$$

Where *RCI* is found in Table 5 and is 0.58 in this case, the value of *CR* is:

$$CR = \frac{0.10444}{0.58} = 0.180$$

The *CR* is less than 0.10, meaning that the judgment of this decision-maker is acceptable, but our *CR* is greater than 0.10, which means we need to revisit our comparison.

A.3 Example Calculation Of Comprehensive Rating

$$CRS = W_{PC}PC + W_{EC}cEC + W_{HC}HC \qquad \textbf{Eq. A-3}$$

$$PC = \sum_{i=1}^{m}(w_i R_i) \qquad \textbf{Eq. A-4}$$

$$EC = \sum_{j=1}^{n}(w_j R_j) \qquad \textbf{Eq. A-5}$$

$$HC = \sum_{k=1}^{o}(w_k R_k) \qquad \textbf{Eq. A-6}$$

PC = (0.103274 * 4) + (0.646587 * 2) + (0.111992 * 5) + (0.138146 * 1) = 2.404376

EC = (0.139967 * 1) + (0.121239 * 4) + (0.221753 * 3) + (0.125648 * 3) + (0.391392 * 2) = 2.44991

HC = (0.493386 * 3) + (0.310814 * 3) + (0.195800 * 3) = 3

CRS = (0.310814 * 2.404376) + (0.493386 * 2.44991) + (0.195800 * 3) = 2.5434

Comprehensive Rating score of 2.5434 belongs to comprehensive rating 2

APPENDIX B

CODE FOR DATA EXTRACTION

```
import PyPDF2
import pandas as pd
import glob
import os

os.chdir(r"D:\PhD\Phase3\Reports")

print("Directory changed")
def read_content(filename):
        pdf_file = open(filename, 'rb')
        read_pdf = PyPDF2.PdfFileReader(pdf_file)
        number_of_pages = read_pdf.getNumPages()
        page1 = read_pdf.getPage(0)
        page_content1 = page1.extractText().split('\n')
        page2 = read_pdf.getPage(1)
        page_content2 = page2.extractText().split('\n')
        return page_content1, page_content2


def find_values(page_content1, page_content2):
        Column_names1 = ['GM','Comprehensive Type of Construction','Comprehensive
Rating','Pipe Diameter Needed (if replaced)','Up Rim to Invert (feet)','Up Grade to Invert
(feet)','Up Rim to Grade (feet)','Down Rim to Invert (feet)','Down Grade to Invert
(feet)','Down Rim to Grade (feet)','Max Grade to Invert (feet)','Depth
Category','FlwMtrBasin','Total Length (feet)','Existent Height (inches)','Existant
Material','Existant Lining Method','DrainageArea','Major Defect','Minor Defect']
        Column_names2 = ['Assessment Rating']
        Column_names = Column_names1 + Column_names2
        values = []
          for i in Column_names1:
            values.append(page_content1[page_content1.index(i)+1])
          for i in Column_names2:
            values.append(page_content2[page_content2.index(i)+1])
          return Column_names, values


if __name__ == '__main__':
        mypath = r"D:\PhD\Phase3\Reports"
        result = []
        for file in glob.glob(mypath + "/*.pdf"):
```

```
        page_content1, page_content2 = read_content(file)
        Column_names, values = find_values(page_content1, page_content2)
        result.append(values)

    df = pd.DataFrame(result, columns = Column_names)
    df.to_csv('output.csv')

print("Program terminated Successfully, output.csv")
```

APPENDIX C

CODE FOR FEATURE IMPORTANCE FOR ONE ATTRIBUTE

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score

dataset=pd.read_csv(r"/Users/nethrachekuri/Documents/Nethra/PhD/Research_Work/Fin
al Output/VCP8Inch_Broadmoor_FinalData_5_Phase3.csv")

dataset1 = dataset.copy()
dataset1['Diameter'] = np.random.permutation(dataset1['Diameter'])

x = dataset1.iloc[:,[2,14]].values
y = dataset1.iloc[:-1].values


x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30,random_state=0)

classifier = KNeighborsClassifier(n_neighbors=9,weights='uniform',algorithm='auto',p=2
)
classifier.fit(x_train,y_train)
y_pred=classifier.predict(x_test)

bias=classifier.score(x_train,y_train)
bias
variance= classifier.score(x_test,y_test)
variance
cm = confusion_matrix(y_test,y_pred)
cr = classification_report(y_test, y_pred)
c = accuracy_score(y_test, y_pred)
```

APPENDIX D

CODE FOR COMPREHENSIVE RATING *K*-NN

```
 import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn. neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score

dataset=pd.read_csv(r"/Users/nethrachekuri/Documents/Nethra/PhD/Research_Work/Fin
al Output/VCP8Inch_Broadmoor_FinalData_5_Phase3.csv")


x = dataset.iloc[:,[2,12]].values
y = dataset.iloc[:-1].values


x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30,random_state=0)

classifier = KNeighborsClassifier(n_neighbors=9,weights='uniform',algorithm='auto',p=2
)
classifier.fit(x_train,y_train)
y_pred=classifier.predict(x_test)

bias=classifier.score(x_train,y_train)
bias
variance= classifier.score(x_test,y_test)
variance
cm = confusion_matrix(y_test,y_pred)
cr = classification_report(y_test, y_pred)
c = accuracy_score(y_test, y_pred)
```

APPENDIX E

CODE FOR COMPREHENSIVE RATING NAÏVE BAYE'S

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score

dataset=pd.read_csv(r"/Users/nethrachekuri/Documents/Nethra/PhD/Research_Work/Fin
al Output/VCP8Inch_Broadmoor_FinalData_5_Phase3.csv")


x = dataset.iloc[:,[2,12]].values
y = dataset.iloc[:-1].values


x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30,random_state=0)

classifier = classifier = GaussianNB()
classifier.fit(x_train,y_train)
y_pred=classifier.predict(x_test)

bias=classifier.score(x_train,y_train)
bias
variance= classifier.score(x_test,y_test)
variance
cm = confusion_matrix(y_test,y_pred)
cr = classification_report(y_test, y_pred)
c = accuracy_score(y_test, y_pred)
```

APPENDIX F

CODE FOR COMPREHENSIVE RATING DECISION TREE

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score

dataset=pd.read_csv(r"/Users/nethrachekuri/Documents/Nethra/PhD/Research_Work/Fin
al Output/VCP8Inch_Broadmoor_FinalData_5_Phase3.csv")


x = dataset.iloc[:,[2,12]].values
y = dataset.iloc[:-1].values


x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30,random_state=0)

classifier = DecisionTreeClassifier(criterion="gini",splitter="best", max_depth=None)
classifier.fit(x_train,y_train)
y_pred=classifier.predict(x_test)

bias=classifier.score(x_train,y_train)
bias
variance= classifier.score(x_test,y_test)
variance
cm = confusion_matrix(y_test,y_pred)
cr = classification_report(y_test, y_pred)
c = accuracy_score(y_test, y_pred)
```

APPENDIX G

CODE FOR COMPREHENSIVE RATING RANDOM FOREST

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score

dataset=pd.read_csv(r"/Users/nethrachekuri/Documents/Nethra/PhD/Research_Work/Fin
al Output/VCP8Inch_Broadmoor_FinalData_5_Phase3.csv")


x = dataset.iloc[:,[2,12]].values
y = dataset.iloc[:-1].values


x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30,random_state=0)

classifier = RandomForestClassifier(n_estimators=200,criterion="gini",
max_depth=None)
classifier.fit(x_train,y_train)
y_pred=classifier.predict(x_test)

bias=classifier.score(x_train,y_train)
bias
variance= classifier.score(x_test,y_test)
variance
cm = confusion_matrix(y_test,y_pred)
cr = classification_report(y_test, y_pred)
c = accuracy_score(y_test, y_pred)
```

APPENDIX H

CODE FOR MARKOV CHAIN MODEL

```
#Load required packages:
library(readxl)
library(msm)
library(expm)
library(markovchain)
library(ctmcd)

#Data Import:
data<-read_excel("/Users/nethrachekuri/Documents/Nethra/PhD/Research_Work/Final
Output/VCP8Inch_Broadmoor_FinalData_5_Phase3.xlsx")

#Summarize multi-state data:
statetable<-statetable.msm(CRFINAL, PipeID, data=data)
states<-matrix(0,5,5)
states[3,]<-statetable[2,]
states[1,]<-statetable[1,]
rownames(states)<-c("1","2","3","4","5")
colnames(states)<-c("1","2","3","4","5")
states

#Relative transition frequencies:
reltransfreq <-rbind((statetable/rowSums(statetable))[1,],rep(0,5),
                     (statetable/rowSums(statetable))[2,],
                     rep(0,5),rep(0,5))
rownames(reltransfreq)<-c("1","2","3","4","5")
reltransfreq

#Average elapsed time between observations (in years):
te<-mean(abs(diff(data$`Installation Year`)))
te

# Generator Matrix:
pr<-list()
pr[[1]]<-matrix(1,5,5)
pr[[1]][5,]<-0
pr[[2]]<-c(rep(1,4),Inf)
pr
gmgs<-gm(tm=states,te=52,method="GS",prior=pr,burnin=1000)

Q<-as.matrix(gmgs[[1]])
Q
#One year transition probability matrix:
p1<-expm((1/56)*Q)
p1
```

```
#Probability variation of states in Markov process:
V0<-c(1,0,0,0,0)
for (step in 1:200) {
        matplot(t(sapply(1:200, function(step) {V0 %*% (expm((Q)*(step/56))})),
             cex=0.7,
             main="Probability of being in any of the comprehensive rating's based on
the pipe's age",
             xlab="Time [Years]", ylab="Probability")
    }

#Sojourntime
Y11<-(-1/(Q[1,1]))
Y22<-(-1/(Q[2,2]))
Y33<-(-1/(Q[3,3]))
Y44<-(-1/(Q[4,4]))
sojourn.time<-c(0, Y11, Y11+ Y22, Y11+ Y22+ Y33, Y11+ Y22+ Y33+ Y44)
time.data<-as.matrix(sojourn.time,ncol=1,byrow=FALSE)
colnames(time.data)<-"Sojourn Time"
```

APPENDIX I

WEIGHTED AVERAGE CALCULATION

This appendix presents about weighted calculation for one Pipe ID

$$Weighted\ Average = \frac{\sum(Weigths * Quantities)}{\sum Weigths} \qquad \textbf{Eq. E-1}$$

$$Weighted\ Average = \frac{(5*5)+(4*4)+(2*2)+(3*3)+(4*4)+(2*2)+(3*3)+(1*1)+(3*3)+(2*2)+(2*2)+(2*2)}{5+4+2+3+4+2+3+1+3+2+2+2}$$

$$Weighted\ Average = 3.1818$$

Weighted average is 3.1818, the COF rank is 3 which means moderate costs planned by utilities are involved.

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