Planning Inspection of Sewer Pipelines Using Defect-Based Risk Approach

Mohamed Elmasry

A Thesis
In the Department
of
Building, Civil and Environmental Engineering

Presented in Partial Fulfillment of the Requirements
For the Degree of
Doctor of Philosophy (Civil Engineering) at
Concordia University
Montreal, Quebec, Canada

January 2018

CONCORDIA UNIVERSITY
SCHOOL OF GRADUATE STUDIES

This is to certify that the thesis prepared

By: Mohamed Elmasry

Entitled: Planning Inspection of Sewer Pipelines Using Defect-Based Risk Approach

and submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

(Civil Engineering)

complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the final examining committee:

______________________________ Chair
Dr. Hua Ge

______________________________ External Examiner
Dr. Mohamed Najafi

______________________________ External to Program
Dr. Ali Akgundus

______________________________ Examiner
Dr. Zhi Chen

______________________________ Examiner
Dr. Zehnhua Zhu

______________________________ Thesis Supervisor
Dr. Tarek Zayed

Approved by ______________________________
Dr. Fariborz_Haghighat, Graduate Program Director

May/10/2018______________________________
Dr. Amir Asif, Dean
Faculty of Engineering and Computer Science

Abstract

Planning Inspection of Sewer Pipelines Using Defect-Based Risk Approach

Mohamed Elmasry, Ph.D.

Concordia University, 2018

Due to the poor conditions of wastewater networks, there is an increasing need in the capital investments allocated for enhancing their condition. As per the Canadian Infrastructures Report Card, one third of the total lengths of sewer pipes in Canada is in fair to very poor condition (Canadian Infrastructures Report Card, 2016). As such, there is an urgent need for inspection planning tools, with which decision makers could assess the condition of pipelines and identify pipes with higher risk of failure. These tools are potentially of service in prioritizing and optimizing inspection activities that lead to decisions regarding appropriate courses of action, especially in cases of limited resources and funding.

The goal of this research is to develop an optimization model for scheduling the inspection of sewer pipelines by performing defect-based risk assessment. The risk of failure is determined to identify critical pipe sections; by combining likelihood and consequence of failure values using the Sugeno Fuzzy Inference System. The developed optimization model determines the inspection sequence of pipeline sections in addition to optimizing the utilization of inspection crews by minimizing both time and cost of inspections. The risk assessment model is divided into two sub-models: likelihood and consequences of failure. Structural and operational defects and pipeline

characteristics in an existing sewage network are used to develop the likelihood model that determines the structural, operational and overall condition ratings of pipelines.

Method-wise, Bayesian Belief Network (BBN) is used to develop a static condition assessment model using probabilities of occurrences and conditional probabilities. Moreover, time dimension is introduced to the developed BBN model using logistic regression as temporal links which are required to convert BBN into Dynamic Bayesian Network (DBN). The accuracy of the model's prediction is examined through referencing of actual data, where the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) for the BBN model are 0.67, 1.06, 0.56 and 1.05, 1.60, 0.95 for structural, operational and overall conditions, respectively.

The second sub-model representing the consequences of failure is developed to determine the impact of sewer pipelines' failure using Cost Benefit Analysis (CBA). Developing this sub-model involves identifying and analyzing costs of failure and benefits resulting from avoiding such failures. In order to validate the CBA model, actual costs from a real failure incident are compared with the proposed model's outputs. During the implementation of the CBA model, it is found that the indirect costs resulting from sewer pipelines' failure represent a significant portion of the total failure costs.

The proposed risk assessment model is validated using actual data derived from inspected sewer pipelines. Cost savings of around 67% could be achieved if the risk assessment model is applied and deployed over ongoing inspection practices followed by municipalities. A Mixed Integer Linear Programming (MILP) model is developed to optimize scheduling of inspection activities by including sewer sections, time and cost of inspections. This model is developed using GAMS and solved using CPLEX to maximize the number of sections and minimize time and cost. The output from the MILP model is compared to the results of another model solved using the

Genetic Algorithm (GA) approach. It is found that the MILP model could perform better than the GA model in terms of optimal solutions. Additionally, a resulting inspection cost reduction of approximately 38% could be achieved when utilizing the MILP model.

It is expected that the proposed inspection scheduling model could help decision makers better assess the condition of sewer pipelines and improve their decision-making on proactive or reactive measures. The proposed model could help allocate budgets more efficiently in addition, to being an enabler for better inspection programs, particularly in cases of limited funds and task forces.

Acknowledgement

I would like to thank my supervising professor Tarek Zayed for his guidance throughout my time as his student, and I am particularly thankful for him providing me with the opportunity to pursue a PhD. I am also thankful for Professor Alaa Hawari, who I enjoyed working with—knowing him has been a gift. I would like to thank Dr. Mohamed Salah, Dr. Mohamed Helwa, Mr. Mohamed Mostafa, and Mr. Ahmed Hegab for their help and financial support in times of limited funds.

I am thankful for a true friend who I made during this period for all the support and help – Mr. Ahmed Elbeheri. He will always be a source of positive energy, warmth, and delicious food. Also, I would like to thank Dr. Adham Ismail for being a good friend and for helping with the optimization model.

I would like to acknowledge project number NPRP 6 - 357 - 2 - 150 titled "Non-destructive Evaluation Based Tools for Managing Waste Water Networks (WWN) in Qatar" for funding my research. I would like to also thank my brother and his family especially Ali and Omar for making the time I spent in Qatar bearable and even enjoyable.

I am indebted to my father who planted in me the love of seeking knowledge. He will always be my inspiration, mentor and my lifetime friend. I would like to thank my best friend Ms. Fatma Tarek for her patience and support. She is the best person one could ask for and she truly showed how someone can be supportive, helpful and patient.

Table of Contents

List of Figures

List of Tables

List of Acronyms

AC Asbestos Cement

CCTV Closed Circuit Television

CBA Cost Benefit Analysis

BBN Bayesian Belief Network

DBN Dynamic Bayesian Network

FIS Fuzzy Inference System

GA Genetic Algorithm

GAMS General Algebraic Modeling System

GUI Graphical User Interface

GIS Geographical Information System

LP Linear Programming

IP Integer Problem

MIP Mixed Integer Problem

MLR Multinomial Logistic Regression

MCS Monte Carlo Simulation

OC Operational Condition

PVC Polyvinyl Chloride

RC Reinforced Concrete

SC Structural Condition

VBA Visual Basic for Application

VC Vitrified Clay

Chapter 1: Introduction

1.1. Wastewater Collection Networks

The function of wastewater systems is to collect wastewater from different households and discharge it at wastewater treatment plants (Grigg, 2003). In wastewater systems, sewer pipelines make up a major portion of the overall system because they are the channels that convey water to these treatment points. Therefore, improper collection and discharging of wastewater can have adverse impacts on public health and the environment. Operation and Maintenance strategies in municipalities are employed to ensure that sewer pipelines, among other components, are in a good state and operating properly. However, due to budget constraints and the vast number of sections that need inspection, the overall condition of these pipeline systems is unacceptable.

As per the Canadian infrastructures report card (Canadian Infrastructure Report Card, 2016), the infrastructure assets in Canada rank between “fair” and “very poor” with an average of 30% of the total assets categories. The total replacement cost for these underperforming assets has been estimated at around $171.8 billion. As for sewage networks in particular, and based on the same report, 24%, 8% and 3% of the total lengths of sewer pipes are in a fair, poor and very poor conditions, respectively. The replacement costs for these pipes would run a total amount of approximately $82 billion.

The condition of sewage infrastructure in the USA, on the other hand, is alarming. A study by the American Water Works Association (AWWA, 2012), indicates that a large portion of water and wastewater pipelines in the U.S. are approaching the end of their lifetime. Another study indicated that these buried pipes are in poor condition overall rating—on average—one grade higher than failure (ASCE, 2013). Restoration of these deteriorated pipes to meet an acceptable operating level is estimated to cost the U.S. a total of $298 billion over the next twenty years. Furthermore, in Europe investments required to restore deteriorated sewer pipelines and upgrade the ones in poor condition are estimated to cost approximately €22 billion for EU member states, according to the European Union (2014). It is forecasted that the extension of the existing wastewater networks, and the rehabilitation of deteriorated pipelines, would cost €25 billion per year between 2015 and 2018.

In summary, sewer pipelines, even in developed countries such as the ones in Europe and North America, suffer from poor condition ratings even as national, state, and municipal governments pump large amounts of money into wastewater system improvements and upgrades. In light of these issues, efficient management and operation planning for those existing wastewater pipelines should be carried out. To ensure this, a reliable prioritization tool should be developed that can help in better understanding the deterioration trends of sewer pipelines and in performing optimized inspections.

1.2. Problem Statement

Irregular maintenance activities and limited budgets allocated for the inspection and management of wastewater pipeline assets are often aggravated by a high demand for the inspection of other, deficient, components. This necessitates the development of prioritization tools. Prioritization tools help in making informed decisions and identifying pipes with a high risk of failure. To assess the risk of failure for sewer pipelines, two main components must be determined: the likelihood, and consequences of failure. To determine the likelihood of failure, deterioration models are developed using statistical techniques indicating the probability that a sewer pipeline will be in a certain condition. The deterioration models are usually developed either on an individual pipe level or on a network level. For deterioration models developed based on network level, pipes sharing the same characteristics must be grouped into cohorts. This doesn't provide the deterioration behavior for the sewer pipes on the individual level, though there are determination models that do analyze this level. This is all critical to determining the likelihood of failure.

Determining the consequences of failure for sewer pipelines is also a multi-step analysis which comprises identifying the implications of pipeline failure on the environment, economy, and social life. Due to the intangible nature for these implications, determining their effect in monetary amounts might be a complex and inaccurate process. To overcome such difficulty, economic concepts and approaches are used to determine the economics of infrastructure loss based on hypothetical scenarios meant to simulate the event of failure, and the prevention of that failure. The risk values for different pipelines are obtained by combining both the likelihood and consequences of failure values which are then used in the prioritization tool to rank pipes based on the resultant risk values that accurately reflect the risk of failure in these pipeline systems.

In the presence of limited funds and budget constraints in most municipalities, determining which critical sections have the priority to be inspected can be considered inadequate because some pipelines in poor condition states shall be inspected leaving out better ones for which their condition would get worse with time until the next inspection. As such, determining the times for these inspections, and which technologies are least expensive and most effective in the inspection process, should provide sufficient information for decision makers. After determining which sections are critical and should be inspected, an optimization tool shall be developed with the objective of minimizing the total cost spent on inspection.

1.3. Research Motivation

There are three research questions that motivate this work. First, what to inspect, and how likely is it to have sections that require further inspections? The answer to this question lies in identifying critical sections based on present defects and different, specific, pipeline characteristics. Additionally, consequences of failure for these pipelines shall be assessed, from which a prioritization list shall be created for all sections that require immediate inspection based on the decision makers' perspective on thresholds for poor sewer conditions. This could be achieved by combining the likelihood of failure and the consequences of failure for the sewer pipelines. Second, when should these critical sections be inspected? To determine inspection intervals, deterioration models are developed for sewer pipelines using the range of possible defects combined with the material characteristics of the specific system in question.

The third question motivating this work is what is the scope of inspection? Based on the results from steps 1 and 2, the inspection technology and the number of pipelines to be inspected are determined in light of budget allocations. This is achieved by minimizing the total inspection costs to meet the budget restrictions. In summary, a risk assessment inspection planning procedure is developed based on the assessment of typical defects for the sewer pipelines that specifies the maximum inspection interval in light of the available inspection funds and limited work forces.

1.4. Research Objectives

The objective of this research is to develop a defect-based inspection planning tool for sewer pipelines. To achieve this objective, the following sub-objectives are determined:

- Identify and study the various defect types in sewer pipelines and the different pipeline characteristics.
- Develop a defect-based risk assessment model for sewer pipelines.

- Develop an optimization model for minimizing the time and cost of inspection while maximizing the number of inspected sections.
- Automate the developed models on a user friendly tool.

1.5. Methodology Overview

The methodology adopted in this research can be divided into two main parts. First, risk assessment is performed using the collected data from GIS database and CCTV inspection reports for previously inspected pipelines. This risk assessment is performed by integrating the likelihood and consequences of failure using fuzzy inference systems. The likelihood of failure is determined by combining the direct condition assessment comprising the defects found in pipelines as a result of aging and the indirect condition assessment that consists of the different pipelines' characteristics contributing in pipelines' deterioration. Static and Dynamic Bayesian Belief networks are used for that purpose with multinomial logistic regression as an aiding technique to determine the temporal links required in the dynamic network.

Analysis of different costs is performed to determine the costs paid by the community and the benefits returned to it in case of pipelines' failure—from which the consequences of failure is then expressed by these two values. Sugeno Fuzzy Inference System is used to assess the risk of failure of sewer pipelines. The second part in the adopted methodology is developing an optimization model to determine which sections shall be inspected to minimize the time and cost of inspections. An objective function is formulated using the previously developed risk assessment model with whether to include the pipeline section in the inspection activity as a decision variable.

1.6. Dissertation Outline

The dissertation consists of seven chapters and two appendices. The literature review and background are presented in Chapter 2. The review covers the topics of deterioration models, risk of failure, inspection scheduling and optimization models developed for different assets in general, and sewage pipelines in particular. A summary of the limitations and gaps in existing methods at the end of the review part is introduced. In the second part of the chapter, the concepts and topics required to build the theoretical background for this research are presented, such as Bayes theory, fuzzy set theory, fuzzy inference systems and the economics of failure.

Chapter 3 describes the methodology adopted in this research. A brief review of the literature is presented followed by a description of the models developed in this research. The first model comprises the likelihood of failure, while the second comprises the consequences of failure and the third is the integration of these two models under the risk umbrella. The fourth model is the optimization model that takes into consideration all these models while considering the time and cost of inspection.

Chapter 4 presents the collected datasets that are used in developing the models described in chapter 3. A description for each dataset and how it was used in developing the models are presented in that chapter. In chapter 5, the developed models are presented, and the underlying techniques used in their development are presented as well. The development of a comprehensive integrated tool for all the models is presented in chapter 6. Chapter 7 discusses the conclusion as well as the contributions and limitations of this research along with suggested future research work as well. In Appendix I, samples from the codes written to develop the automated tool are presented. Appendix II presents the survey carried out to address the experts in order to examine the usability of the developed tool.

Chapter 2: Literature Review

2.1. Introduction

The operation and maintenance of infrastructure depends on the accuracy of information collected on its components. Municipalities need to identify the most critical sections that require inspection, so as to preserve limited municipal resources. Literature shows several approaches that have been used in developing inspection planning and scheduling tools, one of these approaches is using risk assessment to prioritize inspection in which likelihood and consequences of failure are combined to determine the pipelines with the highest risk of failure. Another approach is to determine inspection intervals by modeling deterioration of sewer pipelines using statistical models while adding a cost function from which a decision regarding inspection may be made in a way that minimizes the cost, and extends the life of these pipes.

A third approach is using optimization tools to increase the efficiency of inspections based on a set of constraints, such as budget restrictions or certain conditions set by the users. Figure 2.1 shows the different approaches used in developing inspection planning tools adopted from the literature. In this chapter, the different methodologies developed for inspection planning and scheduling of pipelines are introduced. In addition, different pipeline condition assessment methods, the different common types of sewer pipeline defects, inspection technologies, and definitions such as risk assessment and optimization are also discussed.

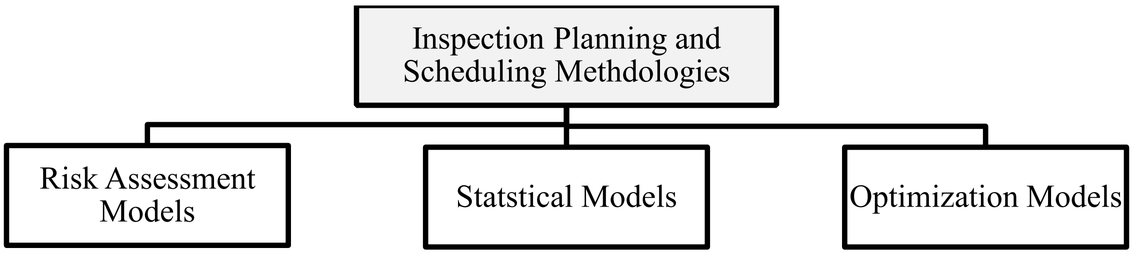


Figure 2.1: Approaches Adopted in Inspection Planning Tools Development

2.2. Sewer Pipelines Condition Assessment

Condition assessment information is the basis of a successful asset management plan. The condition assessment is used in determining the current condition of the asset, and may also forecast the future conditions from which a decision can be made regarding the prioritization of certain competing elements in an action plan. A sewer pipeline's condition assessment can be determined by either direct or indirect assessment as shown in Figure 2.2.

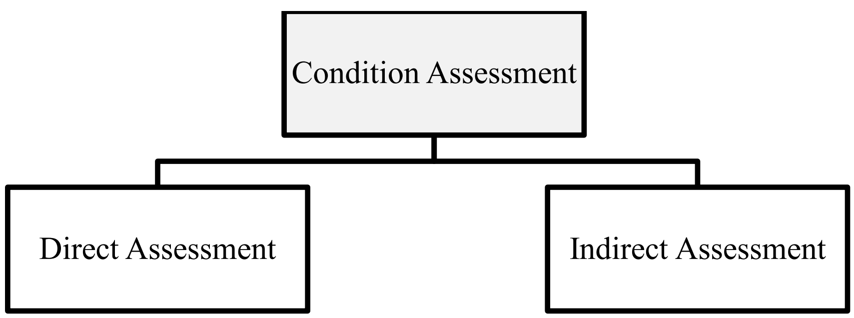


Figure 2.2: Sewer Pipelines Condition Assessment Types

2.2.1. Direct Assessment

In direct assessment, the condition of the sewer pipeline is determined by measuring the severity and the size of physical distress indicators based on predefined scores derived from condition rating systems defined by manuals and standards such as: Manual of Sewer Condition Classification (Water Research Centre, 2001), Pipeline Assessment and Certification Program Manual (NASSCO, 2001), and Manual de Standardisation des Observations Inspections Télévisées de Conduites d′Egout (Centre d′ Expertise et de Recherche en Infrastructures Urbaines

,1997). These physical distress indicators are the typical defects in the sewer pipelines that will be discussed later. To measure these defects, several inspection technologies are used such as CCTV technologies, laser profiling, and sonar (RedZone, 2010). Appropriate inspection technologies are used to determine the presence of defects and their severity, from which an overall condition rating is given to the pipeline segment based on the operators' perspective.

2.2.2. Indirect Assessment

An indirect assessment, as the name implies, requires that the factors which contribute to the deterioration of the assets are identified, and performance values are given to each factor based on its importance and effect from which the condition can be determined. These contributing factors are usually categorized into physical factors that represent the sewer pipelines physical characteristics such as: age, diameter, length, material, and slope, among others. The second category of these factors are environmental, which represents the surrounding environment of the pipelines such as soil properties, traffic load above the pipeline, groundwater level with respect to the pipeline, etc. As for the third and last category, they are factors related to the operational condition of the pipes such as the flow rate inside of the pipeline itself, infiltration issues, and inflows. It is obvious that indirect assessment is cheaper than direct assessment, however it is less reliable in forecasting the condition rating as accurately as other methods.

2.3. Sewer Pipelines Inspection Technologies

Inspection for sewer pipelines is carried out to identify structural and operational defects in the inspected segments. CCTV is one of the most widely used inspection methods for sewer pipelines, also ultrasonic inspection, sewer scanning and evaluation technology (SSET), laser-based scanning, ground penetrating radar and smoke testing. In addition to these methods, wall micro deflections and natural frequency of vibration, and impact echo/spectral analysis of surface waves are used to inspect pipe walls and bedding conditions (Makar, 1999). Each of these inspection technologies have advantages and disadvantages that are discussed separately and requires the user to employ them based on the different types of information sought by the inspection.

2.3.1. Closed Circuit Television (CCTV)

CCTV is the most widely used inspection technology that helps agencies in obtaining and storing detailed information about inspections performed (Najafi, 2005). The CCTV is used in the pipeline context by capturing videos and images via either a stationary or mobile camera. The movable camera is remote controlled, and it inspects the pipelines by the operator who records the different defects recorded by the device. As for the stationary CCTV, the camera is attached at a fixed point, and different images are captured from that location (Najafi, 2005). The CCTV can identify cracks, fractures, sags, infiltration, roots, inflows, and encrustations (WEF/ASCE, 2009).

Advantages of using CCTV:

- When compared to other inspection techniques, it is one of the most cost effective methods.
- A whole length of pipeline can be inspected.
- Since it is one of the most commonly used methods, there is a large body of knowledge available.

Disadvantages for using CCTV:

- Defects under flow line can't be detected (flows with less than 25-30% of depth).
- The accuracy of the inspection depends greatly on the experience of the operator and the quality of captured television pictures (Allouche and Freure, 2002, Chae and Abraham, 2001).
- Difficult to compare between inspections at different times.

2.3.2. Ultrasonic Inspection

To overcome the limitation for the CCTV regarding the defects detection below the flow line, ultrasonic inspection is used. Ultrasonic inspection is where sound waves are used to find defects on the surface of the pipes (Najafi, 2005). This method can help in identifying defects below the flow line, debris present in the pipe, and the capacity of the pipeline. This inspection method can be used in collaboration with other inspection technologies to perform a comprehensive inspection for the pipe (Najafi, 2005). It should also be noted that using ultrasonic inspection can provide inaccurate results when used within certain types of material—such as sewers made of brick—because of the mortar which holds the bricks together interferes with this method (Allouche and Freure, 2002).

Advantages of using ultrasonic inspection:

- Can detect defects above and below flow lines.
- Pipelines whole length can be inspected.
- Comparison between different inspections at different times can be made easily.

Disadvantages of using ultrasonic inspection:

- Difficult to detect cracks.
- Pipes shall be flushed before inspections.
- Not applicable for all types of pipes such as pipes made of bricks where locations of mortar between bricks affect the inspection results.

2.3.3. Sewer Scanning and Evaluation Technology

Sewer Scanning and Evaluation Technology is similar to the CCTV inspection in that it allows operators to capture the walls of the pipelines, resulting in a complete image for the whole pipe (Najafi, 2005 and WEF/ASCE, 2009).

Advantages of using Sewer Scanning and Evaluation Technology:

- Images and videos captured by camera are analyzed by computer software minimizing the inaccuracies that sometimes appear to be due to human error.
- High quality for images of pipe wall surface, which can be obtained easily when using such technology.

Disadvantages of using Sewer Scanning and Evaluation Technology:

- Pipes must be flushed before inspections.
- Results must be analyzed by highly experienced operators.
- Can't detect deformation and the wall condition accurately because images captured for the walls are flat.

2.3.4. Laser Scanning

Using laser scanning can accurately detect defects on pipe wall surface and deformations in the pipe wall itself (Najafi, 2005). This method can help in accurately detecting the amount of debris, capacity of the pipe, and the quality of lining. This method is applied either by using laser cloud or by projecting a laser ring on the pipe wall which identifies defects based on changes in the ring shape (WEF/ASCE, 2009):

Advantages of using Laser Scanning:

- Can accurately detect defect sizes.
- Comparison between different inspections at different times can be made easily, which is important for determining deterioration rates.

Disadvantages of using Laser Scanning:

- Can't detect defects under flow lines
- Costs more than CCTV inspection technology

2.3.5. Ground Penetrating Radar

Ground Penetrating Radar is usually used to detect the empty spaces or water around pipelines (Najafi, 2005). The nature of ground penetrating radar is similar to that of the ultrasonic, where sent and received waves are analyzed to determine defects in the soil (Makar, 1999). Based on the analyzed depth of penetration, voids in soil and ground water levels can be determined.

Advantages of using Ground Penetrating Radar:

- Can detect the outer surrounding for the inspected pipelines.

Disadvantages of using Ground Penetrating Radar:

- Soil condition plays a role in the accuracy of the results.
- Accuracy of results from previous inspections is questionable.

2.3.6. Smoke Test

The smoke test method is performed by inserting smoke inside the pipe and using a smoke blower forcing the smoke to be released from places over the length of the pipe indicating locations that could suffer from infiltration, inflow, joints or connections defects (WEF/ASCE, 2009).

Advantages of using Smoke Test:

- Inexpensive when compared to other inspection methods.

Disadvantages of using Smoke Test:

- Can't be applied when there is heavy inflow inside the pipeline to be inspected.
- Size is a limitation when using the blower.

2.4. Defects in Sewer Pipelines

Defects in sewer pipelines can be divided into structural and operational defects. In the following section, the different defects are described in details and their sub-defects.

2.4.1. Structural Defects

The structural defects are all defects that could jeopardize the structural integrity of sewer pipelines. Table 2.1 shows the different structural defects and sub-categories of these defects.

Table 2.1: Description of Structural Defects in Sewer Pipelines

Defect Category	Defect Type	Description
Cracks and Fractures	Longitudinal	A defect is considered longitudinal if it breaks in a longitudinal direction on the axis of the pipe.
	Circumferential	A defect is considered circumferential if it breaks in a circle forming a right angle with the sewer axis
	Complex	A defect is considered multiple if there is a combination of the longitudinal, and circumferential defects in a relatively small area.
Physical Damage	Broken	Parts of the pipe are visibly apart and are not in their primary place
	Hole	A defect is classified as “hole” when there is a noticeable hole in the pipe wall
	Sag	A bend in the body of the pipe due to pressure
	Collapse	The pipe is said to be collapsed if 50% or more of the cross section is broken in which the pipe is completely damaged and cannot be used
	Spalling	Breaking of the surface material into small pieces usually due to expansion of corroded reinforcement or poor material. It is usually associated with fracture
Surface Damage	Visible Aggregate	When the surface is seriously worn out that aggregates become noticeable
	Projecting Aggregate	When the aggregate is projecting over the pipe’s surface
	Missing Aggregate	When small holes occur due to missing aggregates
	Visible Reinforcement	It occurs when there is adequate missing aggregate that causes the reinforcement to be visible
	Projecting Reinforcement	When the reinforcement is noticeably projecting over the concrete surface
	Corroded Reinforcement	When the damage is due to a visible corrosion and is represented by missing reinforcement parts

2.4.1.1. *Surface Damage*

Surface damages are defects related to the surface condition of the pipelines and include: Visible, missing, and projecting aggregates, corroded and projecting reinforcement and spalling. The following are the different defect categories and a brief description of each of them:

1. Visible Aggregates: This category of defects is when the surface of the pipeline is worn out such that aggregates become noticeable and visible.
2. Missing Aggregates: In this category, there are missing aggregates that could lead to small holes.
3. Projecting Aggregates: Are defects in which aggregates are projecting over the pipeline's surface.
4. Projecting Reinforcement: It occurs when there is adequate missing aggregate that causes the reinforcement to be noticeably visible and projecting over the concrete surface.
5. Corroded Reinforcement: It is when the damage is due to visible corrosion and is represented by missing reinforcement parts.

2.4.1.2. *Physical Damage*

Physical damages are defined as parts of the pipes that are visibly apart and are not in their primary place. They include holes, collapses, breaks, deformation and sags.

1. Holes: Physical Damage is classified as holes when there is a noticeable hole in the pipe wall.
2. Collapse: The pipe is said to be collapsed if half or more of the cross section is broken in which the pipe is completely damaged and cannot be used.

3. Breaks: Is the breaking of the surface material into small pieces, usually due to the expansion of corroded reinforcement or the use of low-quality material which is usually associated with fracture.
4. Deformation: Is measured as a percentage of the actual width (horizontal deformation) or height (vertical deformation) of the pipe that results in a noticeable change in the original cross sectional area of the pipe.
5. Sag: is defined as a bend in the body of the pipe due to an external pressure.

2.4.1.3. ***Cracks and Fracture***

Cracks and fractures are fissures in the wall of the pipeline. Cracks in the pipe wall are not noticeably broken apart, while fractures in the pipeline walls become noticeably open even while the pipe pieces are still in place. Fractures and cracks could be circumferential, longitudinal, multiple (complex) and spiral. The following is a description for the different fissure types:

1. Longitudinal: A fracture or crack is considered longitudinal if it breaks in a longitudinal direction parallel to the axis of the pipe.
2. Circumferential: A fracture or crack is considered circumferential if it breaks in a circle pattern perpendicular to the axis of the pipeline.
3. Complex: A fracture or crack is considered complex if there is a combination of the longitudinal, and circumferential defects in a relatively small area.

2.4.2. Operational Defects

Operational defects are all those defects that decrease the functionality of the pipe when conveying the flow, or otherwise affect the efficiency of operation when conveying the flow. Table 2.2 shows a description for the operational defects and their sub-categories.

2.4.2.4. ***Infiltration***

Infiltration is defined as the inflow of water into pipes and can be attributed to bad joint connections, holes, breaks and physical damages. The infiltration types can be in the form of Dripping, Gushing, Running and Seeping based on flow intensity. Infiltration is considered a type of leakage, which is the intrusion of groundwater through a defect. Leakage may also be an "exfiltration," which is the seeping of sewer flow out of the pipe through a certain defect.

Table 2.2: Description of Operational Defects in Sewer Pipelines

Defect Category	Defect Type	Description
Roots	Fine	Roots that lead to a reduced flow through blocking the pipe's area
	Single	A single root in which its thickness is more than 10 mm which would damage the pipe.
	Dense	Combined roots that might block the whole pipe's cross section
Infiltration	Seeping(1)	A defect is said to be seeping if it is intruding in a slow pattern
	Dripping(2)	A defect is said to be dripping if water is dripping, but not continuously
	Running(3)	A defect is said to be running if water is intruding in a continuous manner
	Gushing(4)	A defect is said to be gushing if water is intruding quickly, as though under pressure
Deposits	Settled Deposits	The settling of deposits on the pipe surface that could reduce the flow capacity
	Encrustation	Encrustation is formed by the effect of evaporating infiltrated water throughout defects along the pipe
	Foul	Attached deposits which are remains of foul sewage
	Grease	Attached grease above the flow on the sewer walls
Soil intrusion		It is the intrusion of surrounding soil into the pipe through certain structural defects
Intruding Services		Some pipe materials that would intrude the pipe causing a reduction in its capacity

1. Seeping: When water intrusion flow is slow, it is said to be seeping.

2. Dripping: When water intrusion flow is dripping but not continuous, it is said to be dripping.
3. Running: If water is intruding in a continuous manner, it is said to be running.
4. Gushing: If water is intruding quickly, as though forced by pressure, it is called gushing.

2.4.2.5. ***Roots***

Roots can be operational defects that cause reduction in the cross sectional area of pipes. Pipes that have foliage above them are more prone to fine, dense, and massive roots. Roots enter from structural defects such as fractures and holes, leading to reduced flow.

1. Fine: When roots intrude the pipelines, they are called "fine" if their thickness is not more than 10 mm.
2. Dense: Dense roots are those that might block the whole pipe's cross section.

2.4.2.6. ***Soil Intrusion***

Soil intrusion is the intrusion of granular materials which could be either dense or fine inside the pipes that would result in reduction of the pipes' cross sectional area.

2.4.2.7. ***Intruding Services***

Similar to soil intrusion, other services could intrude the pipes and affect the flow inside them.

2.4.2.8. ***Deposits***

Deposits are settled material that when accumulated could significantly affect the flow inside the sewer pipes. Deposits can be divided into two kinds; the first are attached deposits, which occurs when foreign materials accumulate and attach along pipe surfaces. The second are called settled deposits, which is when the settling of deposits on the pipe surface cause reduced flow capacity. These settled deposits could be debris, encrustation, or accumulated effluent.

1. Encrustation: is formed by the effect of evaporating infiltrated water throughout defects along the pipe.

2. Debris: Attached deposits which are remains of foul sewage.
3. Effluent: Attached grease above the flow on the sewer walls.

The research carried out addressing sewer pipeline defects can be divided into two main parts. The first part is concerned with automatic detection of defects, while the second part is research addressing conditions of sewer pipelines considering defects. While researching a way to detect and classify defects in sewer pipelines, Moselhi and Shehab-Eldeen (2000) developed an automated tool that detects and classifies cracks in sewer pipelines using neural networks technique. In another study, the authors used artificial intelligence and image recognition techniques to develop a tool for measuring infiltration in sewer pipelines (Moselhi and Shehab-Eldeen, 2005).

In essence, several studies have addressed automatic detection for defects in sewer pipelines to avoid errors resulting from human judgments when identifying defects through traditional CCTV methods or other methods requiring a human element in the designation of defects (Halfawy and Hengmeechai, 2013, 2014a and 2014 b). As for research addressing condition assessment, and how defects affect the health of pipelines, deMonsabert et al. (1999) studied the infiltration and inflow in sewer pipelines and how a defect might affect a decision regarding rehabilitation. This research offered a planning tool to determine which pipelines would require rehabilitation. In a similar study, a planning tool was provided which used infiltration and inflow defects to determine which pipelines would require rehabilitation or replacement using fast messy genetic algorithm.

2.5. Rehabilitation Techniques

To extend the lifetime of sewer pipelines, proper maintenance shall be carried out as deemed necessary. One of the interventions that can be divided into several activities is the rehabilitation of deteriorated sewer pipelines. Figure 2.3 shows the different sewer rehabilitation methods that include repair, renovation and replacement (WEF, 2009).

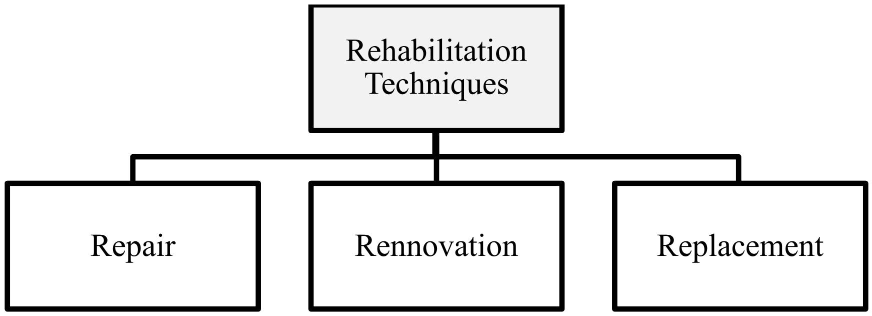


Figure 2.3: Sewer Pipelines Rehabilitation Techniques

2.5.1. Repair

Repairs are concerned with maintaining sewer pipelines by cleaning or fixing leakages. Usually the structural condition of the pipeline is examined to ensure that there are no severe structural defects which could threaten the soundness of the pipeline. Jetting or hydro-mechanics are methods used in cleaning the pipes, while chemical grouting or sleeves are used to stop leakages.

2.5.2. Renovation

If the structural integrity of the pipelines does not meet the standard required, renovation or renewal of the affected pipeline must be carried out. In pipeline renovation, either coating or a lining can be applied to the deteriorated pipeline. In this procedure the cross sectional area of the pipeline is reduced. One of the renovation methods is inserting while pushing and pulling prefabricated pipes through the existing pipeline. Another renovation technique is creating a spiral polyvinyl chloride (PVC) sleeve on site and introducing it to the affected segment. A third technique is to insert a liner in the pipeline and apply hot air or pressure to that lining to treat the defective area.

2.5.3. Replacement

Replacing sewers is considered the conventional technique for sewer rehabilitation, and although it is cheaper than renewing sewer pipelines, it requires more time and work. As such, innovative trenchless technologies such as pipe bursting, directional drilling, micro-tunneling, and Horizontal Directional Drilling, were introduced to replace sewers without the need for excavation work. Trenchless technologies have the advantage of saving cost because no traffic or pavement disruption takes place without affecting businesses or the environment. Table 2.3 shows the different trenchless techniques and the major limitations for using each technique. It can be observed that the sewer diameter plays an important role when determining which technique should be used. It is worth noting that decisions regarding which technique to use when replacing sewers should involve a cost analysis to determine which option is best.

2.6. Criticality of Infrastructures

Critical infrastructures are defined as services for which an interruption or failure in them would have potentially adverse impacts on the social, economic, and environmental wellbeing of the public. Critical infrastructures, also known as critical assets, are usually identified using a risk based assessment methodology as promulgated by the American Electric Reliability Corporation (North American Electric Reliability Corporation, 2006). Risk analysis methodologies help in assessing critical infrastructures, the results of which may form the basis of a proper assessment management plan that can be carried out to protect these infrastructures.

Table 2.3: Different Pipe Replacement Techniques and Main Advantages and Limitations for Each Technique

Technique	**Description**	**Advantages**	**Limitations**
Pipe Bursting	It is a trenchless replacement method in which a bursting tool is inserted inside a pipe and mechanical forces are applied until the pipe is broken (Griffin, 2012). An insertion pit upstream the pipe is installed where a cable attached to a new pipe of the same diameter or larger is pulled from another end until the pipe coincides with the burst location.	- Can be applied to various pipe diameters, materials and soil conditions. - The pipe diameters to be replaced ranges between 50mm and 900 mm.	Bursting length in this technique doesn't exceed 300 meters.
Horizontal Directional Drilling	In this method, a pilot alignment is drilled along the path of the pipe to be installed. A reamer then starts enlarging the pilot alignment to the required diameter. The pipe is then installed by pulling it in the reamed path.	- Doesn't require large excavation pits. - Doesn't interfere with traffic. - Can be used for large spans and pipe diameters (Najafi, 2005). - The pipe diameters to be replaced ranges between 50mm and 1200 mm.	Drilling length in this technique doesn't exceed 300 meters.
Pipe Jacking / Micro-tunneling	The concepts behind pipe jacking and micro-tunneling are almost the same. The two techniques depend mainly on controlling and guiding remotely by applying mechanical or hydro mechanical pressures. In applying the method, shafts are installed at both ends from which the boring machine followed by the pipe segments are jacked from one end and received from the other end. In pipe jacking, the same process is applied; however pipe segments are jacked one after another.	- Doesn't have a size limitation, usually pipes of diameter between 600 mm and 2300 mm) - Can be applied in difficult ground conditions.	- Not recommended for sizes less than 900 mm and more than 2800 mm. - Requires a person on the operating hatch.
Open cut replacement	It is the most widely used method in replacing pipes, however due to the presence of trenchless technologies, this method has been used less over the past two decades. As the name implies, equipment is used to cut open the location of the pipe to be replaced, then pipe is installed and buried under ground.	To determine the cost effectiveness a cost benefit analysis should be carried out.	Sometimes environmental constraints and socioeconomic costs lead to use other methods due to high indirect costs for open cut method.

These are usually carried out by performing a "what-if" scenario for a possible failure event. This hypothetical outcome is then usually assessed in a qualitative or quantitative manner (Emergency Management Australia, 2003). There are three aspects to assess the impact of failure of infrastructure. These are: the geographic area affected by the failure, how long it would take for this failed infrastructure to disrupt the surrounding environment, and the intensity of that failure (European Commission, 2006 and Ministry of the Interior and Kingdom Relations, 2008). Usually the first two aspects are analyzed using qualitative or semi-qualitative criteria whereas the intensity is usually analyzed using detailed qualitative and quantitative criteria.

2.7. Risk Assessment of Infrastructures Failure

The conventional definition for risk assessment is the combination of likelihood of failure with the possible consequences of that failure (Erik et al. 1995). Equation 2.1 represents the risk of a system for different components (i) in a system (j) by considering the likelihood of failure and the associated consequences of failure.

$$R_j = \sum_{i=1}^{n} l_{ij} * C_{ij} \tag{2.1}$$

Where R_j: is the risk in a system (j),

l_{ij}: is the likelihood of failure; and

C_{ij}: is the consequences of failure.

For sewer pipelines, utilizing only the likelihood of failure or consequences of failure values isn't sufficient to describe the relative importance of the pipeline. For two pipelines with equal likelihoods of failure, there could be a wide variation in the consequences of their respective failures. In addition, pipes that have drastic or high consequences of failure usually form fewer portions in the overall network when compared to the ones with medium or minimal consequences of failures. Therefore, when assessing the risk to sewer pipelines, the likelihood should be incorporated with the consequences of failure. One of the simplest forms for integrating both likelihood and consequences of failure is multiplication. The multiplication method helps in differentiating pipes with similar likelihoods of failure but different consequences of failure, however using the product to express risk wouldn't distinguish the values of likelihood and consequences of failure.

The above could be attributed to the fact that two pipes might have similar or close risk values, but they can be resulting from one pipe having a high likelihood value and low consequences of failure value while the other pipe might have low likelihood value and much higher consequences of failure value when compared with the first pipe resulting in inaccurate decisions. To overcome such limitations, risk matrices are used in which a matrix is constructed between the likelihood and consequences of failure by specifying the different levels for each. In the risk matrix the user can determine the resulting risk values as a result of different combinations of likelihood and consequences of failure based on a predefined ordinal scale. Table 2.4 shows a sample for a risk matrix adopted from Salman and Salem (2012).

Table 2.4: Sample for Risk Matrix

		Consequences of Failure				
		Very Low	**Low**	**Medium**	**High**	**Very High**
Likelihood of failure	**Very Low**	Very Low	Very Low	Low	Low	Low
	Low	Very Low	Low	Low	Medium	Medium
	Medium	Low	Low	Medium	Medium	High
	High	Low	Medium	Medium	High	Very High
	Very High	Low	Medium	High	Very High	Very High

When using a risk matrix, the user can identify the different levels of risk resulting from different likelihood and consequences of failure values. On the other hand, in risk matrices the cut off risk values may increase the chances of error occurrence. In addition, risk values are defined over an ordinal scale and shifting to another type of scale (i.e. cardinal) could result in some calculation errors especially for the values on the boundaries. Risk-based inspection planning is an approach used to prioritize and plan inspection based on risk analysis. This type of inspection planning analyzes the likelihood of failure and the consequences to develop an inspection plan. The main causes for damage of a certain asset component are basic risk factors which increase the likelihood of failure.

There are various methodologies which were developed for risk-based inspection planning which may differ in the data used in determining the likelihood of failure of assets susceptible to failure and the consequences of that failure. Most of the developed methodologies use historical failure data when determining the probabilities of failure of a certain element, while some use expert opinions or multi-criteria decision analysis techniques. Tiena et al. (2007) developed guidelines for a risk-based piping inspection. A model was built using risk analysis from which these guidelines were adopted. The model was designed to analyze damage factors, damage models, and potential damage positions of piping in petrochemical plants using failure historical data. The research aimed to provide optimal planning for inspection of the piping system through determining the potential risks and enhancing the degree of safety during operation.

Koriyama, et al. (2009) used Bayesian Transform from failure events available in historical data to determine the probability of rupture, and the frequency at which this rupture would occur in pipe segmenting in nuclear plants. Threshold values for the risk of rupture, as per common practice and standards, were compared with the output of the Bayesian Transform to determine the category of the pipes with respect to a predefined risk scale in order to determine the suitable inspection method. Washer et al. (2014) utilized a risk assessment framework to determine the appropriate inspection frequency and the scope of inspection (i.e. where efforts should be focused). As per this research, risk based inspection was performed by multiplying the occurrence and consequences factors, in which a priority number was calculated that prioritizes the damage mode from which a corresponding inspection interval was identified from preset intervals.

The previous studies focused mainly on researching the different risk factors and damage modes contributing to the likelihood of failure. These studies ignored the consequences of failure, which is a key factor in risk analysis. Risk indexing may be developed without using historical data and using multi-criteria analysis techniques such as Analytical Hierarchy Processing (AHP), which can be used to determine the relative weights of each risk factor that may contribute to the overall failure of the asset. Risk analysis may be conducted based on the information gathered through this technique (Marlow et al. 2012). In a study that adopted this concept, AHP was used to identify the factors that influence failure on specific segments and analyze their effects in oil and gas pipelines.

A risk-based model for inspection was developed in which the likelihood of risk was determined in terms of weights using AHP, while the severity of failure was determined through consequences analysis. Then, the effect of the failure caused by each risk factor was established in terms of cost. For inspection planning in sewer pipelines, and to determine the likelihood of failure, deterioration models were developed by using different pipeline characteristics to predict the condition of the pipeline section in question. The real challenge in performing risk assessment usually lies in determining the consequences of failures. Consequences can be hard to determine because the costs associated with repairing and replacing effected pipeline segments are not static (i.e. they depend on the type of defect, the material of the pipe, etc.), and the intangible consequences of failure, like social and environmental damages, are hard to predict until after an event has already occurred.

To overcome these difficulties, instead of addressing the consequences of failure in monetary values, some studies dealt with these terms by developing indices to identify the severity and importance of impact due to failure. Hahn et al. (2002) developed a knowledge based expert system denoted as “Sewer Cataloging, Retrieval and Prioritization System” (SCRAPS) in the form of a computer support system that determines the criticality of sewer pipelines to prioritize inspection using BBN. The knowledge based expert system was divided into the knowledge base comprising the collected information, and the inference engine which is the algorithm used to navigate through the collected information. The knowledge base was divided into six mechanisms related to the likelihood of failure (structural defects, interior corrosion, exterior corrosion, erosion, infiltration and operational defects) and two mechanisms related to the consequences of failure (socio-economic impacts and reconstruction impacts) which were derived from the United Kingdom’s Water Research Center manual (WRC, 2001).

Interviews with experts from different sectors in the industry were carried out to determine the conditional probabilities that describe the relationships between the different risk factors. The interviews output was used to determine the pipes criticality by assigning different weighting factors based on the different risk levels. BBN was used as the inference engine to aggregate the likelihood and consequences of failure into a final risk of failure value based on information about the pipe in question. The researchers used BBN to integrate the six likelihood and two consequences of failure mechanisms, to overcome the uncertainties inherited from the experts’ opinion. This research offered an intuitive and simple way to determine pipeline criticality; however, it depended greatly on expert opinions, which yielded to more conservative results when compared to actual case studies in real life situations.

2.7.1. Bayesian Belief Network (BBN)

BBNs are acyclic graphical network models that represent the relationships between probabilistic variables through nodes called "parent" and "child" as shown in Figure 2.4. In BBNs, discrete random variables are assigned to parent nodes also known as marginal prior probabilities. Conditional probabilities are used to capture the dependencies between the different nodes and interrelationships that influence the child nodes. BBNs are based on probabilistic Baye's theorem shown in Equation 2.2, to form a graphical model that propagates uncertainties through the network model which could be helpful in constructing decision making problems under uncertainties.

$$p(\frac{A_i}{B})\,\frac{p\left(\frac{B}{A_i}\right)p\ (A_i)}{\sum_{j=1}^{n} p\left(\frac{B}{A_j}\right)p\ (A_j)} \tag{2.2}$$

Where $p\left(\frac{A_i}{B}\right)$: is posterior probability,

$p\left(\frac{B}{A_i}\right)$: likelihood that (B) would occur when $A_i$occurs,

$p\ (A_i)$: is prior probability,

$\frac{1}{\sum_{j=1}^{n} p\left(\frac{B}{A_j}\right)p\ (A_j)}$: is constant of proportionality which ensures that the total probability equals 1.

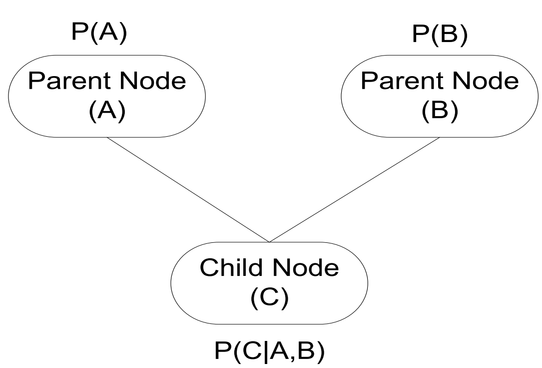


Figure 2.4: Components of Bayesian Belief Network

The dependency and relationships between a child and parent node are quantified by means of Conditional Probability Tables (CPTs). CPTs represent the links between the different nodes that can be considered as a quantification of uncertainties using probabilities. The probability distribution over a child node can be determined based on the parental configuration denoted by (Π) that forms a collection of probabilities distribution over the child node, from which CPTs are constructed. To determine the number of parental configurations in a problem, the states of parent nodes are raised to a power equal to the number of parent nodes. Equation 2.3 represents the number of probabilities required to construct the CPTs.

$$\Pi = k^n \tag{2.3}$$

Where (Π) is the parental configuration based on the number and different states a parent node can take,

(k) is the number of states for child node; and

(n)is the number of parent nodes.

BBN has been applied in various applications such as system security (Langseth and Portinale, 2007), Network analysis to protect network attacks (Zhang and Song, 2011), forensic analysis (Dawid et al. 2002). In addition, BBN has been widely used in biological research and epidemiology (Friedman et al. 2000, and Greenland et al. 1999). Also BBN has been used in robotics, risk management and machine learning applications (Pourret et al. 2012) and as a risk-based decision support tool for the marine industry (Faber et al. 2002 and Hansesn, 2000). The use of BBN has extended to software engineering, where it was used to estimate the effort required for the development of software (Mendes, 2007) and to estimate the productivity of software development projects (Stamelos et al. 2003) which was further enhanced by using DBNs (Bibi and Stamelos, 2004). DBNs were used in predicting defects in software and in investigating their effects from one phase to another (Fenton et al. 2004). Straub (2009) developed a DBN based framework for stochastic modeling of deterioration processes in steel structures. Nielsen and Sørensen (2011) have demonstrated the use of this approach in risk-based inspection planning of offshore wind turbine foundations.

Rafiq et al. (2015) used BBNs and DBNs in bridges management and in predicting the condition of concrete bridges. The static BBN was built for the different bridge components using relative weights from the relative importance of each component. The temporal links required for the DBN were derived from common practice. BBN could accommodate the uncertainty in estimating certain outcomes when the evidence was incomplete and could provide concrete understanding for the relationship between this uncertainty and the outcomes. This allows a user to understand the impact of various parameters on the output, though the effort for deriving the interrelationships between parent and child nodes is huge and could lead to a cumbersome problem that requires significant time and high computational effort.

Another risk assessment model was developed by Hintz et al. (2007), where different factors such as pipe depth, closeness to environmentally vulnerable areas, flow rate and likelihood of failure, were assessed on a 1 to 3 criticality scale, where 1 is the minimum and 3 is the maximum. This research provided a simple assessment tool, however it was subjective and didn't consider other important factors such as age, diameter, length, and soil conditions surrounding the pipelines. In a similar study, but with a wider range of 1 to 5 instead of 1 to 3, Halfawy et al. (2008) used that scale to describe the consequences of failure, where additional factors such as sewer type, function, diameter, depth, soil type, seismic zones, land use, road category, traffic, proximity to critical assets, and overall socioeconomic impact were all also considered. A risk index was identified by multiplying the different values of impact for each of the aforementioned factors by their relative weights.

2.7.2. Risk Assessment Using Fuzzy Inference Systems

Fuzzy logic enables the user to employ qualitative variables in their planning through the incorporation of fuzzy sets. The idea of fuzzy sets was first introduced by Zadeh (1965) in order to express the ambiguity, uncertainty and so-called “fuzziness” in an elements membership to a particular set. Unlike the ordinary sets, element membership is more like binary logic (i.e. either belong to a set which is 1 or doesn’t belong to a set which is 0). The concept of fuzzy sets introduced by Zadeh (1965) allows the membership values of an element to vary between 0 and 1, thus giving a more accurate representation of an elements membership—especially when the boundaries of the set can’t be determined in terms of crisp values. Support of a membership function are usually the range of values over which the membership function of a fuzzy set is defined (Ross, 2010). This support of membership function is divided into regions which are the core with a membership value equal to 1 and the boundaries where the membership function varies between 0 and 1 (Ross, 2010).

To incorporate the knowledge of the user and to establish the link between the input variables and outputs, fuzzy inference systems are used by employing an “if-then” framework. Fuzzy rules combine the antecedents and consequents to determine the output. In case of multiple variables “AND” or “OR” operators are used to combine the antecedents and consequent (Ross, 2010). Using “AND” operator results in the intersection of the rule outputs, whereas using “OR” operator results in the union of the rule outputs. Fuzzy rules are processed by using either Mamdani inference method (Mamdani and Assilian, 1975) or Sugeno (Takagi and Sugeno, 1985) method. The former method is the most widely used inference method where the consequent is modeled as a fuzzy function (Ross, 2010) while in the latter; the consequent is modeled as a crisp function of the input variables (Ross, 2010). It has been reported that Sugeno inference method performs better with different optimization techniques and can be integrated with genetic algorithm or any other optimization technique which is considered an advantage when compared to Mamdani FIS (Kaur and Kaur, 2012).

Fuzzy rules normally take the form "$if\ x\ is\ X_i\ then\ y = f_i(x)$" in which "$x\ is\ X_i$" is the antecedent and "$y = f_i(x)$" is the consequent (Ross, 2010). In case of multiple inputs "AND" and "OR" operators are used to connect the antecedents. In Sugeno fuzzy inference method, each fuzzy rule is used to determine the area under the corresponding consequent fuzzy set. The resultant output for each fuzzy rule is combined to determine a crisp output by using weighted average method as shown in Equation 2.4.

$$y(x) = \frac{\sum_{i=1}^{n} \mu_{X_i}(x) f_i(x)}{\sum_{i=1}^{n} \mu_{X_i}(x)} \tag{2.4}$$

Where $y(x)$: Consequent,

$\mu_{X_i}(x)$: Membership function value for variable (x),

$f_i(x)$: Corresponding value of the membership function (singleton) and

n: is the number of fuzzy rules.

As previously discussed, risk is the integration of probability of failure and the consequences of that failure. The failure represents the failure to meet the designed level of service which can be calculated using system models or analytical techniques. As for the consequences of failure it represents the socioeconomic losses and environmental impact due to that failure. When representing the likelihood and consequences of failure on ordinal scale and risk of failure consequently, there is no definitive or one way to select their levels. Based on psychologists' experiments, the pieces of information handled should be in order of 7 plus or minus 2. As such, and as recommended by Karwowski and Mital (1986), the number of categories shouldn't be more than seven.

The IPCC (2012) uses a seven level to assess the likelihood as shown in Table 2.5. Also, selecting a particular shape of a membership function depends mainly on the information that is required to be represented and how certain the user is. Several methods are used to select the appropriate shape for membership functions; however, in engineering applications the shape of membership functions has little influence on the results (Klir and Yuan, 1995). Membership functions could be triangular, trapezoidal, Gaussian and others; Triangular Fuzzy Numbers (TFNs) are usually used because of their suitability and simplicity in engineering applications (Lee, 1996).

Table 2.5: Risk Level as per IPCC (2012)

Risk Level	Description	Probability
1	Virtually certain	99-100%
2	Very likely	90-100%
3	Likely	66-100%
4	About as likely	33-66%
5	Unlikely	10-33%
6	Very unlikely	0-10%
7	Exceptionally unlikely	0–1%

Figure 2.5 shows the triangular fuzzy membership functions for the likelihood, consequences and risk of failure and the corresponding membership value (α).

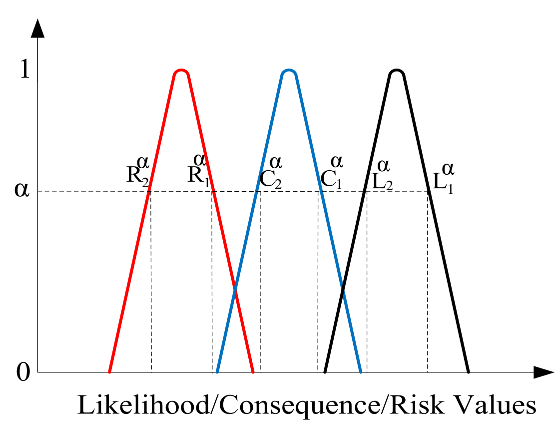


Figure 2.5: Fuzzy Membership Functions for Likelihood, Consequences and Risk of Failure

Since the membership function shape is triangular, the likelihood $\tilde{l}(x)$and consequences of failure $\tilde{C}(x)$for any value x can be denoted by:

$$\tilde{l}(x) = \begin{cases} \frac{x-a_1}{b_1-a_1}, a_1 < x < b_1 \\ \frac{c_1-x}{b_1-a_1}, b_1 < x < c_1 \\ 0, \text{otherwise} \end{cases} \tag{2.5}$$

$$\tilde{C}(x) = \begin{cases} \frac{x-a_2}{b_2-a_2}, a_2 < x < b_2 \\ \frac{c_2-x}{b_2-a_2}, b_2 < x < c_2 \\ 0, \text{otherwise} \end{cases} \tag{2.6}$$

$$\alpha = \mu_L(x) = \frac{L_1^\alpha - a_1}{b_1-a_1} \; and \; \frac{c_1 - L_2^\alpha}{b_1-a_1} \tag{2.7}$$

$$\alpha = \mu_C(x) = \frac{C_1^\alpha - a_2}{b_2-a_2} \; and \; \frac{c_2 - C_2^\alpha}{b_2-a_2} \tag{2.8}$$

Therefore

$$L_1^\alpha = (b_1 - a_1)\alpha + a_1 \tag{2.9}$$

$$L_2^\alpha = c_1 - (c_1 - b_1)\alpha \tag{2.10}$$

$$C_1^\alpha = (b_2 - a_2)\alpha + a_2 \tag{2.11}$$

$$C_2^\alpha = c_2 - (c_2 - b_2)\alpha \tag{2.12}$$

And since risk is the product of likelihood and consequences, then:

$$R_1^\alpha = L_1^\alpha * C_1^\alpha = (b_1 - a_1)(b_2 - a_2)\alpha^2 + [(b_1 - a_1)a_2 + (b_2 - a_2)a_1]\alpha + a_1 a_2 \tag{2.13}$$

$$R_2^\alpha = L_2^\alpha * C_2^\alpha = (c_1 - b_1)(c_2 - b_2)\alpha^2 + [(c_1 - b_1)c_2 + (c_2 - b_2)c_1]\alpha + c_1 c_2 \tag{2.14}$$

To determine the value of membership function corresponding to (x), Equations 2.13 and 2.14 are solved as a quadratic equation with the roots the value of (α) as per Equation 2.15.

$\alpha = \mu_R(x)$

$$= \frac{-[(b_1 - a_1)a_2 + (b_2 - a_2)a_1] \pm \sqrt{[(b_1 - a_1)a_2 + (b_2 - a_2)a_1]^2 - 4[(b_1 - a_1)(b_2 - a_2)][a_1a_2]}}{2(b_1 - a_1)(b_2 - a_2)}$$

$, a_1a_2 < x < b_1b_2$

$$= \frac{[(c_1 - b_1)c_2 + (c_2 - b_2)c_1] \pm \sqrt{[(c_1 - b_1)c_2 + (c_2 - b_2)c_1]^2 - 4[(c_1 - b_1)(c_2 - b_2)][c_1c_2]}}{2(c_1 - b_1)(c_2 - b_2)}$$

$, b_1b_2 < x < c_1c_2$

= 0, otherwise (2.15)

Salman and Salem (2012) developed a risk assessment tool to determine criticality of sewer pipelines using fuzzy inference systems. To determine the consequences of failure, a weighted scoring method was used after identifying important factors, their relative importance and summarizing the overall performance of sewer pipes in terms of these factors based on collected historical data. Three different logistic regression techniques were used to develop a deterioration model for sewer pipes that identifies the likelihood of failure. Binary logistic regression was found to be the most suitable technique. Risk values resulting from combining the consequences and likelihood of failure values using simple multiplication, risk matrices, and fuzzy inference systems were compared, and a risk map was created to help in identifying sewer pipe sections that require immediate action.

Mamdani Fuzzy inference system was used to determine the risk of failure values based on probability and consequences of failure enabling users to use “what-if” scenarios. This research provided a useful comparison between different available techniques to determine the risk of failure; however, the risk assessment performed was only based on the structural condition of pipelines without considering the operational conditions. Multinomial logistic regression was used to develop a model for forecasting the need for rehabilitation of sewage networks over a specific planning horizon of years in terms of monetary amounts (El-Assaly et al. 2006). The cost in this model was estimated as the product of the predicted defected pipe and the cost of the repair method for the same pipe. Different pipes were arranged in an ascending order to determine the ones with the highest cost, and which would need to be rehabilitated.

Fuzzy inference systems were used by Kleiner et al. (2005) in order to model the failure risk of water mains. In this research, deterioration of water main pipes was modeled using rule based fuzzy Markov procedures, which assumed that the consequences of failure value was known by the model developer. In this particular study, the deterioration of a certain pipe was modeled on results of only two inspection points and a rule based database. The probability values obtained from this procedure were combined with the consequences value—which was assumed to be known by using fuzzy rule based method. The same procedure was applied to sewerage infrastructure as well (Kleiner et al. 2007). While the use of fuzzy rule based Markov deterioration modeling is applicable to water mains due to scarce data on water main failures, data related to sewer inspections is more readily available due to the ease associated with CCTV inspections compared to inspection of pressurized water mains.

Fares and Zayed (2010) used a Hierarchical Fuzzy Expert System in which likelihood of failure was modeled under three categories, namely, "environmental", "physical", and "operational" and consequences of failure was modeled under the category of "post failure." A hierarchical structure was selected in order to reduce the number of rules to be evaluated by the system. Also, Kleiner et al. (2004) applied fuzzy sets (Zadeh, 1965) to combine the consequences and possibility of failures to determine the risk of failure by using a fuzzy-rule based system. By using fuzzy rules, the expert opinion regarding important factors that affect the likelihood and consequences of failure of water mains was incorporated into a fuzzy risk assessment procedure. The main advantage of using

Fuzzy inference system in determining the risk of failure in pipelines is its ability to handle problems with a combination of numeric and linguistic variables, resulting in availability of system knowledge in the problem. In addition, fuzzy inference system provides an easily understood and robust algorithm when dealing with vague or little data.

2.8. Likelihood of Failure

Deterioration models are built by incorporating data available in databases and records in municipalities to model the behavior of sewer pipes over time. Deterioration Models can be either physical or mathematical and they can be deterministic or stochastic. Physical models are usually deterministic because they are based on the physical properties and the mechanics of a certain phenomenon. The deterministic models yield in a single value for condition ratings as an output. Ordinary least squares regression analysis is considered a common example of mathematical deterministic models. The stochastic models provide the user with information regarding the probability of failure of the asset, and the time at which the asset would fail. One of the most common examples of stochastic models is the Markov chains.

Most of the research addressing sewer pipeline condition assessment models presents the mathematical models developed for this purpose, while very few discuss the physical models. The mathematical models determine the relationship between certain factors, such as: pipe age, length, diameter, material, slope, bedding condition, soil type, traffic above the pipes, etc and the expected condition rating—or the time at which the pipe would reach a certain condition rating. Table 2.5 shows the different deterioration models developed for sewer pipelines with the advantages and limitations for each technique used.

2.8.1. Multinomial Logistic Regression

Multinomial logistic regression can be used when dependent variables are categorical and have two or more categorical levels. Assuming that, the dependent variables are divided into (*k*) categories, from which a reference category is chosen, so a generation of (*k*) logits from the remaining (*k – 1*) categories can be determined as per Equation 2.16.

$$ln\frac{P(Y=i|x_1 \ldots\ldots x_p)}{P(Y=k|x_1 \ldots\ldots x_p)} = \beta_0 + \beta_{i1}x_1 + \beta_{i2}x_2 + \cdots . + \beta_{ip}x_p \tag{2.16}$$

Where i = 1, 2, …, k – 1 correspond to categories of the dependent variable,

x_s: are independent variables,

β_0 : is the intercept for category i,

β_{is} : are the regression coefficients of independent variables defined for each category (i).

α and β values for each (*k –1*) logit equation and can be estimated by multinomial logistic regression (Agresti ,2002). Therefore, for a dependent variable with (*k*) levels and a total number of (*p*) independent variables, the multinomial logistic regression models estimate (*k –1*) intercepts, and *p*(k – 1*) regression coefficients. Calculation of probabilities associated with each category of the dependent variable is shown in Equations 2.17 and 2.18.

$$P(Y = i|x_1 \ldots \ldots x_p) = \pi_i(x) = \frac{\exp(\beta_0+\beta_{i1}x_1+ \beta_{i2}x_2+\cdots.+\beta_{ip}x_p)}{[1+\sum_{i=1}^{k-1}(\beta_0+\beta_{i1}x_1+ \beta_{i2}x_2+\cdots.+\beta_{ip}x_p)]} \quad for\ i = 1,2, \ldots k-1 \tag{2.17}$$

$$P(Y = k) = \pi_k(x) = \frac{1}{[1+\sum_{i=1}^{k-1}(\beta_0+\beta_{i1}x_1+ \beta_{i2}x_2+\cdots.+\beta_{ip}x_p)]} \quad for\ i = k \tag{2.18}$$

2.9. Consequences of Failure

Sewage networks help to minimize contact between citizens and wastewater, thereby strengthening public health while reducing the likelihood of disease. When these systems fail, society suffers. A failure as defined by the French AFNOR standard on maintenance terminology NFEN 13306 is: "*a defect or a performance deficiency, defined in reference to a required level of performance leading to termination of the ability of a pipe or of a network to perform in the required function*." There are subjectivity issues and other uncertainties associated with estimating environmental, social, and economic impacts when determining the consequences of sewer pipeline failures which present a challenging problem for academics and policy makers alike.

Although the direct economic impacts of sewer failure, such as replacement and repair costs, can be estimated from historical datasets; the variation in physical characteristics of different sites can affect the accuracy of these estimates. As for estimating the socioeconomic impacts of sewer failures, it can be more complicated due to the intangible nature of these factors and the wide variation between their presence and severity from one place to another.

2.9.1. Economics of failure

Often the pre-existing data from previous studies is both old and unique to the place studied—few sewer systems are exactly the same. To use data from these previous studies, it is important that they reflect accurately the costs at the time the study was conducted. The Gross Domestic Product (GDP) index assesses the value of a currency in the short term and takes into account the country's inflation, purchasing power changes, and other regional economic aspects. Critical infrastructure systems can play an important role within an economy because they help provide avenues for distribution as well as the basic framework for industrial production. Both direct and indirect costs for failure of these critical infrastructures can be reflected in the economy. Therefore, in an incident of critical infrastructure failure there would be an impact across different economic sectors.

There are several methods that measure the economics of infrastructure failure which is generally based on the measurement of change of individuals' well-being due to the failure. Whatever method is chosen, economic loss is the integrated difference of economic output in ordinary situations minus the economic output in the disaster scenario.

Table 2.6: Different Techniques Used in Developing Deterioration Models for Sewer Pipelines

Technique	Considered Factors	Advantages	Limitations
Multiple Regression (Chughtai and Zayed, 2008)	Age, diameter, material, depth, length, bedding factor and street type.	Multiple Linear regression is considered as a simple method and doesn't require large computational effort.	The model assumes a linear relationship between the factors forming the explanatory variables and condition rating which is considered a breach for the actual relationship.
Logistic Regression (Ariaratnam et al. 2001 and Salman and Salem 2012)	Age, diameter, material, effluent type, and depth.	The probability that a pipe is in a certain condition state can be obtained.	Usually this method is used to identify the probability in the form of fail- no fail which is somehow misleading.
Artificial Neural Networks (Najafi and Kulandaivel, 2005)	Age, length, material, depth, slope, and effluent type.	Can model complex relationships without knowing beforehand the relationship exactly.	Extensive dataset is required to train the data and learn the different possible combinations.
Markov Chains and Nonlinear Optimization (Wirahadikusumah et al. 2001 and Sinha and McKim, 2007)	Material, ground water level, soil type, and depth	Probability of a pipe segment to be in a different condition state can be obtained and transition matrices can be generated based on experience of experts.	Deterioration rates are assumed time independent. In addition, datasets should be divided into cohorts (Pipes with the same characteristics) and a new Markov chain deterioration curve has to be generated for each cohort unless other complementary technique is used to estimate transition probability.
Semi-Markov chain (Kleiner, 2001)	Expert opinion, and age		
Fuzzy Rule-Based Markov Chains (Kleiner et al. 2004)	Age		
Markov-Chains – Metropolis-Hastings Algorithm (Micevski et al. 2002)	Diameter, material, Soil, and proximity to vital locations		

Table 2.6 (Cont'd): Different Techniques Used in Developing Deterioration Models for Sewer Pipelines

<table>
<tr><th>Technique</th><th>Considered Factors</th><th>Advantages</th><th>Limitations</th></tr>
<tr><td>Markov Chains and Ordered Probit (Baik et al. 2006)</td><td>Length, size, material type, age, and slope of the pipe</td><td rowspan="3">Probability of a pipe segment to be in a different condition state can be obtained and transition matrices can be generated based on experience of experts.

Pipe segments in each condition state percentages with respect to time can be obtained.</td><td rowspan="3">Deterioration rates are assumed time independent. In addition, datasets should be divided into cohorts (Pipes with the same characteristics) and a new Markov chain deterioration curve has to be generated for each cohort unless other complementary technique is used to estimate transition probability.</td></tr>
<tr><td>Markov Chains and Gompit (Le Gat, 2008)</td><td>Diameter category, sewer type, and installation period Category</td></tr>
<tr><td>Survival Functions(Baur and Herz ,2002)</td><td>Age, material, function of sewer, shape of profile, slope, and Street type</td></tr>
<tr><td>Rule-Based Simulation (Ruwanpura et al. 2004)</td><td>Age, material and length</td><td>Limited data can be used to determine condition ratings and confidence levels.</td><td>Data points with no information are assumed to have the same deterioration trend as the ones after or before.</td></tr>
</table>

Therefore, economic models take into account the complex relationship between different critical infrastructure systems as well as the complex relationship between infrastructure and the economy.

2.9.1.1. Cost Benefit Analysis (CBA)

An economic cost benefit analysis is crucially important for effective resource allocation to evaluate the economic costs of interventions and the resulting benefits especially when there are many criteria to determine where these resources need to be allocated. Although estimating the benefits of an improved health or wastewater network is impossible, there are factors that can be measured that would improve these services. Cost benefit analysis aims to better understand the social and economic wellbeing in a community after the restoration or upgrading of failed pipelines.

The procedures for a CBA usually comprise: determining costs and benefits, quantifying the non-market impact, and including indirect costs and calculation of economic performance indicators (i.e. Economic Net Present Value (ENPV), Internal Rate of Return (IRR), etc.) which is usually done by analyzing macro-economic and social conditions in a community. When applying CBA in sewer projects, the social benefits are evaluated by estimating the fulfilled demand for sewage and the investments pumped for that purpose. This is done by the evaluation of illnesses and deaths avoided as a result of an efficient drains service; and the value derived from preserving or improving the quality of the water bodies or the lands in which the wastewater discharges (Hutton and Haller, 2004). Equation 2.19 shows the(B/C) formula used in the cost benefit analysis.

$$B/C = \frac{\sum_{t=1}^{T} \frac{B_t}{(1+r)^t}}{\sum_{t=1}^{T} \frac{C_t}{(1+r)^t}} \tag{2.19}$$

Where T: is the total number of years of the study period

B_t: is the benefits per year (Values of harm avoided each year)

C_t: is the total costs paid

2.9.2. Costs of failure

There are two approaches that are used to determine the consequences of failure. The first one is by determining the cost of this failure in monetary value. These costs can further be divided into direct and indirect costs. The direct costs are costs necessary for reinstating the affected underground infrastructure. As for indirect costs, they are costs that don't necessarily appear on the invoices but are paid by society and people affected by the failure of sewers. Determination of indirect costs can be challenging due to its intangible nature, therefore alternative approaches are used to identify the consequences of failure values such as Multi-Criteria Decision Analysis, in which the impact of each pipe is ranked and compared relative to the rest of the pipes based on predetermined factors measuring the criticality of these pipe failures. One of the methods used in this approach is the weighted scoring systems (Salman and Salem, 2012).

Many studies have been conducted that help define those expenses that are not direct costs. These studies addressed the costs borne by the whole society (Allouche et al. 2000). Gilchrist and Allouche (2005) developed a matrix that distributes the various social costs into 4 major categories: traffic, economics, pollution and ecology. Other studies have also been conducted to identify the social costs in order to separate the restoration costs of the affected infrastructure such as Manuilova et al. (2009) and Rahman et al. (2005), where costs related to the rehabilitation of infrastructure damaged were categorized into 3 major categories, namely: direct costs, indirect costs, and immaterial costs. The following section describes the cost estimation for the different categories of infrastructure failure.

2.9.2.1. Loss of time as a result of traffic disruption

The loss of time as a result of traffic disruption can be calculated by computing the extra time needed to travel the same distance allowing quantification of costs of congestion as shown in Equation 2.20 (Rahman et al. 2005).

$$C_{TD=} \sum_{i=1}^{n} (N_v^i * \ o_v^i * r_p^i) * t * d \tag{2.20}$$

Where C_{TD}: Cost of time loss due to traffic diversion,

N_v^i: Number of vehicles of type (i),

o_v^i: Occupancy ratio of vehicle of type (i),

r_p^i: Hourly rate of passenger in vehicle of type (i),

t: Detour time (h),

d: Number of days (Days) and

(n) is the total number of vehicles of type (i).

2.9.2.2. Increased running costs for vehicles

Traffic congestion causes an increase in vehicle operating costs due to detours. Consumption of vehicles and their maintenance costs are proportional to the travel distance; therefore, an increase in the travel distance would result in an increase in vehicles' running costs (Rahman et al. 2005). Thus, it is possible depending on the speed and type of vehicle to establish an average maintenance cost per kilometer which can be considered an increased running cost for vehicles (Gourvil and Joubert , 2004) as shown in Equation 2.21.

$$C_{dis} = \sum_{i=1}^{n} c_v^i * \sum_{j=1}^{m} N_v^j * D \tag{2.21}$$

Where: C_{dis}: Additional cost due to additional distance,

c_v^i: Running cost per kilometer for vehicle of type (i) ($/km),

N_v^j: Number of vehicles of type (i) impacted per day (j) (Vehicles/day), n and m: Total number of vehicles of different types and the total number of days spent in restoration works, respectively and

D: Additional travelling distance.

2.9.2.3. Loss of parking spaces

It is important to account for reduced ground spaces and areas dedicated to car parking in case of a sewer pipelines' failure located underneath roads in highly populated areas (Boyce and Bried, 1994). Therefore, loss in parking spaces can be considered a loss of revenue which can be calculated as per the model of Pucker et al. (2006) shown in Equation 2.22.

$$C_{lp} = N_{na} * c_p * R_o * d * t \tag{2.22}$$

Where C_{lp}: Loss of parking spaces cost,

N_{na}: Number of non-accessible parking spaces,

c_p: Hourly cost of parking ($/h),

R_o :Rate of occupancy (%),

d: Re-construction period (day) and

t : Number of operating hours per day (h/day).

2.9.2.4. Reduced productivity as a result of vibration and noise

Employees' productivity is affected by noises and vibrations resulting from activities during restoration work on failed sewer pipelines. Gilchrist and Allouche (2005), developed a model to estimate the cost of decreased productivity resulting from noise in work places per Equation 2.23 (Gilchrist and Allouche, 2005).

$$C_{nw} = d * \sum_{i=1}^{n} (F * r_h * N)_i \tag{2.23}$$

Where C_{nw}: Cost of noise pollution and vibrations in the workplace,

d: Duration of the project (hours),

F: Reduction factor for worker (i) where the reduction percentage could be taken: 10%, 20%, 40%, 65%, 90%, and 100% for a unit increase of 10 dB with an initial noise level (normal noise levels) of 60 dB (Gilchrist and Allouche, 2005) and,

r_h: Average hourly rate of worker (i) ($/h).

To determine the consequences of failure and as a part of the Computer Aided Rehabilitation of Sewer and Storm Water Networks (CARE-S) project in Europe, a study was carried out to investigate the social and economic costs of sewer failures (Torterotot et al. 2006). The factors that were included in this study were the damages as a result of floods, the overflow due to blockages, and service and traffic disruption. As for the environmental impacts of failures, they were surface and ground water degradation and annoyances due to odor and the presence of insects and rodents as a result of sewage overflow. Interactive elimination procedure was used to balance the impact of the previously mentioned factors, however the criteria adopted in the elimination procedure wasn't clear enough.

Another approach to determine the consequences of failure in sewer pipelines, was adopted by authorities in Seattle, where a risk assessment tool was developed that determines the consequences of failure in monetary amounts. The costs for replacement and repair were used in calculating the monetary amounts by multiplying these costs by adjustment factors based on sewer pipelines attributes (Martin et al. 2007). The likelihood of failure in this research was determined using Weibull distribution plotted from analyzing historical data and inventory of inspection datasets. The likelihood and consequences of failures were multiplied to calculate the risk of failure in monetary amounts. Pipelines were divided into cohorts based on pipe materials due to the fact that Weibull analysis is a network analysis tool, which resulted in grouping the pipes by deterioration pattern which may not be considered an accurate approach. In addition, calculating the consequences of failure in monetary amounts with the intangible nature for those factors may not provide accurate estimations due to high uncertainties and difference in the method of calculating them from one place to another.

2.9.3. Consequences of failure using performance values

In this approach, determining the consequences of failure values is considered a multi-criteria decision making problem, where different pipes are considered as alternatives and the different factors' weights, each with different degrees of importance, are considered as the criteria. The weight scoring method is usually used in this approach to determine the consequences of failure. The decision makers assign performance values to different alternatives. The summation of the product of each criterion weight, and the performance value of each alternative, yields the total performance value of this pipe. The different factors are identified and ranked based on decision makers' preference and perspective on the relative importance of these factors and their impact on the social, economic and environmental levels. Salman and Salem (2012) employed the above mentioned approach in determining the consequences of failure values by using a previously developed methodology by the Cincinnati Municipality in which 15 performance values were studied and relative weights were given based on their importance to determine the overall performance value for each pipe.

The different factors that were considered in both studies to determine the consequences of failure values were: the type of roadway above the sewer pipe, the location of sewer pipes relative to railroad tracks, the location of the sewer pipe relative to the combined sewer overflow, the distance of the sewer pipe from the nearest building, depth cover, the number of building lateral connections, the location relative to business district areas, the location relative to recreational area, distance from rivers and streams, the diameter of pipes, the location relative to the pavement right of way, the landslide potential of the area, the building type, the wet weather flooding capacity, and the number of complaints received concerning a particular section. The weight for different factors varied between 0 and 10 while performance values varied between 0 and 100.

In a similar study, different criteria were set to determine the performance value from which consequences of failure values were calculated (Ana, 2009). The criteria were grouped based on criteria relevant to: structural, hydraulics, environmental, coordination and financial concerns. Each of these criteria was sub-grouped into sub-criteria with different performance values based on the decision makers' preference and perspectives. Oreste Multi Criteria decision making algorithm was used to determine the performance values for each alternative (pipes and project). The performance values for each criterion were between 1 and 5 and investments (financial) were determined by rate of money spent divided by the length of sewers. Although the multi criteria decision making algorithms used to determine the total performance values of each pipe overcomes the subjectivity accompanying these problems, uncertainties remain a challenge due to the weights and performance values differing from one person to another and from one place to another.

2.10. Inspection Scheduling

Asset management is concerned with the maintenance and operation of assets, the analysis of which allows for informed decisions regarding asset renewal or rehabilitation. Figure 2.6 shows the different components of asset management in which inspection planning plays an important role. Inspection is a repetitive, resource intensive, process that is performed over the life time of the asset (Hegazy et al. 2012). The aim of an efficient inspection plan is to prioritize inspection of components within the confines of narrow budget constraints. Inspection planning is an important aspect of keeping assets in good working condition without the need for costly renewal and replacement actions.

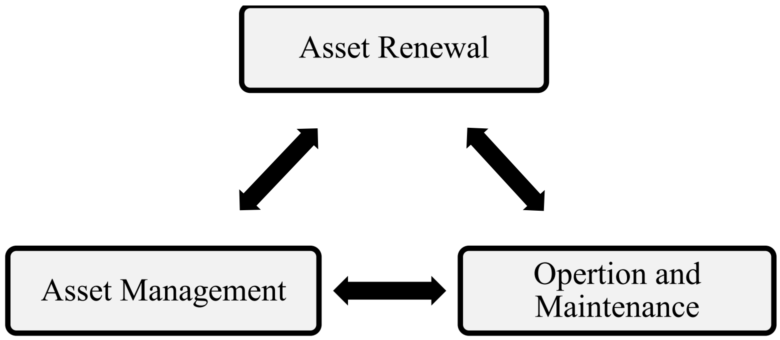


Figure 2.6: Asset Management components

As the asset becomes older, interventions—either proactive or reactive—become necessary within shorter time durations. As such, inspection planning identifies critical assets prioritizing their inspections. In addition, inspection planning helps decision makers make informed decisions regarding the action plans. This allows them to determine the most advantageous interval between inspections. Efficient inspection planning helps in determining the critical components to be inspected and the times for inspecting them, this results in an efficient inspection procedure that can be employed even within the constraints of a limited municipal budget.

The previously discussed methodologies and approaches tackle the topic of inspection from a risk indexing point of view without studying the critical step of determining the inspection intervals. In the following section, methodologies addressing inspection scheduling in terms of inspection intervals are discussed. These methodologies can be divided into those using statistical models while considering time and/or cost, and optimization models that employ either evolutionary optimization techniques or mathematical models to determine optimal inspection intervals.

Analysis of Variance (ANOVA) is a statistical technique that can be used to measure the performance of a network component using certain parameters that could affect aging. This technique was used to link the relationship between the parameters of Pressure Safety Valves

(PSV) in pressurized networks affecting the performance of the valves and aging (Chi-Hui et al. 2009). The authors developed a semi-quantitative risk-based inspection strategy using the data for failure available in historical records. Inspection interval, based on the risk was estimated using the developed strategy, and the outcomes were compared with the inspection intervals that were specified in the standards and regulations to validate the developed strategy.

A deterioration model was developed for large diameter sewers with diameters greater than 0.9 meters by McDonald and Zhao (2001). This model used six pipeline characteristics where the impact of each factor was evaluated to be low, medium and high. The first factor—location—was identified based on the land use, traffic and how easy the pipe can be repaired in terms of accessibility and the adverse effect of the pipe failure on the environment. The second factor—soil type—was evaluated based on its plasticity. Soils with low plasticity were assigned high impact values and vice versa. Pipe depth was the third factor, where pipes with greater buried depth were assigned high impact factors. As for the pipe sizes, as they increased, they were assigned high impact factors. The fifth factor included in the model was the pipe functionality, which included sub-factors like whether the pipe is for sewage, storm runoff, or both, and also whether the pipe was close to the treatment plant or was only a collector pipe. Seismic zones were also used as an assessment factor, where pipes located at areas of high seismic activities were assigned high impact factors. A weighted scoring method was used to combine the condition impact rating to identify the inspection priority and frequency.

Kliener (2001) used a Semi-Markov Chain to model the deterioration of large buried pipes from which decisions regarding inspection or renewal can be made. In this model, the transition probabilities were derived using the Semi-Markov Chain and a Weibull distribution. Weibull distribution was used to determine the distribution of waiting time, where expert’s opinions were used to determine the Weibull distribution's parameters. The sum of waiting time in different states of the asset, which represented the cumulative probability function, was calculated using a Monte-Carlo simulation.

Monte-Carlo Simulation (MCS) is usually applied to study the stochastic processes, in which the inputs are of a probabilistic nature. MCS can be a useful tool when the input for the process is accompanied by uncertainty due to different distributions (Hartford and Baecher, 2004). Monte Carlo simulation procedure involves two operations which are: "sampling" and "running iterations" (Salem et al. 2003). A large number of sets of randomly generated values for uncertain parameters are created, from which a random sample is taken. In the sampling operation, the input parameters values are obtained randomly based on the probabilistic distributions. In the running iterations, results from the model are calculated based on the input parameters and Cumulative Distribution Function (CDF) is computed based on this random sampling.

The simulation models allow the user to derive probability distributions associated with the outcome events based on the uncertainty involved in the input variables. Based on the overall number of iterations, one sample is drawn from each input probability distribution, the probability distribution sampled values will distribute in a way that would approximate the input probability distribution. When the last iteration is reached, the single-valued output results are aggregated to produce one output distribution. This operation is done several times based on the number of iterations from which an observation is being extracted. Figure 2.7 shows the random sampling operation in MCS, from which a user can determine the biasness and uncertainties, resulting in eliminating the uncertainties.

To determine the optimal time of intervention, different costs were considered along with the different probabilities of the deterioration model. The costs included the failure costs, the inspection and condition assessment costs, cost of intervention (i.e. replacement or rehabilitation) and adjustment factors for these costs to account for the time value of money.

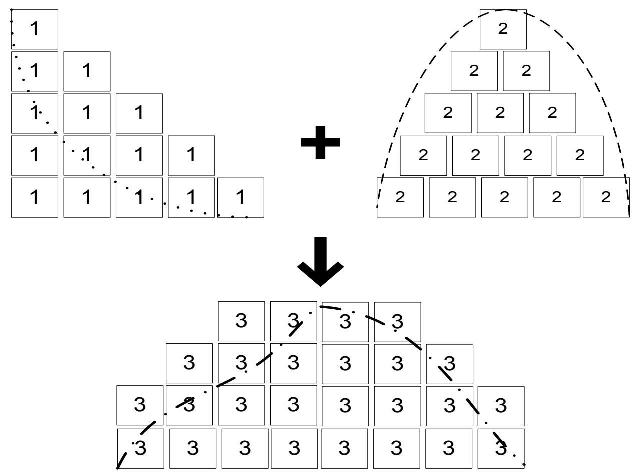


Figure 2.7: Random Sampling in Monte-Carlo Simulation

By determining the different costs over different stages of the asset life cycle, the optimal time corresponding to the minimum cost was specified representing the time at which intervention shall be feasible for inspection to be performed. In the Semi-Markov Chain, the lack of data problem required for determining transition probability can be solved by using the expert's opinions. However, in order to determine the distribution of waiting time in the developed models, an adequate dataset is required for the condition of pipes and history of inspections which might be challenging due to lack of data in some municipalities.

Survival Functions were used in the analysis of an existing sewage network in Germany to assess the condition of said network (Baur and Herz, 2002). Pipes' material, age, location, and type of waste carried were all factors used to predict the probable date of the pipes entering a critical condition class. Historical data was used to build a pattern to indicate when pipes would transfer from a certain condition class to a lower one. Weighted least squares method was used to estimate the parameters of transition functions. By using the transition curves, the number of years that would take the pipes with certain characteristics to transfer from a certain condition state to another, was calculated from which subsequent inspection dates were determined. The number of years were calculated using the median transition age under each condition state in predefined five condition states, namely cc1, cc2, cc3, cc4, and cc5.

The inspection dates were determined by setting a threshold condition state in which the pipes would be considered in a good state, and then adding the median transition age to the construction year of these pipes. In this study, the authors addressed a limited number of factors to build the model which needed extensive historical data for the same cohorts of pipes over a period of time. Although this was one of the very first attempts to address the scheduling of inspection dates in sewer pipelines, inspection dates were somewhat conservative and were based on single pipe characteristics, which could have been combined with more characteristics to result in more accurate or less conservative inspection dates.

One of the major limitations of modeling sewer pipes' deterioration using survival function is the need for an extensive dataset (Fenner, 2000). In addition, survival functions depend mainly on forming cohorts of sewer pipes with similar features or characteristics and in order to achieve that goal, sufficient data points and adequate information about the pipes' condition should be available to create the transition probabilities. Furthermore, the groups that form cohorts should be homogenous which is usually achieved by creating small groups, however these groups should also be large enough to be statistically significant–which could add to the challenges accompanying the use of such a technique (Kleiner et al. 2007).

2.11. Optimization Algorithms

In any optimization problem there is a goal. This goal is known as the objective function; and it can be either minimized or maximized, depending on the decision variables and other constraints. An optimization model can either by static, in which the decision variables remain unchanged during the optimization process, or dynamic, in which the decision variables can change during the optimization process. Linearity and nonlinearity of the optimization model is defined based on the formulated equation for the objective functions and constraints. If the optimization problem is linear, linear programming algorithm is used to solve the problem, while if the problem is nonlinear, nonlinear programming algorithm is used to solve the problem. If all decision variables are integers, the problem is called an integer programming problem. Otherwise, the problem is called a mixed integer programming problem.

Combinatorial optimization problem is one of the most difficult optimization problems, because it involves different discrete alternatives, in which the problem variables seek combinations of these alternatives until an optimum combination is achieved. Consequently, as the problem size increases the complexity of the problem increases (Csiszar, 2007 and Elhakeem and Hegazy, 2010). One of the most powerful tools that have been proved suitable for combinatorial problems is Evolutionary Algorithms (EAs) (El Elbeltagi et al. 2005). Performance of the optimization process is highly affected by how well the problem is formulated and the way the objective function, decision variables and constraints intertwine—especially in large scale problems. Mathematical tools have not been considered suitable for large scale problems, however, with the advancement in computer science and the introduction of advanced helping techniques, mathematical optimization's relative capability has increased such as to become suitable for these types of problems (Winston and Venkataramanan, 2003).

As previously discussed, most municipalities suffer from limited funds allocated for infrastructures operation and maintenance which make it necessary for them to come up with prioritization tools. These prioritization tools could help with better decision making regarding which pipelines to inspect, and from which a decision can be made as to which intervention measures are appropriate and when they should be carried out. Optimization algorithms are usually used to search for the optimal combination of components in the presence of certain predefined constraints. Selecting a certain optimization algorithm depends primarily on the shape of the objective function along with the constraints in addition to the type and number of decision variables. The most widely used optimization algorithm used in infrastructures optimization problems are described below as per Nunoo (2001).

2.11.1. Linear Programming

As the name implies, in these algorithms the objective function and constraints are in a form of linear equations. Although this algorithm is considered simple and easy to use, it can't handle a large number of decision variables and combinatorial problems (i.e. integer and non-integer variables). If variables in the objective function have a linear relationship, then this problem is called a linear problem. Integer Linear Problem (ILP) is a special type of linear problem that has integer variables. ILP are solved using integer programming in which the solution for the decision variables is binary (i.e. 0 or 1). If some of the variables are required to be integers, then this problem is called mixed integer programming.

2.11.2. Non Linear Programming

Unlike the linear programming, these algorithms have an objective function in a nonlinear form. Although this algorithm can overcome some of the limitations in the previous one, it remains unable to deal with combinatorial problems.

2.11.3. Integer Programming

In these algorithms, a mix between the linear and nonlinear objective function is formed. The decision variables in this algorithm is similar to a binary code formed with zeros and ones. Similar to the previously mentioned two algorithms, integer programming algorithm can’t handle combinatorial problems and a large number of variables.

2.11.4. Heuristic Optimization

This algorithm can be used instead of integer programming when there is a large number of variables. However, there is an approximation in the process of searching for the optimal solution leading to an approximate solution. One of the most widely used algorithms in asset management area is Genetic Algorithms (GAs). In GAs, the search for an optimal solution follows the behavior of genetics in human beings. The search in GA starts in a randomly generated population representing the solution space. In each iteration, a generation is selected from the population which represents the best fit and then this population is randomly mutated to form a better population. This algorithm can handle combinatorial problems with a large number of decision variables, however sometimes there is a sacrifice in the process of searching for an optimal solution leading to an approximate one.

2.11.5. Dynamic Programming

In case of required sequential decisions, dynamic programming is used. Although this algorithm doesn’t follow a predefined mathematical formulation it can provide the user with an optimal combination for decision variables in a sequence. The major advantage to this method over the other methods is that it avoids the exhaustive search for optimal combinations.

2.11.6. General Algebraic Modeling System (GAMS)

GAMS has the ability to solve constrained mixed integer programming problems (MIP) which are usually asset related. In these problems, linear programming (LP) sub-problems are generated and relaxed using a branch and bound method (Winston and Venkataramanan, 2003), in which the problem is branched based on the decision variables and bounded by the results, until a global optimum is reached (Winston and Venkataramanan, 2003). In addition, dynamic heuristic search is used to generate solution fasters than conventional methods. One of the main limitations in solving the IP mathematical problems is the inability to converge on a global optimum—especially in large scale problems—and to overcome such limitation GAMS-IP solvers, use a 'relative termination tolerance' which reports an optimum solution within a specific range from the estimated best solution, thus finding a near-optimum solution much faster (Winston and Venkataramanan, 2003).

Table 2.7 shows a comparison from literature for the different optimization approaches employed in the asset management topics. As shown, GAMS with CPLEX solver provides a fast and flexible solution for large scale optimization problems. This could be attributed to the fact that the solution space on the network level is vast which would highly affect the solution accuracy if some conventional techniques such as Genetic Algorithm (GA) were used for which the performance is affected by different aspects such as the size of the problem, the formulation of the problem, and the initial population (Csiszar, 2007).

Table 2.7: Comparison between Optimization Approaches as per Hegazy and Rashedi (2013)

Technique	**Limitations**
Exhaustive Search	Poor Solution Quality
GA (Hegazy and ElHakeem, 2011)	Limited to 800 assets
GA + Segmentation (Hegazy and Rashedi, 2013)	Applicable to large-scale, long processing time and suitable for nonlinear problems
GAMS/CPLEX (Rashedi and Hegazy, 2014)	Applicable to large-scale, very fast and provides close to global optimum results
EBCA Heuristic (Saad, 2014)	Applicable to large-scale, high quality solutions and provides economic justifications

Different optimization methods were used in different areas of infrastructure management such as sewer networks, bridges management, and portfolio management (Halfway 2008, Hegazy et al. 2004, Tong et al. 2001, Osman et al. 2012, and Berardi et al. 2009). In addition, GA has been used in different areas of asset management and civil engineering, such as the site-layout optimization of facilities (Cheung et al. 2002, Li and Love, 2000, and Osman et al. 2003). When optimizing fund allocation decisions –and to ensure that the maximum return is achieved in case of limited funds—a cost benefit analysis was performed (Higgins and Harris, 2012, Polinder et al. 2011, Adey and Hajdin, 2011). Several cost benefit analysis approaches have been addressed in literature; to valuate decisions in terms of benefits gained (Higgins and Harris, 2012, Polinder et al. 2011, Moayyedi and Mason, 2004). Approaches such as: benefit maximization (Shohet and Perelstein, 2004), cost minimization (Olsen et al. 2007, Sarma and Adeli, 2000), benefit cost ratio (Adey and Hajdin, 2011, Vacheyroux and Corotis, 2013), cost-effectiveness (Irfan et al. 2009, Singh et al. 2007, Labi and Sinha, 2005), cost utility (Marinoni et al. 2011, Hajkowicz et al. 2008) and utility maximization (Karande et al. 2013, Gharaibeh et al. 2006) differ based on the objectives for evaluation of decision alternatives.

In these approaches, either the costs or benefits were considered as an objective without considering the other aspect (i.e. cost is only considered or benefits are only considered). Moreover, in the approaches that consider both aspects (i.e. costs and benefits), there was a need to combine monetary and nonmonetary benefits, which was considered a challenge. Although these approaches are useful in evaluating alternative decisions, very few (or nearly none) of them was developed for fund allocation, especially when inspection needs are large, the budget is limited, and strict operational constraints will be imposed over several years.

2.12. Sewer Pipelines Inspection Scheduling Using Optimization

Statistical models can be used to establish an optimum cost-based inspection plan and monitoring (Kim et al. 2013). The optimum inspection and maintenance alternatives and periods are obtained through formulating an optimization problem to maximize the expected service life and minimize the expected total life-cycle cost consisting of inspection and maintenance costs. Figure 2.8 shows the different approaches used to solve optimization problems to schedule inspection of assets.

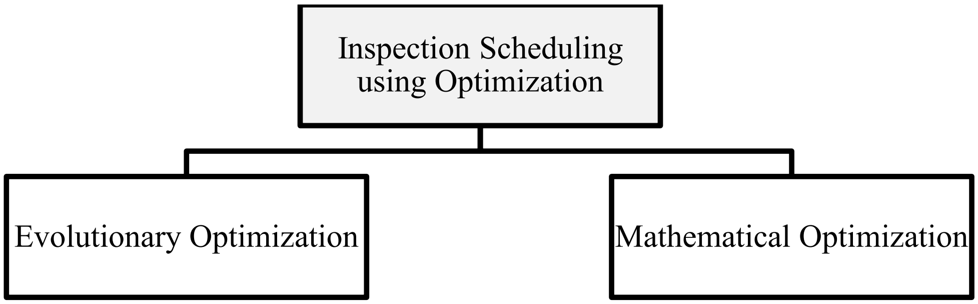


Figure 2.8: Approaches Adopted in Literature for Optimizing Inspection Scheduling

Plevris et al. (2010) presented a decision support system related to inspecting and repairing damaged infrastructures by unpredictable natural disasters such as earthquakes and flooding. Particle Swarm and Ant Colony Optimization based framework was presented to reach an optimal infrastructure condition assessment. Based on the condition of deteriorated infrastructures, the different inspection groups were assigned to elements that needed inspection. The other part of the formulated optimization problem was to select the optimal route for each group of workers to minimize the distance that each inspection group has to cover. Samrout et al. (2009) used ant colony system in optimizing the system component inspection period. The cost in the optimization problem was set equal to the sum of action costs applied during the preventative maintenance, as well as the costs caused by system unavailability.

Berardi et al. (2009) presented a model for selecting pipes to be inspected by formulating a multi-objective optimization problem to develop an inspection program by using Genetic Algorithms (GA) aiming to minimize the total cost of the inspection program and then the prioritization strategy based on repair costs resulting from emergency repairs due to blockages and collapses in sewer pipelines. GA was used to identify a set of Pareto-optimal inspection programs by proposing a prioritization process, based on the pipe rankings. The objective functions formulated represent the sum of the cost of inspection for all pipes in the inspection set using Closed Circuit Television (CCTV) inspection. The indirect costs as a result of sewer blockage and collapses were calculated to include types of buildings affected, pollution, and traffic disruption costs. Blockage and collapse models were developed to determine the optimal inspection scheme for which objective functions could be minimized over both the cost of inspection and the emergency repairs due to the blockages and collapses.

Emergency repairs were represented by the cost of Cured in Place Pipes (CIPP) rehabilitation technique per linear meter of pipe. To develop the blockage model; pipe blockage rate, diameter and length were the pipe characteristics considered in the model. As for the collapse model, the depth, and age were used in the development of that model. An optimum decision is made on whether to inspect the sewer pipelines which are more prone to collapses and/or blockages while taking into consideration the adverse economic effects of these pipe failures by minimizing the developed objective functions.

GA was used in another study for solving a multi-objective optimization problem for allocating budgets for condition assessment of water and sewer networks (Osman et al. 2012). The developed methodology employed partially observable Markov decision process and GA to determine the most appropriate condition assessment technology and interval between inspections from which the condition of the pipelines could be assessed. This methodology addressed the pipes on the individual level to determine the suitable condition assessment technology and inspection interval; in addition, it addressed the asset level by determining where to allocate the budget used in condition assessment. The objective function formulated in this research aimed to reduce costs spent as a result of imperfect inspections which could be translated into reducing the risk of failure of the pipeline. The formulated objective function was solved by employing GA, where a random time interval was generated at which the condition assessment technique and value of information were calculated. This step was performed several times from which the solution (i.e. time) with the highest fitness in the population was chosen representing the optimal inspection interval yielding minimum cost as a result of pipe failure and within the available budget allocated for inspection.

Hegazy et al. (2012) presented two techniques to support the inspection and fund-allocation decision for assets. The two techniques could be implemented, individually or combined, into any asset management system. The multiple optimization and segmentation technique formulated large scale optimization problems involving thousands of assets simultaneously, maximizing the return value of money invested. Ugarelli and Federico (2009) presented a cost-based model to schedule the replacement year of deteriorating assets which are subject to operational and maintenance cycles, such as buried pipes in urban water and wastewater systems. The developed model used risk cost as a framework to define the optimal replacement time prediction value, based on the balance between investment for replacing and expenditures for maintaining the asset. The model was based on a conceptual framework to estimate the costs arising from the operation, maintenance, and management of single pipes. The total cost function included all the annual costs involved to maintain the appropriate level of service.

Maji and Jha (2007) presented a mathematical model for condition assessment of elements in highways that can be used while considering budget constraints to determine the optimal maintenance schedule over a specified period of time using genetic algorithm. The rehabilitation costs, threshold values for deterioration, and budget, were used as input for this model. The output for the model was the optimum maintenance schedule of an element. In order to determine the optimum schedule for maintenance, total maintenance costs in the design period were optimized to minimum while taking into consideration the budget limitation in a given year.

Chung et al. (2006) presented an approach using statistical models for selecting the most suitable nondestructive inspection techniques and optimal schedule for inspection of fracture critical members on steel bridges. The probability of detection function was combined together with numerical Monte Carlo Simulation of the crack propagation of the fracture-critical detail. A cost function was formulated that included the expected cost of inspections and failure resulting from the chosen Non Destructive Inspection (NDI) technique and alternative inspection schedules. The formulated optimization problem aimed to select the NDI technique with associated inspection schedule for fracture-critical inspections to get a minimum total cost. The inspection frequency was determined as part of the optimization problem with constraints on inspection intervals and a minimum acceptable structural safety level.

The above studies addressed inspection intervals from a multi-objective optimization perspective with the intent of reducing the cost or maximizing the value of condition assessment achieved for the inspected assets. The common attribute between the formulated objective functions is the huge global search space which made choosing GA suitable for the nature of the problem. However, additional computational effort is required to ensure that convergence of population is achieved but without locating the global maximum in the process which is also known as "slow finishing" (Kapelan, 2002). The problem of difficulty in converging towards the Pareto optimal frontier is usually due to the absence in gradient in the fitness function which can be solved by considering additional objectives to increase the pressure of fitness function to push the population towards an optimal frontier.

In addition, there is usually a sacrifice in one or more objectives to achieve the rest of the objectives when moving from one Pareto solution to another, and to overcome this, the Pareto optimal sets can be increased with the increase of number of objectives (Deb 2001). Therefore, GA might seem an appropriate technique to be used in multi-objective optimization problems, but care should be given because of the computational effort and the sacrifice required when determining the solution for different objectives especially in large scale problems. As such other techniques that outperform GA, such as other evolutionary algorithms like Particle Swarm Optimization (PSO) and more advanced approaches like the general algebraic modeling systems, can be used to solve similar optimization problems.

2.13. Findings of Literature Review

Previous research studies were reviewed to search for suitable inspection scheduling methodology for sewer pipelines. It was found that methodologies are divided into those that determine the order of inspection or the different pipelines to be included in the inspection. Several optimization algorithms were found in literature, the different evolutionary and mathematical optimization algorithms were discussed in this chapter. The reviewed literature covered the different deterioration models from which the likelihood of failure of sewer pipelines can be determined. The following are the basic findings of the literature review:

- Some of the previously developed methodologies focused mainly on studying the different risk factors and damage modes contributing to the likelihood of failure while ignoring the consequences of failure which is a key factor in risk analysis.
- There are statistical techniques used in predicting the risk of failure such as BBN that could accommodate the uncertainty in estimating certain outcomes when evidence is incomplete and could provide concrete understanding for the relationships influence on outcomes,

from which a user can understand the impact of various parameters on the output. However, the effort for deriving the interrelationships between parent and child nodes is huge and could lead to a cumbersome problem that requires high computational effort and time.

- The methodologies addressing the risk of failure for sewer pipelines adopted the relative weights of performance factors when dealing with the consequences of failure while using a multi-criteria decision analysis technique to eliminate subjectivity; however such approaches do not truly express the consequences of failure.
- A majority of the methodologies addressing the risk of failure in sewer pipelines were only based on the structural condition of pipelines without considering the operational conditions.
- Fuzzy inference system is capable of handling problems with combinations of numeric and linguistic variables, resulting in the availability of system knowledge in a problem. In addition, fuzzy inference system provides an understandable and robust algorithm when dealing with vague or little data.
- Using certain techniques such as the Semi-Markov Chain can be challenging when used in inspection planning, due to the problem of a lack of data required for determining transition probability, in which an adequate dataset is required for the condition of pipes and history of inspections.
- One of the major limitations of modeling sewer pipe deterioration using survival function is the need for an extensive dataset (Fenner, 2000). In addition, survival functions depend mainly on forming cohorts of sewer pipes with similar features or characteristics. In order to achieve that goal, sufficient data points and adequate information about the pipes' condition should be available to create the transition probabilities.

- In some cases, when using Genetic Algorithms (GAs), additional computational effort is required to ensure that convergence of population is achieved but without locating the global maximum in the process which is also known as “slow finishing” (Kapelan, 2002).
- In GAs, the problem of difficulty in converging towards the Pareto optimal frontier is usually due to the absence in gradient in the fitness function which can be solved by considering additional objectives to increase the pressure of fitness function to push the population towards an optimal frontier. However, there is usually a sacrifice in one or more of the objectives to achieve the rest of the objectives when moving from one Pareto solution to another, and to overcome this, the Pareto optimal sets can be increased with the increase of the number of objectives (Deb 2001).
- Very few, or nearly none, of the developed cost benefit analysis methods addressed fund allocation especially when inspection needs are severe under a limited budget and strict operational constraints over several years.
- In cost benefit analysis models, either the costs or benefits are considered as an objective without considering the other aspect. Moreover, in the approaches that consider both aspects, monetary and nonmonetary benefits need to be combined—which can be challenging.

Chapter 3: Research Methodology

3.1. Introduction

In this chapter the proposed research methodology is presented where the different developed models are highlighted and how the collected datasets are processed in each model. The methodology can be divided into three main parts in which the first part is a review of the previous work addressing inspection scheduling, deterioration, risk assessment and optimization models. The second part of the methodology is the collection of data where different types of data are used and the basis on which they are collected to develop the risk assessment and optimization models is described. The third and last part of the methodology is the development of models which includes the development of a deterioration model required for determining the likelihood of failure and then the cost benefit analysis model developed to determine the consequences of failure. In addition to the risk assessment model, the formulation of the optimization problem along with the different decision variables and constraints in the optimization model are also described.

3.2. Research Methodology

Figure 3.1 shows an overview for the proposed methodology adopted in this research. The methodology starts with a review for the state of art of inspection planning and scheduling for infrastructures and sewer pipelines. Different methodologies developed in these topics are investigated and the major limitations and areas for enhancements are then concluded. The methodological framework for this research comprises two parts. These are assessing the risk of failure for sewer pipelines and optimizing the pipeline inspection plan. The risk assessment is performed by combining both the likelihood and the consequences of failure. The likelihood is determined by employing the direct and indirect assessment methods for sewer pipelines. As for the consequences of failure, the costs resulting from sewer pipelines failure are identified and the benefits from avoiding these failures are analyzed. To combine both likelihood and consequences of failure, fuzzy inference system is used.

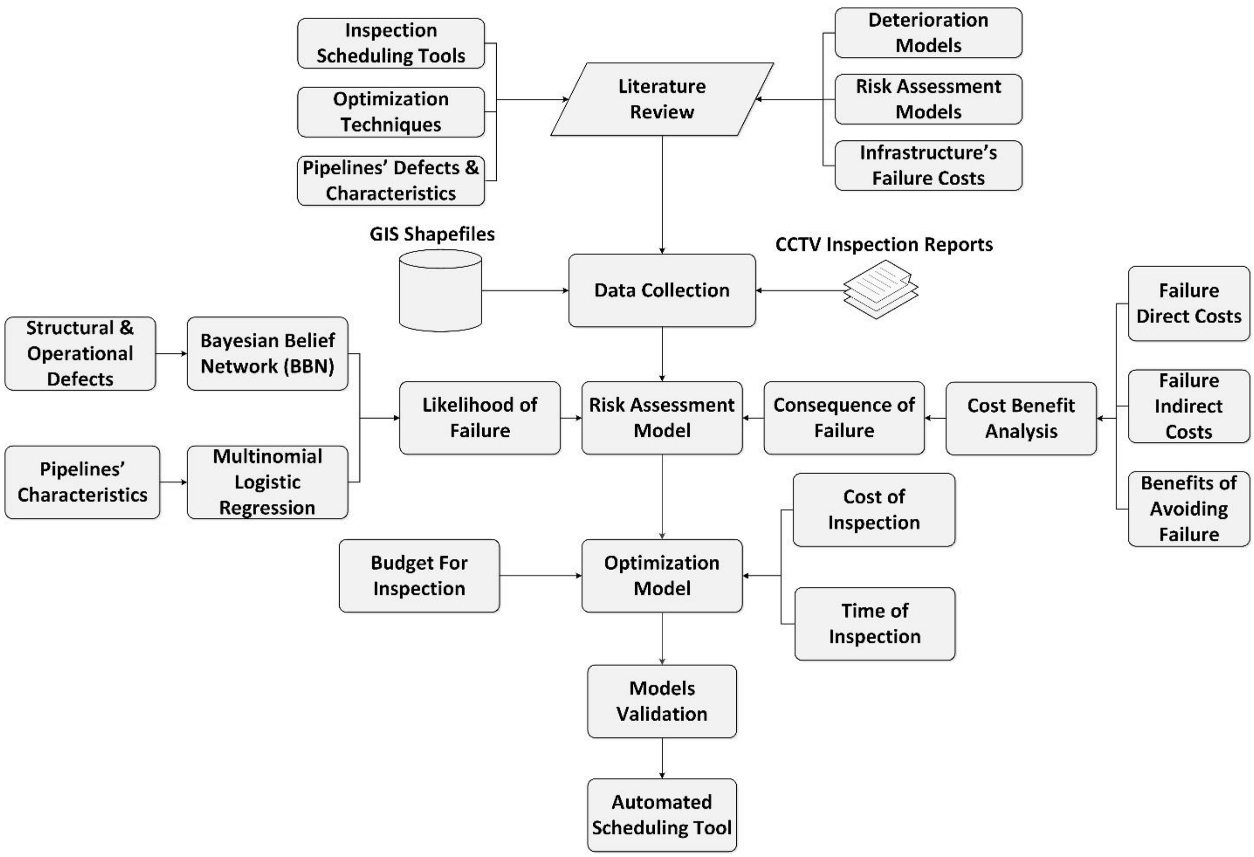


Figure 3.1: Research Methodology

The risk assessment model is used to determine the criticality of deteriorated pipe sections that require inspection to avoid failure, by creating a risk index for pipelines under study. The risk index helps in creating a priority list for deteriorated sections based on the probability for pipelines to be in a certain condition and the adverse potential impacts of failure on society and the economy. To optimize inspection scheduling based on a constrained budget, mathematical optimization is performed. In the optimization problem maximizing the number of sections that need inspection while minimizing the inspection cost and time are considered the objectives, whereas the sections to be inspected, and inspection crews with the inspection technology are the decision variables. To combine the aforementioned two models, an add-in inspection scheduling tool is developed to be integrated in the Arc-GIS environment and/or MS Project, where the user can identify critical sections and the inspection dates for each of these sections based on the available inspection funds.

3.2.1. Literature Review

As previously discussed, the literature review includes reviewing methodologies developed to plan and schedule inspections in terms of the different techniques used, while identifying both the advantages and limitations for each of these techniques and methodologies. The methodologies that are investigated include models developed for water, sewage, oil and gas pipelines, bridges, and industrial and nuclear plants. In addition, different attempts done to estimate the cost and consequences of failure for sewer pipelines are studied. Figure 3.2 shows a break down for the reviewed literature types addressing sewer pipeline inspection scheduling and planning. In this figure the interaction between the different developed methodologies is described. It can be seen that some researchers developed deterioration models from which times of failure are determined and the costs resulting from that failure were introduced to determine the optimal inspection times or any other intervention.

The other group of studies addressed scheduling inspections from a risk assessment point of view in which probability and consequences of failure were determined to create a risk index for inspection prioritization. If these two methodologies are combined they would result in the third methodology as shown; in which optimization is performed after determining the risk and defining the costs of failure. In the process of reviewing the developed methodologies, different deterioration and failure models for different assets are studied. The different mathematical models and statistical techniques behind those models are also studied. In addition, the different optimization techniques and approaches used to optimize inspection intervals based on resources and budget availability are also investigated. The major limitations and areas for enhancements are then concluded.

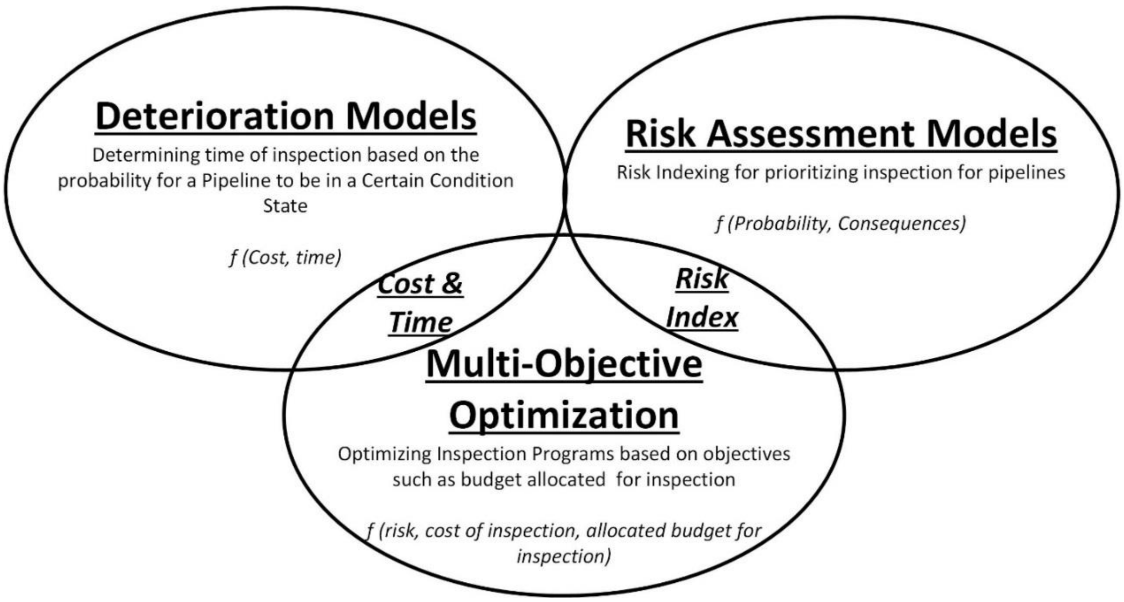


Figure 3.2: Different Methodologies Developed for Sewer Pipelines Inspection Scheduling

3.2.2. Data Collection

In the data collection stage, different datasets used in the development of models are collected. These datasets comprise data extracted from CCTV inspection reports for two existing sewage networks in Qatar and Canada, GIS database files for sewer pipelines in Qatar, and from literature as shown in Figure 3.3. As shown in Figure 3.4, each dataset is used for a certain specific purpose. For instance, defects extracted from CCTV inspection reports for Qatar and Canada networks are used to identify the basic range of defects that could occur in different sewage pipeline materials and diameters. This information is then used to build the BBN model. At first different defects are categorized based on the same category (i.e. family) where different sub-categories are grouped under the same family of defects. Then the defects are transformed from numerical values into three linguistic variables, namely: Light, moderate, and severe—in which they are used as an input for the different states of variables in the BBN model.

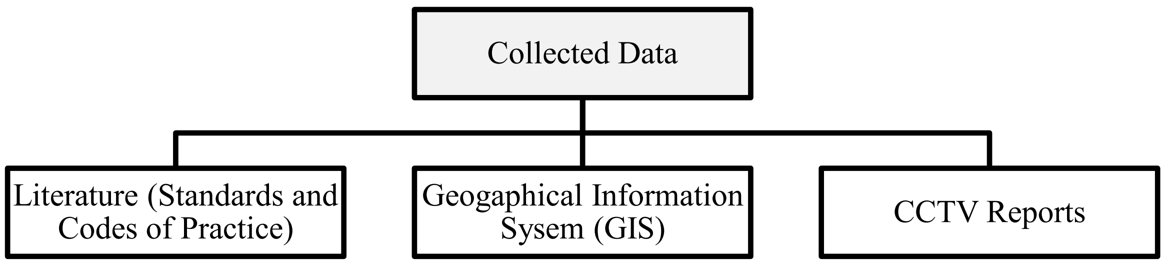


Figure 3.3: Collected Data Types used in Models Development

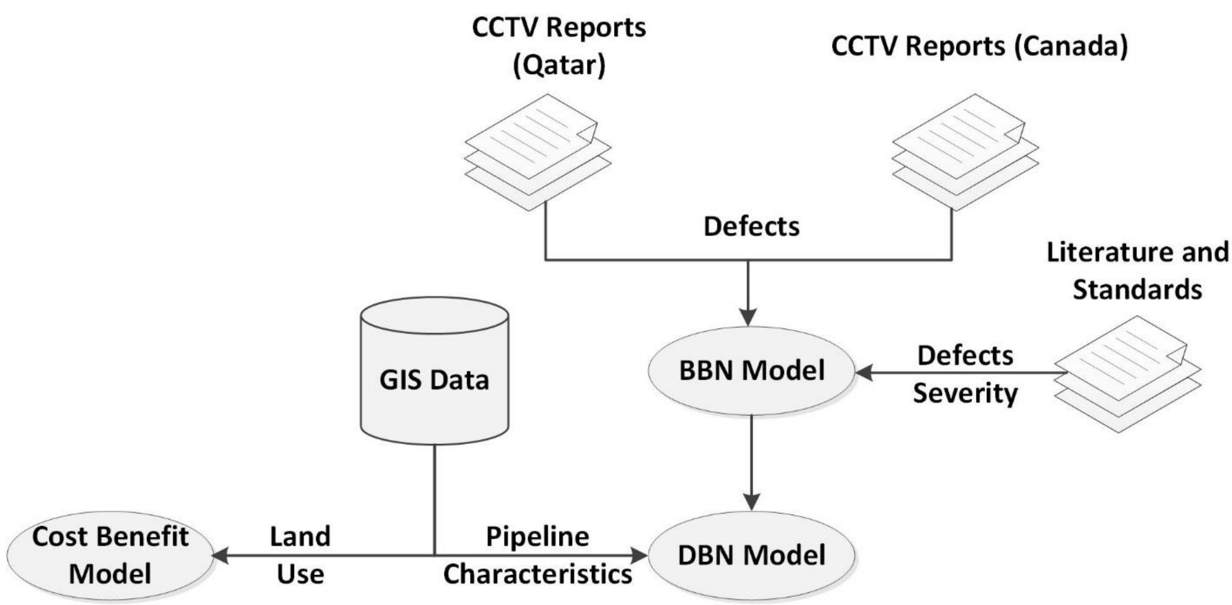


Figure 3.4: Interaction between Different Datasets in Models' Development

Sewer manuals and standards like PACP and WRC are used in determining the thresholds for these defects from which severities are determined, and to convert the defects numerical values into linguistic variables. The risk assessment model is developed using direct and indirect condition assessment methods. The data used in the indirect methods, comprises the physical characteristics of pipelines such as age, diameter, length, material, etc., in addition to operational factors such as flow rates and inflows and the environment surrounding the pipeline, such as the ground water table level, soil type, etc. Like most of the deterioration models in literature that utilize pipeline characteristics in creating these models (Davies, 2001, Wirahadikusumah et al. 2001, Baur and Herz, 2002, Chughtai and Zayed, 2008, Younis and Knight, 2010, Khan et al. 2010 and Salman and Salem, 2012). GIS dataset are used with the aid of multinomial logistic regression technique to build the DBN model using different pipeline characteristics.

In order to convert the BBN into a dynamic model, the age factor is introduced to the model. The GIS information, which is in the form of shape files, are analyzed using MS excel from which the data could be easily handled. This information (i.e. material, diameter, age, length, street category, etc.) is used to build a multinomial logistic regression model, that is used to determine the transition probabilities for the BBN model from one-time step to another. Additionally, the GIS files contain information about land use from which the consumer numbers, road type, and average daily trips can be estimated that is in turn used in the cost benefit analysis model when estimating the consequences of failure.

3.2.3. Models' Development

Different models were developed using the collected data to determine the optimal sequence of pipelines' inspection. Figure 3.5 shows the interaction between the different models and how they collaborate until an inspection schedule is created. Using the different pipeline defects and characteristics in the development of BBN and DBN models, the year at which a pipeline would reach a certain condition state could be determined. To determine the consequences of failure, different costs of failure and health benefits of avoiding such failure are determined using CBA technique. By combining the values of both likelihood and consequences of failure, a risk index for the different pipeline sections could be determined. The risk indices and corresponding time and costs of inspection form a combinatorial problem from which the sequences of inspecting the different pipeline sections is determined.

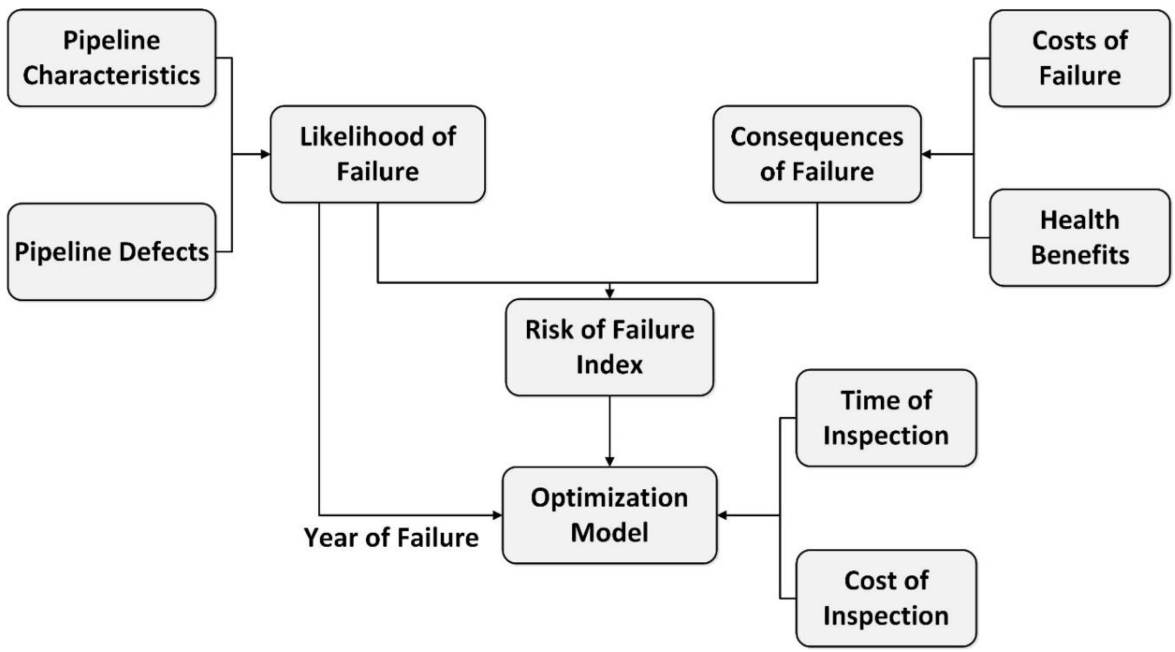


Figure 3.5: Interaction between Different Models to Plan Inspections

3.2.3.1. Likelihood of Failure Model

Performing risk assessment can be divided into two components: determining the likelihood of failure, and determining the consequences of failure. To determine the likelihood of failure, a defect based deterioration model is built by employing Bayesian Belief Network statistical technique using defects found in CCTV inspection reports. Bayesian Belief Network is used to combine the different conditional probabilities of the different defects that contribute to the structural and operational deterioration of the pipeline, and for determining the probability that a pipe will be in a certain condition. Monte Carlo simulation is performed to determine both the marginal and conditional probabilities that the pipeline is in a certain condition based on different types of defects. The developed static BBN is shown in Figure 3.6.

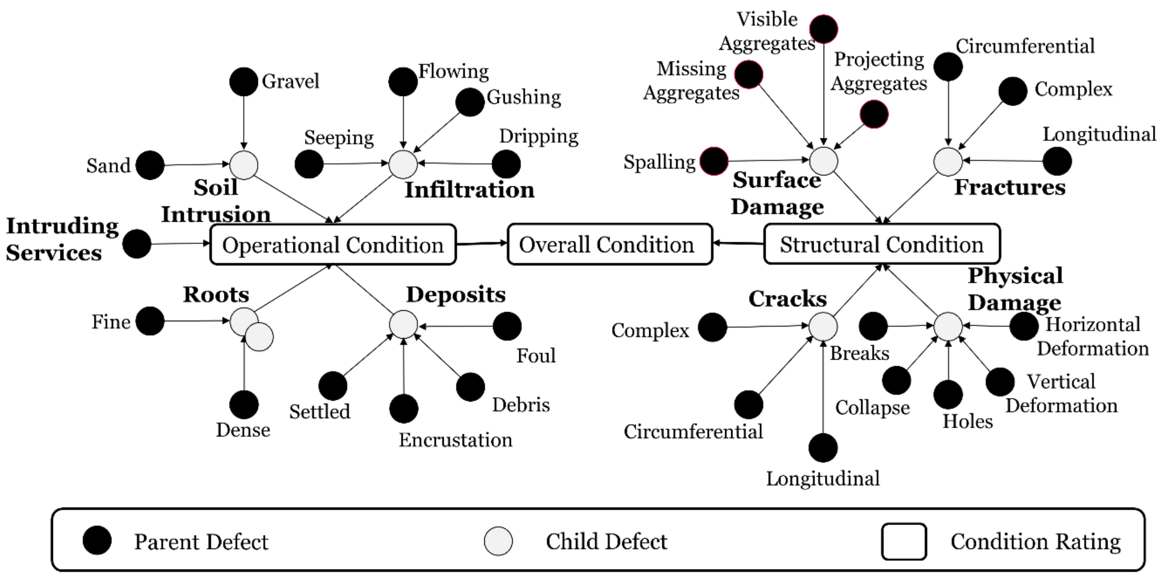


Figure 3.6: Defect Based Bayesian Belief Network Model for Sewer Pipelines

Multinomial Logistic Regression is used to introduce the dimension of time to the BBN, by determining the different time intervals that the pipe require for transfer from one condition state to another. In this part, the GIS data is used to capture the dynamic nature of the deterioration process, where the probability is determined using BBN at a certain time slice and then the transitional probability for DBN is determined from which the new probability at the next time slice is calculated. Figure 3.7 shows the scheme for determining the likelihood of failure along with the different techniques and statistical models used for that intent.

There are some assumptions made to develop the models in this research. These assumptions can be summarized as follows:

1. The pipeline's defects have three states which are: light, moderate, severe.
2. There are five condition ratings for the pipelines which are: Excellent, Very Good, Good, Poor, and Fair. These five condition ratings are grouped into three categorical groups which are 1 for Excellent and very good, 2 for good and 3 for poor and fair.

3. The probability that the defects would transfer from one state to a poorer state is assumed to be the same as the probability by which the pipeline transfers from one condition state to a poorer one.
4. The deterioration models consider the joints and pipeline length to be one entity.

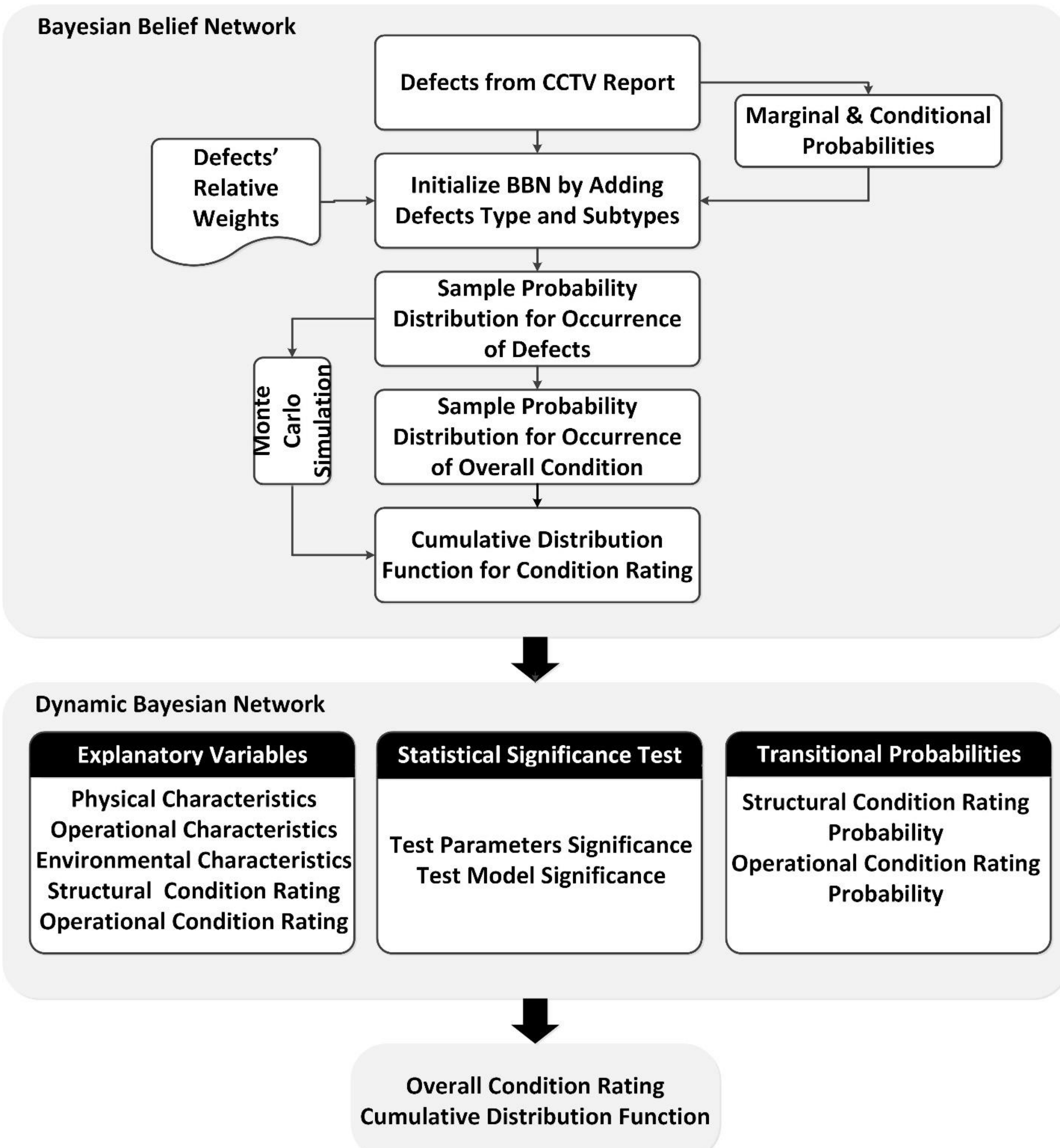


Figure 3.7: Scheme for Determining Likelihood of Failure

Different defects present in sewer pipelines would have an impact on both operational and structural conditions based on their severity. BBN models the influence of different defects propagating this influence through the network and determines its impact on the overall pipeline condition rating probability. Figure 3.6 shows the BBN created to determine the "Structural Condition" and "Operational Condition" as probability distributions over the respective random variables (different defect types), from which the probability value for overall pipeline condition would be determined. In this BBN, different defects are considered the "parent nodes" divided into three different states, namely: light, moderate, and severe. Each group of defects is grouped under a category based on the nature of these defects which are considered another level of parent node. The states of defects are classified as light, moderate, or severe according to the size, number, and shape of the defects. Different codes and practices specify the different thresholds for determining a defect's severity.

The developed BBN would result in a cumbersome problem and in order to make it more tractable and simpler; another algorithm is required to decrease the amount of effort and time required in calculations. Numerous techniques have been presented to determine the probabilities and information required to formulate the CPTs in large problems in a time and effort saving manner (Druzdzel and Van der Gaag, 1995, Van der Gaag et al. 1999 and Das, 2004). In conventional BBN models, experts are sought to assign probability values to predict the likelihood of the occurrence of some events through interviews and questionnaires from which conditional probabilities can be elicited, however this could be challenging in large problems.

The CPTs are calculated using weighted sum algorithm defined by Das (2004). The weighted sum algorithm considers the strength between the child and its parent variable as a conditional probability. By employing this concept, conditional probabilities can be interpreted as relative weighting factors representing the importance of each parent variable condition in establishing the condition of their child variable. As such, the input for the BBN model can be set to relative weights that quantify the relative strengths of the influence of the parent on the child and probability distributions over the independent variables (parent node). Equation 3.1 shows the algorithm utilizing relative weights instead of conditional probabilities for parental configuration used in developing BBN models (Das, 2004).

$$p(A|B) \sum_{j=1}^{n} w_j p(A|\Pi) \tag{3.1}$$

Where w_j,…..w_n: Relative weights, to the parents $(\mathrm{A}_1, \ldots \ldots \mathrm{A}_n)$ respectively, such that

$\sum_{j=1}^{n} w_j = 1$.

The developed BBN model presents the interdependencies among the independent variables represented in the form of different defect types and their impact on the structural, operational, and overall condition of the sewer pipes. This is achieved by incorporating the different impacts due to simultaneous occurrence of independent variables (i.e. Defects). These independent variables may be considered random variables, with different probabilities distributions. On the other hand, MCS models the internal uncertainties between these random variables and the external uncertainties among the different defect families using probability distributions to represent their occurrence. As such, a BBN model in an MCS based frame of reference is developed to capture the interdependencies between the different defect types and their effect on the pipe condition propagating the uncertainties over the network and the uncertainties among the random probability variables. The BBN model is initialized using the marginal and conditional probabilities determined by analyzing data gathered from inspection reports, and the relative weights of defects which is then iterated.

The BBN model serves as a snapshot model to estimate the probability of a sewer pipeline to be in a condition state based on defects at a certain point in time. Since deterioration is a time dependent process, modeling the variation in condition of a pipeline with time included as a factor is important to accurately model the deterioration process. Dynamic Bayesian Network is considered a useful tool in modeling such a process. In the basic Dynamic Bayesian model, a time slice is connected to its successive time slice through temporal links to form a time varying model. Similar to the concepts of the BBN, conditional probabilities for the temporal links which are also known as transitional probabilities are used to express the relationships between the variables in successive time slices. Figure 3.8 shows the DBN components.

In a BBN, only parent variables are the independent variables, as such they are the only variables linked to the successive time slice through temporal links. BBN is used to compute the condition for all the child variables (i.e. different defect families) using the condition of the parent variables at each time slice. Transition probabilities related to successive time slices for each defect are the required input to define a DBN model. Multinomial logistic regression is used to determine the probability that the pipe in question will be in a certain condition state, and the point at which the pipe would be in that condition state. Figure 3.9 shows the DBN Configuration for defects of sewer pipelines.

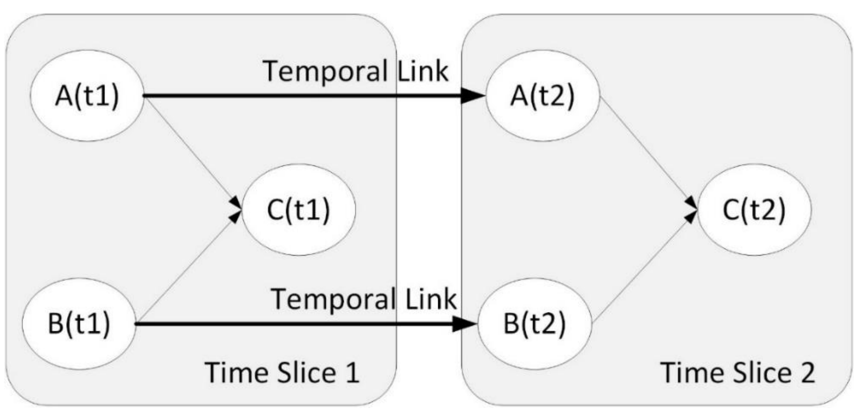


Figure 3.8: Dynamic Bayesian Networks Configuration

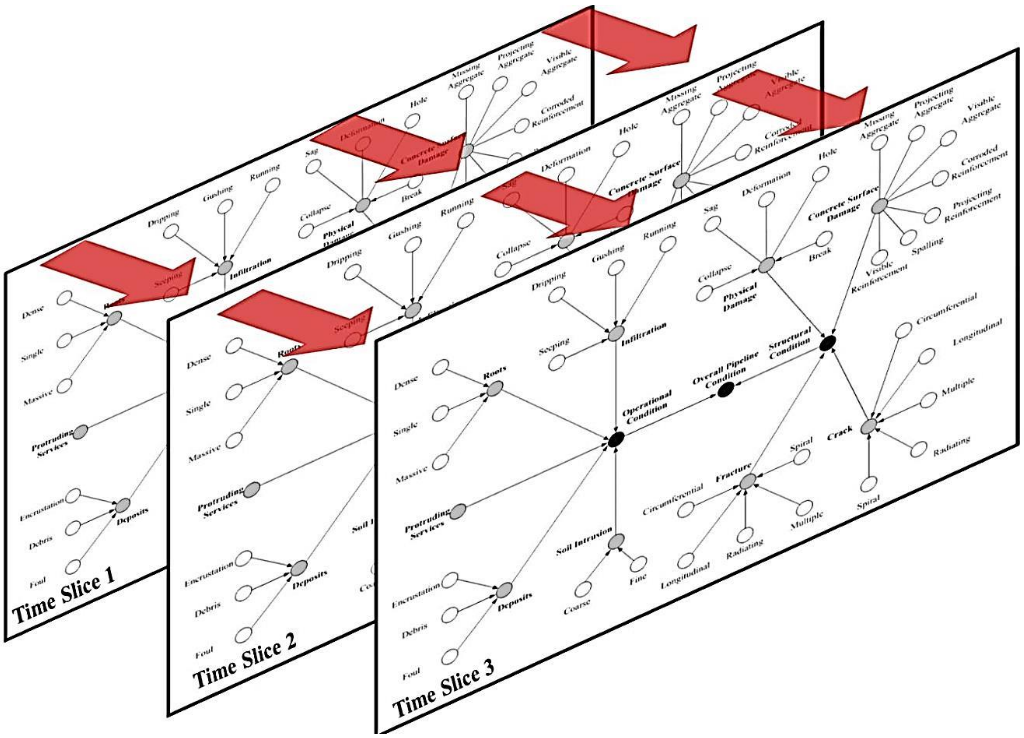


Figure 3.9: Dynamic Bayesian Network for Defects of Sewer Pipelines

Multinomial logistic regression is an appropriate method to use when the categories of the dependent variables are not ordered. It allows modeling the relationship between independent variables and a dependent variable, resulting in a determination of the probability associated with each level of dependent variable for a given set of independent variables. In order to calibrate the model, the outcome is estimated from condition rating of CCTV inspections (i.e. the worst two condition ratings represent the failed condition and the other condition ratings represent good conditions).

3.2.3.2. Consequences of Failure Model

After determining the likelihood of failure, the consequences of failure are determined by the use of hypothetical scenarios. The different costs, including the direct and indirect costs, are estimated from the data found in the GIS information (i.e. Street category, land use, etc.) as shown in Figure 3.10. Due to the uncertainties and the variation in the methods to calculate these costs, a cost benefit analysis is performed to analyze the costs paid in case a failure takes place and the benefits that return to the consumer after the pipeline is repaired. This economic approach helps reduce uncertainty by estimating the costs from one place to another.

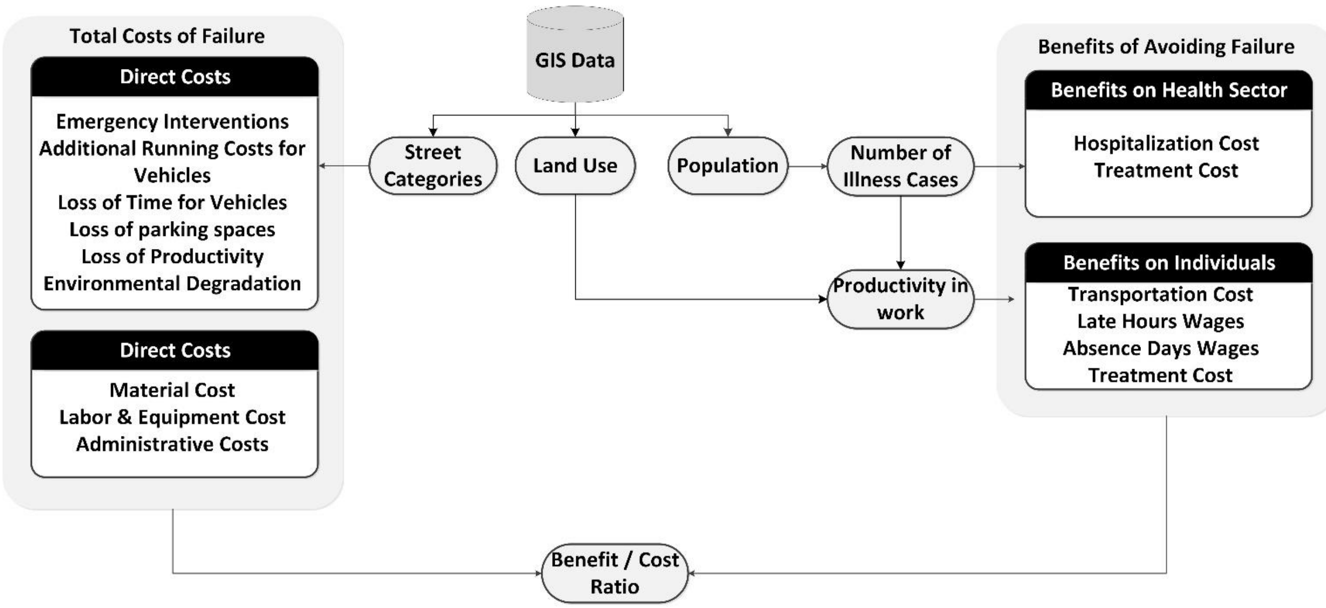


Figure 3.10: Scheme for Determining Consequences of Failure

To determine the consequences of sewer pipelines' failure, direct and indirect costs as a result of that failure were estimated. Total costs of failure included in this research are depicted in Figure 3.11 and can be determined using Equation 3.2.

$$T.C._f = \sum_{i=1}^{n} DC_i^f + \sum_{j=1}^{m} IC_j^f \tag{3.2}$$

Where $T.C._f$: Total costs of sewer pipelines' failure,

DC: Direct cost of failure for cost category (i) with total number of cost categories (n)

IC: Indirect cost of failure for cost category (j) with total number of cost categories (m)

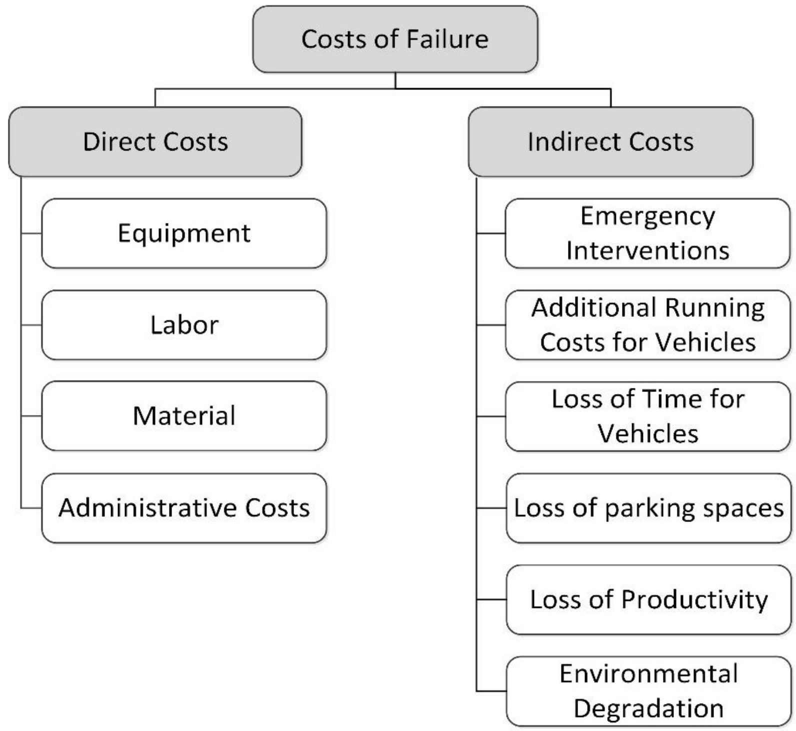


Figure 3.11: Costs of Failure Considered in the Cost Benefit Analysis

3.2.3.2.1 Direct Costs of Failure

Direct costs can be categorized as all costs related to the reconstruction of the underground infrastructure. These costs are easily spotted and identified because they correspond mostly to tangible costs like those associated with materials and other resources involved in restoration work.

3.2.3.2.1.1 Costs of replacement materials

These are the costs related to materials used in the replacement of affected sewer pipelines. When a partial or a complete rupture takes place in a sewer pipeline, it requires a complete repair to return it to its initial level of service. These costs differ based on the rehabilitation and renewal techniques used. Equation 3.3 can be used to determine the costs of sewer pipelines' material used in restoration works.

$$C_m = (C_l^d + C_l^b) \,.\, l \tag{3.3}$$

Where C_m: Cost of material for pipe with a length (l),

C_l^b: Unit cost of bedding material and

C_l^d: Unit cost of linear length for pipe material used in repair with diameter (d).

3.2.3.2.1.2 Costs of equipment

Failed sewer pipelines may require the use of specialized equipment such as loaders, compactors and excavators in case of conventional methods or winches if trenchless technologies are used. These costs are attributed to the original value of the equipment used during repair work and can be translated into hourly costs, which is a function in the duration of repair works.

3.2.3.2.1.3 Costs of labor

Costs of labor are the costs allocated for the workforce required to conduct repairs. Workers at the scene of failure incidents are required to be more qualified, which may have an impact on the cost per hour. The urgency of appearance is also a governing factor (i.e. sometimes working hours are considered overtime) and could raise the direct costs of restoring the failed sewer pipelines. Equation 3.4 can be used to determine the costs of resources used in reinstating failed sewer pipelines (i.e. labor and equipment).

$$C_R = d.\left[\sum_{i=1}^{n} C_l^i + \sum_{j=1}^{m} C_e^j\right] \tag{3.4}$$

Where C_R: Cost of resources used in restoration works,

d: Total duration of restoration works,

C_l^i: Hourly rate of labor of type (i) (\$/h) with total number of types (n) and

C_e^j: Hourly rate of equipment of type (j) (\$/h) with total number of types (m).

3.2.3.2.1.4 Administrative and project management costs

The repair of failed sewer pipelines can be considered an emergency which could require the implementation of an emergency plan as developed by the project management team. The aim of this plan is to ensure smooth operations despite an unplanned event (Khogali and Mohamed, 1999) which would require the availability of engineers, project managers, and other personnel. Therefore, there are costs associated with the project management which include administrative and file monitoring fees. These costs are estimated to be taken as a percentage of the total direct costs and usually range between 5 to 10 % (Kerzener, 2013).

3.2.3.2.2 Indirect Costs of Failure

As previously discussed, analyzing the consequences of failure takes into account the direct costs or reconstruction costs first, then other costs that qualify as indirect. It is difficult to give an exact definition regarding the indirect costs associated with the failure of an asset in general, and sewer pipelines in particular. However, the indirect costs can be arbitrarily defined as costs associated with loss of productivity for other functioning parties and lost wages as a result of the failure. These costs are attributable to: damages as a result of flooding, loss of business, traffic disruption due to soil depression, surface and ground water quality degradation, service interruption, reduction in quality of hygiene as a result of flooding on the street, odors, and emerging rodents and insects. Not only does a failure affect daily life, but it could also have an adverse effect because of the complications associated with reconstruction and asset rehabilitation. These costs can be attributed to construction noises, dust due to construction work, service interruption, traffic disturbances, and business losses. The following section provides a description for the different costs included in the economic loss model to determine the consequences of failure.

3.2.3.2.2.1 Costs of emergency interventions

Sewer pipeline failure can be considered a disastrous event that could jeopardize the lives of the public. Thus, emergency interventions such as paramedics (health services), police forces and members of the civil defense department might be needed to help those threatened by floods and roads' failure. The costs related to the use of these resources are taken into account as indirect costs even though they are not necessarily present in all cases. Equation 3.5 shows the costs of emergency interventions which includes the personal wages and the hourly costs of the vehicle.

$$C_{PS} = \sum_{i=1}^{n} c_v^i * t_R^i \tag{3.5}$$

Where C_{PS}: Total cost of intervention of public services ,

c_v^i: Hourly rate of vehicle of type (i) (\$/h),

t_R^i: Duration that the vehicle of type (i) will spend on the incident location (hrs) and

(n) is the total number of emergency vehicles deployed.

3.2.3.2.2.2 Costs of additional fuel consumption as a result of traffic disruption

Affected zones from sewer pipelines' failure could be partially or totally closed. This closure might further extend outside the premises of the failure, resulting in numerous costs (Gourvil and Joubert, 2004). Diversion work or road closure could cause traffic congestions. This could be attributed to the increase in traffic volume with either constant or reduced road capacity. Traffic congestion could lead to additional costs as a result of fuel overconsumption for vehicles with reduced speed. Equation 3.6 shows the costs of fuel overconsumption due to traffic congestion.

$$C_{Con} = D * f_c * \sum_{i=1}^{n} (Con_{dis}^i - Con_{nor}^i) * \sum_{j=1}^{m} N_{V(i)}^j \tag{3.6}$$

Where, C_{Con}: Cost of overconsumption due to congestion,

D: Disruption distance (km),

f_c: Fuel price (\$ / L),

Con_{dis}^i: Average consumption of vehicles of type (i) during disruption (L/km),

Con_{nor}^i: Average consumption of vehicles of type (i) during normal cases(L/km),

$N_{V(i)}^j$: Number of vehicles of type (i) impacted per day (j) (Vehicles/day) and

N and M: Total number of vehicles and total number of days, respectively.

3.2.3.2.2.3 Costs of environmental degradation

The environmental impact of failed sewer pipelines can be divided into impacts during the event of failure and those incurred during the restoration work. Although the impacts of sewer pipelines are not instantly visible, many of these impacts might be costly and irreversible. For instance, flooding of failed sewer pipelines affects the surrounding soil, surface and ground water quality. Surface damage and broken parts of sewer pipelines can lead to groundwater and soil contamination. Once the plume is formed (i.e. contaminants discharged from broken pipelines), it starts moving horizontally based on the hydraulic gradient of groundwater. As the plume advances, it starts to dilute due to infiltration, sorption, time and distance of travel.

Usually the concentration of plume decreases as the distance from the source increases. Dispersion; which is the movement of chemicals in longitudinal and transversal directions forming a cone shape plume downstream of the source, is affected by the velocity and porosity of aquifers (Gulliver, 2012). The effluent that leaks from broken sewer pipelines is usually untreated raw sewage that seeps to groundwater and soil surrounding the location of failure. This results in the introduction of nitrates, phosphates, harmful microorganisms and bacteria to the groundwater and soil (Gulliver, 2012). Equation 3.7 is used to determine the concentration of chemical intrusion from which the volume of contaminated soil and/or groundwater can be estimated (Gulliver, 2012).

$$C_{max} = \frac{M}{8*\varepsilon*\left(\frac{\pi t}{R}\right)^{3/2} * \sqrt{D_x D_y D_z}} \tag{3.7}$$

Where, M: Mass of contaminant which is equal to the product of the flow and initial concentration at the contamination source point,

ε: Soil porosity,

D_x: Horizontal spread of the plume which is equal to the product of bulk velocity and diameter of soil particles,

D_y: Transversal spread (in y direction),

D_z : Vertical spread (in z direction) and $D_y = D_z = 0.1 * D_x$,

t: Duration of the leak and

R: Retardation rate.

Equation 3.8 (Gulliver, 2012) shows the retardation rate *(R)* of plume as a result of the reaction between its components and saturated soil constituents.

$$R = 1 + \frac{\gamma_b}{\varepsilon} * k_d \tag{3.8}$$

Where R: is the retardation rate,

$k_d = \beta f k_{ow}$, (f = 0.01 in sandy soil to 0.10 in muck),

β= 0.41 and k_{ow} is a constant),

γ_b: Bulk density of soil and

ε: Soil porosity.

By using the initial concentration and the spread of contaminant, the maximum concentration downstream the contamination source can be calculated using parameters related to the medium in which it is disposed. Equations 3.9 and 3.10 (Gulliver, 2012) show the plume spread which is assumed to follow a Gaussian distribution from which the volume of contaminated soil is calculated.

$$4\sigma_x = \frac{4*\sqrt{2*D_x t/R}}{3} \tag{3.9}$$

$$4\sigma_y = \frac{4*\sqrt{2*D_y t/R}}{3} \tag{3.10}$$

Equation 3.11 shows how the volume of contaminated soil and groundwater resulting from advancement of the plume is calculated. In this equation cost of treatment is calculated by multiplying the contaminated volume by the unit cost of treatment.

$$V_{Con} = \frac{16}{3}\pi\, \sigma_x \sigma_y \sigma_z \tag{3.11}$$

Where V_{Con}: Volume of contaminated soil and groundwater and

$\sigma_{x,}\sigma_{y,}\sigma_z$: are the plume spread in the horizontal, transversal and vertical directions, respectively.

The above discussed environmental degradation model provides the user with an approximate method to calculate the contaminated volume of soil and groundwater. Therefore, care should be given when using these equations in the context of plume (i.e. effluent) transfer. Additionally, the environmental degradation model, does not take into consideration several important aspects of plume transfer in different media such as diffusion. Also, the environmental degradation model takes into consideration the transfer of some constituents of the raw sewage water such as nitrates and phosphates while ignores others such as Total Suspended Solids and Biochemical Oxygen Demands (BOD_5).

3.2.3.2.2.4 Costs related to economic impacts

General activity of businesses and industries are often impacted by asset failures and disturbances. This can be reflected in the economy in terms of reduced productivity, loss of income, and delays to work. Traffic disruption, loss of parking spaces, and restoration work, can result in delays or even absences from work due to the difficulty in accessing affected areas. Equation 3.12, estimates the cost of delays and absences from work as a result of restoration works.

$$C_a = \sum_{i=1}^{n}(r_h^i * N_i * t) \tag{3.12}$$

Where C_a: Cost of absence from work,

r_h^i:Hourly rate of employee of type (i) (\$/hour),

N_i: Number of employees of type (i),

t: Duration of delays or absence by employee of type (i) (hrs) and n: is the total number of employees of different types.

3.2.3.2.3 Benefits from Avoiding Sewer Pipelines' Failure

Failure of pipelines and the improper collection of wastewater can have adverse potential impacts on health, environment, and the economy. Contaminated surface and ground water bodies can, for instance, lead to an increase in illness rates in areas that suffer from waste water contamination. This increased disease burden can result in medical expenditures for illness treatment. Just a few indirect costs resulting from illness are: time lost from work, decreased productivity, premature death, and disability. As such it can be concluded that the costs paid by patients seeking health care, and increased running costs in addition to costs paid for remediation of contaminated water bodies, could significantly increase costs paid by society for that purpose. Studying the aforementioned impacts and identifying the remediation measures to remediate or avoid such impacts would have beneficial health impacts and potential benefits on societies. As per a study carried out by the World Health Organization (WHO, 2001), these benefits can be summarized as follows:

- Avoiding diarrheal diseases would result in direct economic benefits.
- Health improvement would lead to indirect economic benefits.
- Non health benefits due to increase in productivity, or regaining original productivity levels.

Contamination of water bodies and soil as a result of wastewater discharge could lead to an increase in illness rates for individuals living in the affected areas (WHO, 2001). Figure 3.12 shows the bacterial life cycle and how bacteria is transferred from effluent water to crops and drinking water until illnesses occur. The increase in illness rate can be represented by an increase in the disease burden which could lead to an increase in the expenses paid by individuals seeking treatment. The increase in disease burden could result in indirect expenses such as: delays to work or absences costs. In some extreme cases exposure to contaminated water or soil could lead to disabilities and premature deaths (WHO, 2001). One of the most common diseases resulting from water bodies' contamination by raw wastewater are diarrheal diseases, the reduction or elimination of which would result in significant direct economic benefits (i.e. increasing productivity or regaining original productivity). The following section discusses the different benefits resulting from avoiding sewer pipelines' failure.

3.2.3.2.3.1 Cost of treatment

The costs of treatment for patients seeking medical care are considered a burden on the health sector and individuals. In cases of diarrheal diseases and as per a study by the World Health Organization (WHO, 2001), 14% of the population in the premises of water contamination could be infected. Out of the total affected population, 92% are categorized as outpatients (i.e. patients seeking medical treatment for only a few hours), while 8% are categorized as inpatients (i.e. patients seeking hospitalization for a period of 2-5 days).

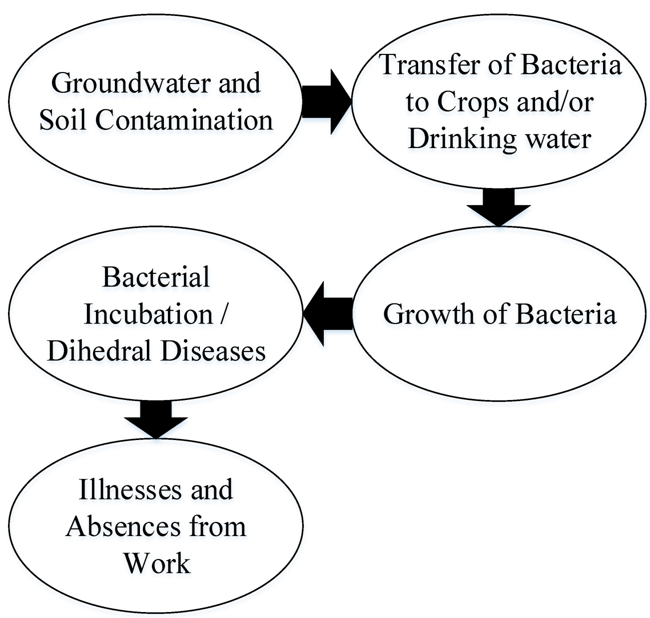


Figure 3.12: Bacterial Infection Cycle Resulting from Groundwater Contamination

Cost of treatment differs based on region and whether the patient is an inpatient or outpatient (WHO, 2001). Equation 3.13 shows the cost of treatment borne by the health sector that would be saved if failure was avoided.

$$CT_{Health} = 0.14 * P * (0.08 * C_{in} + 0.92 * C_{out}) \quad (3.13)$$

Where CT_{Health}: Cost of treatment paid by health sector,

C_{out}: Unit cost of treatment for outpatients,

C_{in}: Unit cost of treatment for inpatients

P: Total population in the premises of failure incident.

The general definition of utility is the satisfaction of customers resulting from the consumption of certain goods or services (Pass et al. 1993). Quality Adjusted Life Years (QALYs) (McCrone, 1998 and Weinstein and Stason, 1977) is used in health economy with the aim of measuring the value of such satisfaction as a result of certain interventions. QALYs can be used to combine the quality and length of life which are the two aspects resulting from better sanitation. As such, financial estimates represented by QALYs can be used in the CBA analysis to represent the betterment in the individual's wellbeing and health improvements.

3.2.3.2.3.2 Cost of illnesses avoided

Similar to the costs spent by health sector in treatment of illnesses, there is a portion in these expenses that would be paid by individuals. As per several commonly used health insurance plans; 10% is usually borne by individuals with the rest covered by health insurance plans (WHO, 2001). Also, transportation costs paid by the patients seeking treatment are borne by the individuals. Equation 3.14 shows the cost of illness borne by individuals.

$$CT_{Ind} = 0.14 * P * [0.1(0.08 * C_{in} + 0.92 * C_{out}) + C_{TR}] \quad (3.14)$$

Where CT_{Ind}: Cost of treatment paid by individuals,

C_{in}: Cost of treatment for inpatients,

C_{out}: Cost of treatment for outpatients,

C_{TR}: Transportation cost

P: Population affected in the premises of the incident.

3.2.3.2.3.3 Cost of avoided delays to work and absences

Illnesses could cause delays to work or absences which can be translated into costs. Such costs are considered indirect and would have an impact on the economy. Equation 3.15 shows the cost of delays and absences of workers.

$$CD_{Ind} = 0.14 * \%_{Workers} * hr_{ind} * P\,(0.08 * h_A + 0.92 * h_D) \quad (3.15)$$

Where CD_{Ind}: Cost of delays paid by individuals,

$\%_{Workers}$: Percentage of workers in the affected district,

hr_{ind}: Hourly rate of individuals,

h_A: Number of absence hours

h_D: Number of delay hours.

Table 3.1 shows the different variables included when studying how the health sector and patients would benefit from avoiding the failure of assets and subsequent contamination of wastewater.

3.2.3.3 Risk Assessment of Failure Model

To perform risk assessment, fuzzy inference system is used to combine both the likelihood and consequences of failure. Sugeno Fuzzy Inference System is used to combine them by constructing two input variables, one for the likelihood and another for the consequences. The Fuzzy inference system rules are derived from a risk matrix for the resultant risk values based on different combinations of likelihood and consequences of failures. The goal for a risk assessment model is to create a risk index by which the different critical pipes are identified and inspections are prioritized based on their needs.

Table 3.1: Benefits on Society as a Result of Avoiding Wastewater Contamination

<table>
<tr><th colspan="2">Beneficiary</th><th>Variable</th><th>Value</th></tr>
<tr><td rowspan="7">Health Sector</td><td rowspan="7">Expenditures saved, due to less illness</td><td rowspan="2">Unit cost per treatment</td><td>Cost Per Visit (US$7) (WHO,2001)</td></tr>
<tr><td>Cost Per Day (US$28) (WHO,2001)</td></tr>
<tr><td>Number of cases</td><td>Variable by region</td></tr>
<tr><td rowspan="2">Visits or days per case</td><td>1 outpatient visit per case (WHO,2001)</td></tr>
<tr><td>5 days for hospitalized cases (WHO,2001)</td></tr>
<tr><td rowspan="2">Hospitalization rate</td><td>92% of cases ambulatory (WHO,2001)</td></tr>
<tr><td>8% of cases hospitalized (WHO,2001)</td></tr>
<tr><td rowspan="8">Patients</td><td rowspan="6">Expenditures saved due to less illness</td><td>Transport cost per visit</td><td>Variable by region</td></tr>
<tr><td>Number of cases</td><td>Variable by region</td></tr>
<tr><td rowspan="2">Visits or days per case</td><td>1 outpatient visit per case (WHO,2001)</td></tr>
<tr><td>5 days for hospitalized cases (WHO,2001)</td></tr>
<tr><td rowspan="2">Hospitalization rate</td><td>92% of cases ambulatory (WHO,2001)</td></tr>
<tr><td>8% of cases hospitalized (WHO,2001)</td></tr>
<tr><td rowspan="2">Money saved by avoiding days lost from work</td><td>Days off work</td><td>2 days (1-4) (WHO,2001)</td></tr>
<tr><td>Number of people of working age</td><td>Variable by region</td></tr>
</table>

3.2.3.3.1 Likelihood of failure

The likelihood of failure is identified by developing system models or past observations. System models are used to calculate the performance of the system and how likely it is that the system in question would fail to function. The calculated performance is then converted into fuzzy membership function through the "fuzzification" process. The seven linguistic categories representing the probability of failure are represented by triangular shaped membership functions as shown in Figure 3.13.

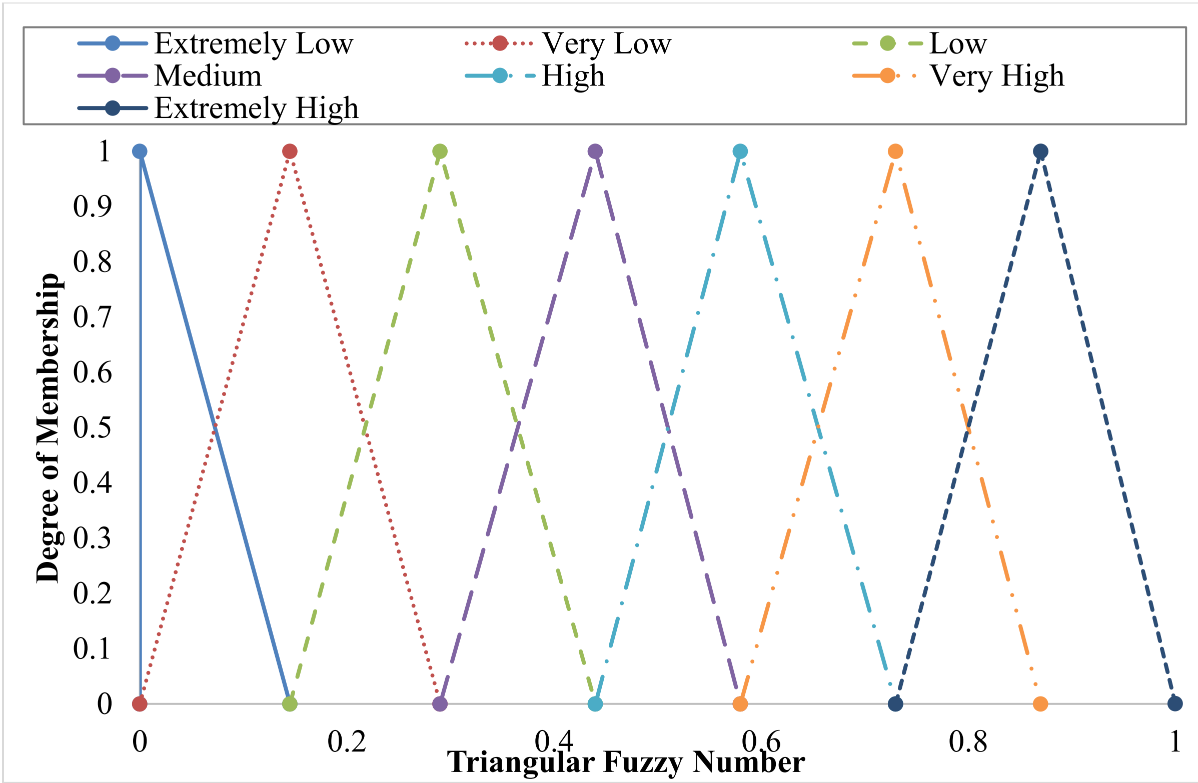


Figure 3.13: Levels for Likelihood of Failure to Calculate Risk

The threshold values for plotting the fuzzy membership functions are adopted using Jenk's natural break. The values between 0 and 1 represent the relative magnitude of likelihood, where 0 implies that there is no impact on the systems performance and 1 implies a complete system failure. When a likelihood value intersects with numerous membership functions and it is required to determine the corresponding membership value, a fuzzy mapping operation is usually required where maximum operator is used in which the value of the higher membership function is chosen.

3.2.3.3.2 Consequences of failure

The consequences of failure proposed in this research are: Extremely Low, Very Low, Low, Medium, High, Very High, and Extremely High which are normalized on the interval in which the severity level can be represented by the fuzzy numbers between 0 and 1. Figure 3.14 shows the fuzzy membership functions for consequences of failure.

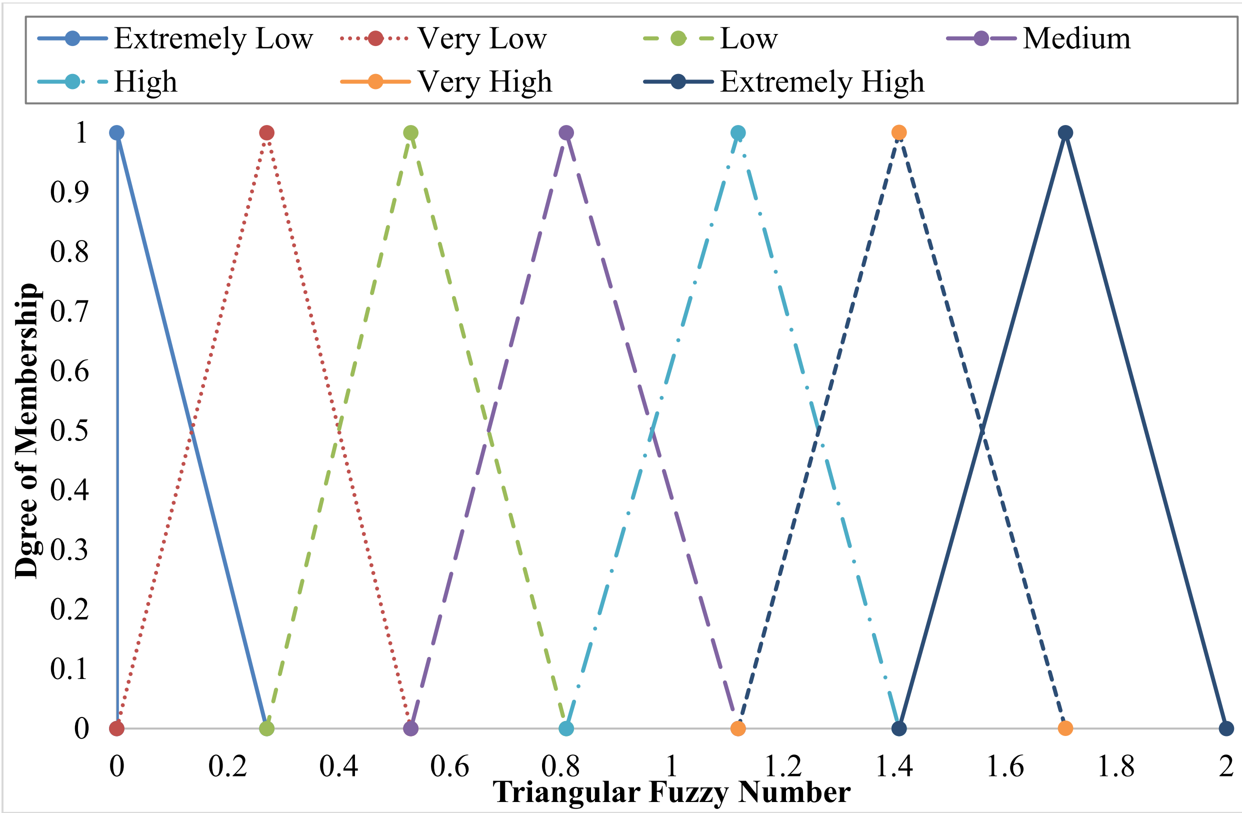


Figure 3.14: Levels for Consequences of Failure to Calculate Risk

The base of rules was derived from the color coded risk matrix shown in Table 3.2. The "de-fuzification" process would yield the output of that operation, which is the risk of failure. A description is shown in Table 3.3 for the different levels of likelihood, consequences, and risks of failure. To determine the risk of failure the fuzzy controller scheme shown in Figure 3.15 is proposed, where the inputs that would be converted into fuzzy numbers using the "fuzzification" process are the likelihood and the consequences of failure.

3.2.3.3.3 Risk of Failure

Using fuzzy logic to relate likelihood and consequences of failure with the overall risk of sewer pipes eliminates the problems associated with risk matrices while allowing the users to use "if-then" type rules to incorporate their experience. To overcome the drawbacks for using risk values that are products or risk matrices, FIS can be used to provide more flexibility to users when assigning the different values for the likelihood and consequences of failures by grouping them into discrete ordinal groups and assigning values for each combination. Using FIS to determine risk values can help users to overcome the uncertainty accompanying the use of linguistic variables describing either likelihood or consequences of failure that could create misconceptions due to the difference in perspective from one person to another.

Table 3.2: Color Coded Risk Matrix Used in Fuzzy Inference of Risk

Likelihood / Consequences	Insignificant	Very low	Low	Medium	High	Very high	Catastrophic
Extremely Low	Extremely Low	Very Low	Very Low	Low	Low	Medium	Medium
Very low	Very Low	Very Low	Low	Low	Medium	Medium	High
Low	Very Low	Low	Low	Medium	Medium	High	High
Medium	Low	Low	Medium	Medium	High	High	Very High
High	low	Medium	Medium	High	High	High	Very High
Very high	Medium	Medium	High	High	Very High	Very High	Extremely High
Extremely high	Medium	High	High	Very High	Very High	Extremely High	Extremely High

Table 3.3: Likelihood, Consequences and Risk of Failure Values and Description

Level	Likelihood of Failure			Consequences of Failure			Risk
Extremely Low	0	0	0.15	0	0	0.27	Acceptable Level for Risk
Very Low	0	0.15	0.29	0	0.27	0.53	Tolerable Level for risk
Low	0.15	0.29	0.44	0.27	0.53	0.81	Mitigations shall be taken
Medium	0.29	0.44	0.58	0.53	0.81	1.12	Risk to be reduced
High	0.44	0.58	0.73	0.81	1.12	1.41	Risk should be reduced
Very High	0.58	0.73	0.87	1.12	1.41	1.71	Risk must be reduced
Extremely High	0.73	0.87	1	1.41	1.71	2	Risk of failure occurs for sure

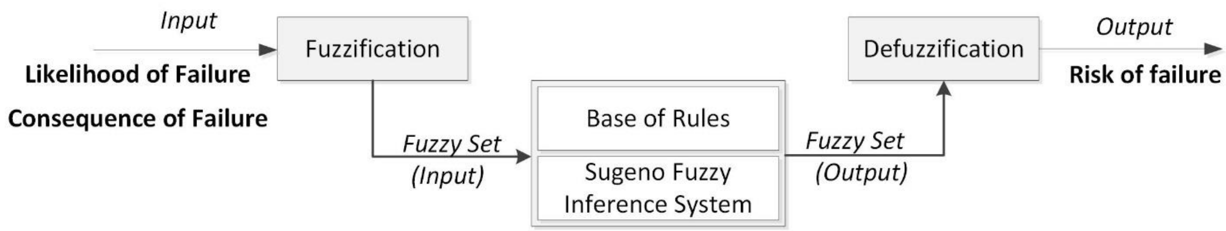


Figure 3.15: Fuzzy Controller Scheme for Predicting Risk of Failure

FIS can help in determining the resulting risk value accurately especially in cases where pipelines are in two different ordinal groups with values near the boundaries of the matrices which could cause loss of information. Different cut-off values for the likelihood and consequences of failure were determined using data classification based on their distribution (Salman and Salem, 2012). There are two methods for FIS, namely Mamdani (Mamdani, and Assilian, 1975) and Sugeno (Sugeno and Kang, 1988). In both methods, crisp inputs are "fuzzified" using fuzzy sets and fuzzy membership functions, then antecedent statements (i.e. AND or OR operators) are used to determine the area under the consequent fuzzy membership function. The main difference between Mamdani and Sugeno FIS is in the aggregation operation which combines the resulting fuzzy rules.

In Sugeno method weighted average is used based on the relative weights of the different output levels, while in Mamdani de-fuzification is carried out using different methods. Although Mamdani FIS is the most widely used method in engineering applications, Sugeno method has proven to be more computationally efficient and suitable when combined with other algorithms and optimization techniques. To model risk using FIS, Sugeno method was used because the resultant risk map would usually be optimized to determine the optimal combination for inspection or intervention activities; as such it was deemed more suitable for use in assessing risk of failure.

Likelihood and consequences of failure were represented on an ordinal scale indicating their different levels. Usually pieces of information handled should be in order of 7$\pm$2 (Karwowski and

Mital, 1986). Therefore, 7 levels were chosen to represent likelihood, consequences, and risk of failure to provide the user with more flexibility when expressing the notion of these parameters. The likelihood and consequences of failure were calculated for all pipelines in the collected data, then different combinations for each class were optimized to reduce the variance between the means of each class. Equation 3.16 shows the membership functions of likelihood and consequences of failure based on the adopted 7-degree scale.

$$\mu_1^l(x_l) = \mu_1^c(x_c) = \begin{cases} 1 - 7x, & 0 \leq x < 0.13 \\ 0, & 0 \leq x < 0.13 \end{cases} \qquad (G = 1)$$

$$\mu_G^l(x_l) = \mu_G^c(x_c) = \begin{cases} 0, & 0 \leq x < \frac{G-2}{6} \\ 7x - (G-2), & \frac{G-2}{6} \leq x < \frac{G-1}{6} \\ G - 7x, & \frac{G-1}{6} \leq x < \frac{G}{6} \\ 0, & \frac{G-1}{8} \leq x < 1 \end{cases} \qquad (G = 2, 3,4,5,6) \qquad (3.16)$$

$$\mu_7^l(x_l) = \mu_7^c(x_c) = \begin{cases} 0, & 0 \leq x < 0.85 \\ 7x - 6, & 0.85 \leq x < 1.0 \end{cases} \qquad (G=7)$$

Where $\mu_1^l(x_l), \mu_G^l(x_l), \mu_7^l(x_l), \mu_1^c(x_c), \mu_G^c(x_c), \mu_7^c(x_c)$ are the membership functions of likelihood and consequences based on the different grades (i.e. scales) (G) of the fuzzy numbers,

x_l and x_c are the latent uncertain variables for likelihood and consequences, respectively.

In the proposed risk assessment model, likelihood and consequences of failure were considered the input while the risk of failure was considered the output. The relationship between the input and output variables were represented in the form of if then rules as shown in Equation 3.17.

F_i: $if\ x_i\ is\ A_i\ and\ x_j\ is\ A_j, then\ y\ is\ B_{ij}$ (3.17)

Where, Fi is the fuzzy relation, x_i and x_j are the inputs (antecedent) linguistic variable, A_i and A_j are the input linguistic constants, y is the output (consequent) linguistic variable and B_{ij} is the consequent linguistic constant. Each rule was regarded as a fuzzy relation: $\mathrm{F_i(x \times y) \rightarrow [0,1]}$ which was computed by using fuzzy conjunctions. "AND" operator was used in the proposed base of rules in the risk assessment model for which the fuzzy conjunction was "AxB" computed by a minimum operator as shown in Equation 3.18.

$$F_i = A_i \times B_i,\ \ \mu_{Fi}(x_i, y) = \mu_{Ai}(x_i) \cap \mu_{Bi}(y) \quad (3.18)$$

Table 3.4 shows the base of rules used to construct the fuzzy inference surface shown in Figure 3.16 which represents the relation between the risk and both the likelihood and consequences of failure.

Table 3.4: Base of Rules Used to Determine the Risk of Failure in Sewer Pipelines

Rule No		**Likelihood**		**Consequences**		**Risk**
R_1	*If*	Extremely Low	*And*	Insignificant	*Then*	Extremely Low
R_2	*If*	Extremely Low	*And*	Very Low	*Then*	Very Low
R_3	*If*	Extremely Low	*And*	Low	*Then*	Very Low
R_4	*If*	Extremely Low	*And*	Medium	*Then*	Low
R_5	*If*	Extremely Low	*And*	High	*Then*	Low
R_6	*If*	Extremely Low	*And*	Very High	*Then*	Medium
R_7	*If*	Extremely Low	*And*	Catastrophic	*Then*	Medium
R_8	*If*	Very Low	*And*	Insignificant	*Then*	Very Low
R_9	*If*	Very Low	*And*	Very Low	*Then*	Very Low
R_{10}	*If*	Very Low	*And*	Low	*Then*	Low
R_{11}	*If*	Very Low	*And*	Medium	*Then*	Low
R_{12}	*If*	Very Low	*And*	High	*Then*	Medium
R_{13}	*If*	Very Low	*And*	Very High	*Then*	Medium
R_{14}	*If*	Very Low	*And*	Catastrophic	*Then*	High
R_{15}	*If*	Low	*And*	Insignificant	*Then*	Very Low

Table 3.4 (Cont'd): Base of Rules Used to Determine the Risk of Failure in Sewer Pipelines

Rule No		Likelihood		Consequences		Risk
R_{16}	*If*	Low	*And*	Very Low	*Then*	Low
R_{17}	*If*	Low	*And*	Low	*Then*	Low
R18	*If*	*Low*	*And*	*Medium*	*Then*	*Medium*
R19	*If*	*Low*	*And*	*High*	*Then*	*Medium*
R20	*If*	*Low*	*And*	*Very High*	*Then*	*High*
R21	*If*	*Low*	*And*	*Catastrophic*	*Then*	*High*
R_{25}	*If*	Medium	*And*	Medium	*Then*	Medium
R_{26}	*If*	Medium	*And*	High	*Then*	High
R_{27}	*If*	Medium	*And*	Very High	*Then*	High
R_{28}	*If*	Medium	*And*	Catastrophic	*Then*	Very High
R_{29}	*If*	High	*And*	Insignificant	*Then*	low
R_{30}	*If*	High	*And*	Very Low	*Then*	Medium
R_{31}	*If*	High	*And*	Low	*Then*	Medium
R_{32}	*If*	High	*And*	Medium	*Then*	High
R_{33}	*If*	High	*And*	High	*Then*	High
R_{34}	*If*	High	*And*	Very High	*Then*	High
R_{35}	*If*	High	*And*	Catastrophic	*Then*	Very High
R_{36}	*If*	Very High	*And*	Insignificant	*Then*	Medium
R_{37}	*If*	Very High	*And*	Very Low	*Then*	Medium
R_{38}	*If*	Very High	*And*	Low	*Then*	High
R_{39}	*If*	Very High	*And*	Medium	*Then*	High
R_{40}	*If*	Very High	*And*	High	*Then*	Very High
R_{41}	*If*	Very High	*And*	Very High	*Then*	Very High
R_{42}	*If*	Very High	*And*	Catastrophic	*Then*	Extremely High
R_{43}	*If*	Extremely High	*And*	Insignificant	*Then*	Medium
R_{44}	*If*	Extremely High	*And*	Very Low	*Then*	High
R_{45}	*If*	Extremely High	*And*	Low	*Then*	High
R_{46}	*If*	Extremely High	*And*	Medium	*Then*	Very High
R_{47}	*If*	Extremely High	*And*	High	*Then*	Very High
R_{48}	*If*	Extremely High	*And*	Very High	*Then*	Extremely High
R_{49}	*If*	Extremely High	*And*	Catastrophic	*Then*	Extremely High

Figures 3.17 and 3.18, they show how the risk value increases with the increase of likelihood and consequences of failures.

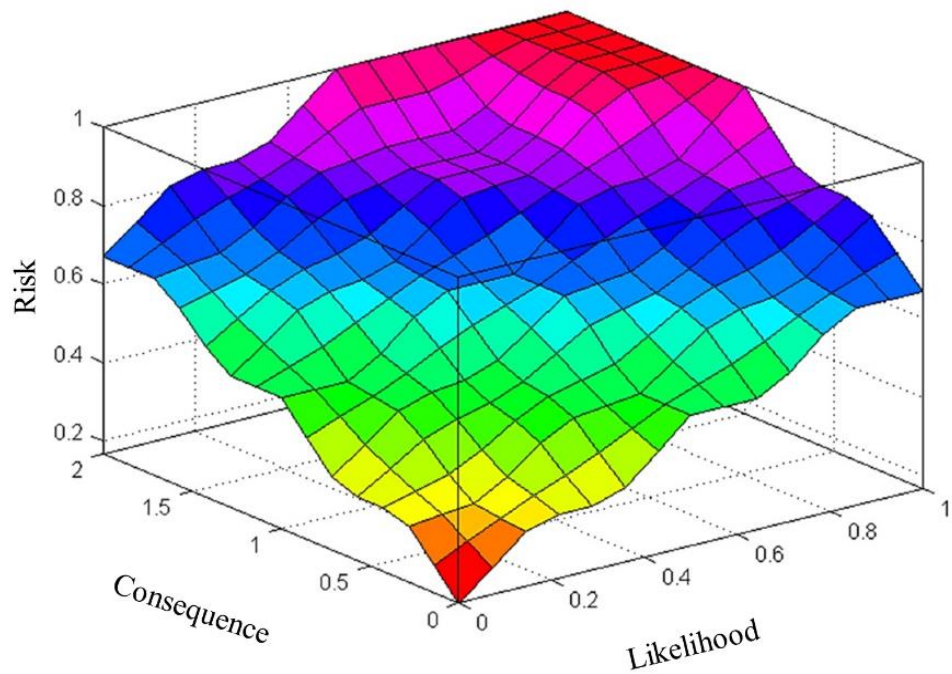


Figure 3.16: Fuzzy Surface for Risk of Failure

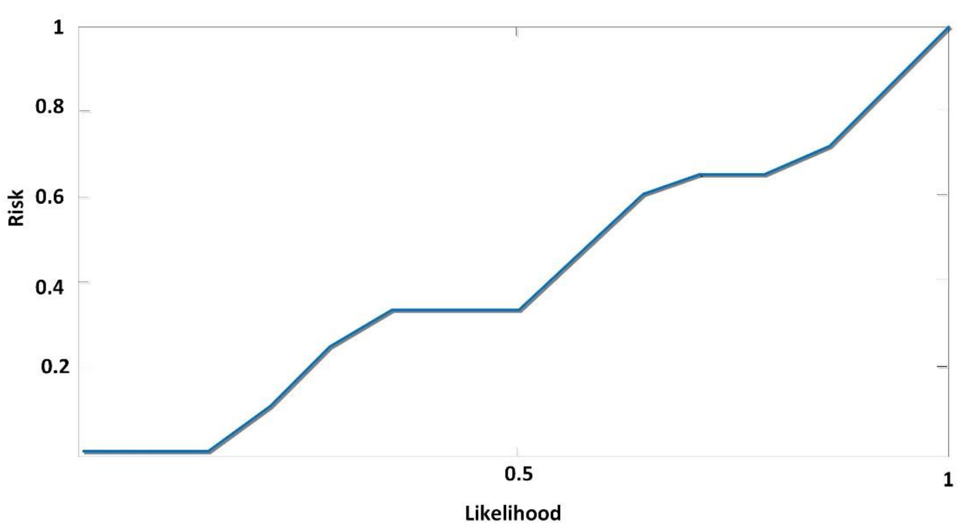


Figure 3.17: Likelihood versus Risk of Failure

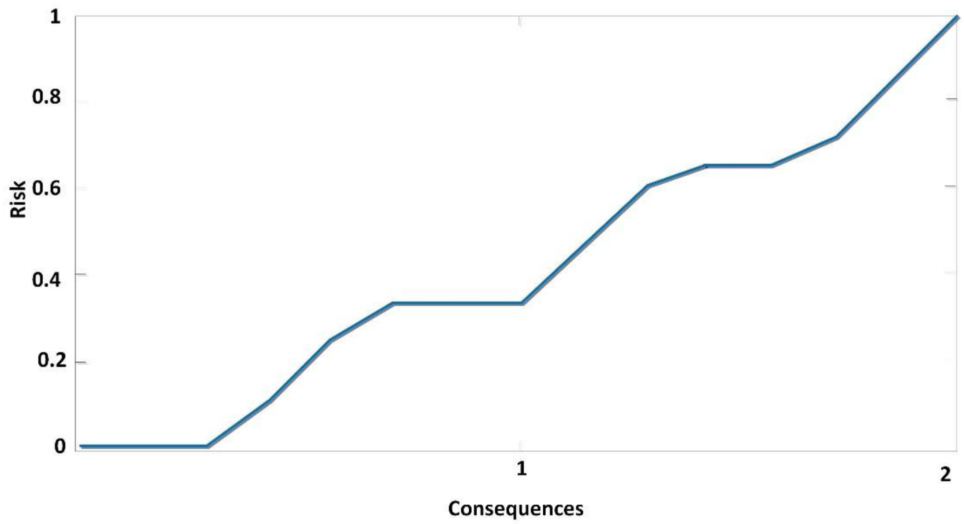


Figure 3.18: Consequences versus Risk of Failure

3.2.3.4 Optimization Model for Inspection Scheduling

From the above, one can conclude that to determine which pipelines should be inspected first, criticality indexes aren't always enough because there might be an endless amount of combinations for the critical sections that require inspections. Also, the presence of limited funds allocated for inspection may increase the complexity of decision making regarding which pipe sections should get inspected first. As such, an optimization problem is formulated using the different ranks of the pipelines, their defects, and the available budget. Based on the different types of defects and the cost for inspection technologies, a ranking for the pipelines inspection and the inspection intervals are identified. The optimization problem in this research is categorized as combinatorial optimization problem for which solving it depends on a well-known concept called branch and bound where the different possible solutions are divided into nodes and each node is further divided into other nodes. Figure 3.19 shows the algorithm used in solving the optimization problem modelled in GAMS using branch and bound method where the upper and lower bounds represent the different nodes after dividing them.

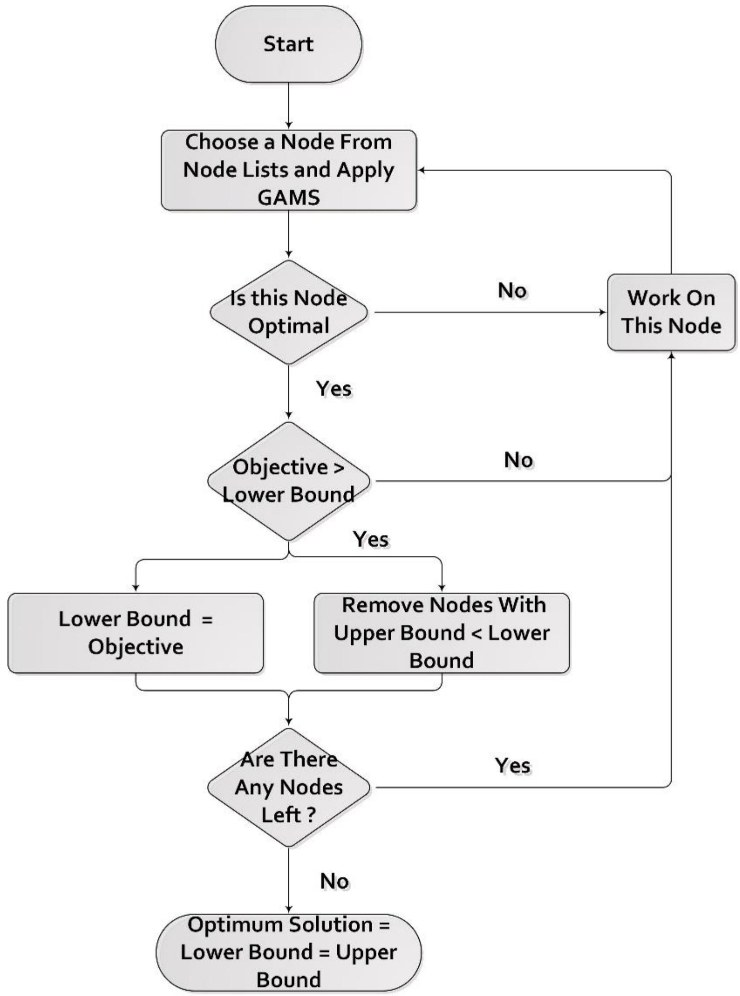


Figure 3.19: Optimization Problem Solution Using General Algebraic Modelling System

Figure 3.20 summarizes the proposed inspection scheduling model. The different pipelines to be inspected having different defects and risk indices, each risk index is compared to the other pipelines' risk indices and pipelines with a higher risk index are the ones that should be chosen for inspection. The inspection costs are calculated for the chosen pipelines and the summation of these costs is compared to the allocated budget which is the restraining criteria for the proposed algorithm. General algebraic modeling systems are designed to solve optimization problems that are large and complex and that can be either linear, nonlinear, or mixed integer.

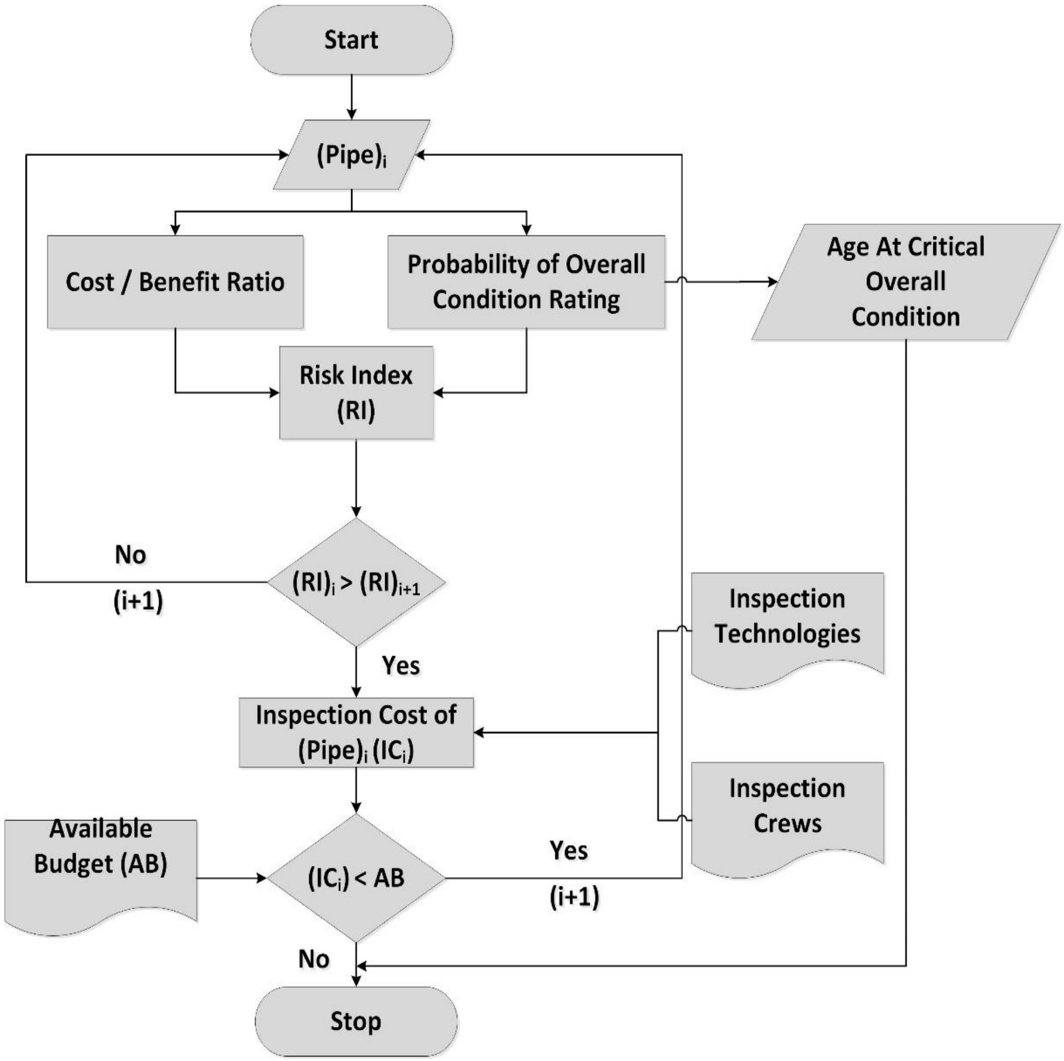


Figure 3.20: Proposed Inspection Scheduling Model

One of the major advantages of using GAMS is its ability to save computational effort and time by simplifying the formulated problem as much as possible. When using GAMS, the optimization problem is formulated into a high level modeling language at first, then GAMS solver starts breaking down this problem into solvable parts to carry out optimization (GAMS User Guide, 2010). Usually problems concerned with decision making regarding asset renewals, inspections, and fund allocation are large scale problems that require robust techniques to solve them, such as the GAMS optimizer tools.

3.2.3.4.1 Multi-objective optimization for inspection scheduling

The deterioration and risk assessment models should yield a priority list for all pipelines that require inspection and the corresponding time of failure (probability of condition rating of 3 or higher at a certain time t). The presence of numerous pipelines that require inspection at the same time with budget constraints could result in a tradeoff problem between which pipelines should be inspected without exceeding the allocated budget for inspection. As such multi objective optimization problem is formulated to select the optimal inspection technology to minimize total cost and time subject to budget constraints. The base of the formulated MILP is a combination of the traditional knapsack and travelling salesman optimization problems. The main three objectives in the proposed problem is to maximize the number of inspected pipeline sections, decrease the cost and time of inspecting these pipeline sections and relocation of the crew assigned for the inspection activity. Equation 3.19, 3.20 and 3.21 show the three objectives of the proposed optimization model.

$$\textbf{\textit{Minimize}}\ T.I.C. = \sum_{i\in P}\sum_{j\in C}\sum_{k\in T}(x_{j,k}^{i} * \ CI_{j,k}^{i}) + \sum_{i\in P}\sum_{j\in C}\sum_{k\in T} z_{j,k}^{i,l} * [\, C_R + C_M] \qquad (3.19)$$

$$\textbf{\textit{Minimize}}\ T.I.T. = \sum_{i\in P}\sum_{j\in C}\sum_{k\in T}(x_{j,k}^{i} * \ TI_{j,k}^{i}) + \sum_{i\in P}\sum_{j\in C}\sum_{k\in T} z_{j,k}^{i,l} * T_R \qquad (3.20)$$

$$\textbf{\textit{Maximize}}\ T.I.P. = \sum_{i\in P}\sum_{j\in C}\sum_{k\in T} x_{j,k}^{i} \qquad (3.21)$$

$\forall\ i \in P, j \in C, k \in T, l \in P \setminus\{i\}\ , i \neq j \neq k \neq l$

Where, $T.I.C.$: Total inspection cost for pipeline sections,

$T.I.T.$: Total inspection times required to inspect all pipeline sections

$T.I.P.$: Total inspection times required to inspect all pipeline sections

$x_{j,k}^{i}$: is a decision variable that takes a value of 1 when pipeline (*i*) is inspected by crew (*j*) using technology (*k*) and 0 otherwise,

$CI_{j,k}^{i}$: Inspection cost of pipeline section (*i*) by crew (*j*) using inspection technology (*k*),

C_R: Relocation cost between site location of pipeline (i) and site location of pipeline (*j*),

C_m: Site mobilization costs,

$TI_{j,k}^{i}$:Time taken for inspecting pipeline section by crew (i) at location (j) using inspection technology (k)

T_R: Relocation time between site location of pipeline (i) and site location of pipeline (*j*),

C, P, T are sets of available number of crews, pipeline site locations and inspection technologies, respectively.

3.2.3.4.2 Budget and resources constraints

As a result of crew relocation between different sites, a new decision variable would appear in Equations 3.19 and 3.20 representing pipeline (*l*) to be inspected (i.e. $x_{j,k}^{l}$) which should be multiplied by the original decision variable previously defined (i.e. $x_{j,k}^{i}$). To avoid the arising non linearity an exact reformulation of the equations was carried out to convert such problem into a linear mixed integer one. A new decision variable $z_{j,k}^{i,l}$ was introduced to Equations 3.19 and 3.20 in which the value of this variable would only take a value of 0 or 1 if $x_{j,k}^{i}$ and $x_{j,k}^{l}$ were 0 or 1 as shown in Equations 3.22 to 3.25.

Subject to:

$$z_{j,k}^{i,l} \leq x_{j,k}^{i} \qquad (3.22)$$

$$z_{j,k}^{i,l} \leq x_{j,k}^{l} \qquad (3.23)$$

$$z_{j,k}^{i,l} \geq x_{j,k}^{i} + x_{j,k}^{l} - 1 \qquad (3.24)$$

$$x_{j,k}^{i}, x_{j,k}^{l}, z_{j,k}^{i,l} = \{0, 1\} \qquad (3.25)$$

Equation 3.26 shows another constraint from which the user can determine the number of pipelines so that the corresponding inspection costs would not exceed a certain budget. Additionally, to enhance the performance of the model two conditions as shown in Equations 3.27

and 3.28 were defined to not take pipelines having a risk index less than and a year of failure more than the ones specified by the user from which a subset of pipelines would be the new search space.

$$\sum_{i\in P}\sum_{j\in C}\sum_{k\in T}(x_{j,k}^{i} * \; CI_{j,k}^{i}) \; \leq B_{All} \tag{3.26}$$

$$x_{j,k}^{i} * R_{j,k}^{i} \geq R_{Threshold} \tag{3.27}$$

$$x_{j,k}^{i} * T_{i}^{f} \leq T_{DM}^{PH} \tag{3.28}$$

Where B_{All}: Budget allocated from the municipality for inspection,

$R_{Threshold}$: Risk of failure for pipeline set by the decision maker,

$R_{j,k}^{i}$: Risk of failure for pipeline (i) inspected by crew (j) using technology (k),

T_{i}^{f}: Time at which pipeline section would reach failure and

T_{DM}^{PH}: Year set by the decision maker as planning horizon.

Several constraints were defined for the formulated problem; a constraint to ensure that the inspection costs for inspected pipe sections won't exceed the allocated budget was defined as per Equation 3.26. Also, to reduce the search space and as per Equations 3.27 and 3.28, a condition was defined in the model to take into consideration the pipelines having a year and risk of failure values exceeding the planning horizon and risk threshold value set by the user. To ensure that the same inspection crew will not work on two separate pipeline sections at the same time, disjunctive constraints were defined along the other problem constraints as shown in Equation 3.29 using if statements.

$$\sum_{i\in P}\sum_{j\in C}\sum_{k\in T} x_{j,k}^{i} \; \leq |C| - 1 \tag{3.29}$$

Where $|C|$ is the subset of the crews {C1, C2, C3, …..,Cn} = {1,2,3,…n}

To solve the multi-objective using MIP in the GAMS environment, a single objective problem was formulated using dynamic weights as shown in Equations 3.30 and 3.31. The different dynamic weights were generated randomly from which an optimum Pareto frontier for the optimum solution set can be obtained.

Minimize $F(x) = \sum_{n=1}^{N} w_n f_n(x)$ (3.30)

Using dynamic weighted aggregation to determine the three weights

$$w_i = \frac{\mu_i}{\sum_{i=1}^{n} \mu_i} \tag{3.31}$$

The resultant single objective function would be as shown in Equation 3.32.

$$F(x) = w_1 * T.I.T + w_2 * T.I.C - w_3 * T.I.P. \tag{3.32}$$

Such that $\sum_{n=1}^{N} w_n = 1$ and N is the total number of objective functions (i.e. 3).

3.3. Recap

In this chapter, the methodology adopted in this research was presented. The different topics of related literature were briefly discussed. Different developed models such as the likelihood, consequences, and risk assessment of failure were presented. The assumptions and concepts used in the development of each model were discussed. The model developed to optimize inspection of sewer pipeline sections was also introduced.

Chapter 4: Data Collection

4.1. Introduction

To develop the different models in this research, three types of datasets were used. The first dataset comprised GIS information about the pipelines characteristics. The second type of datasets were CCTV inspection reports that include pipeline defects. The third type was the codes of practice from which the different defect severities were identified. Figure 4.1 shows a description of the different collected data.

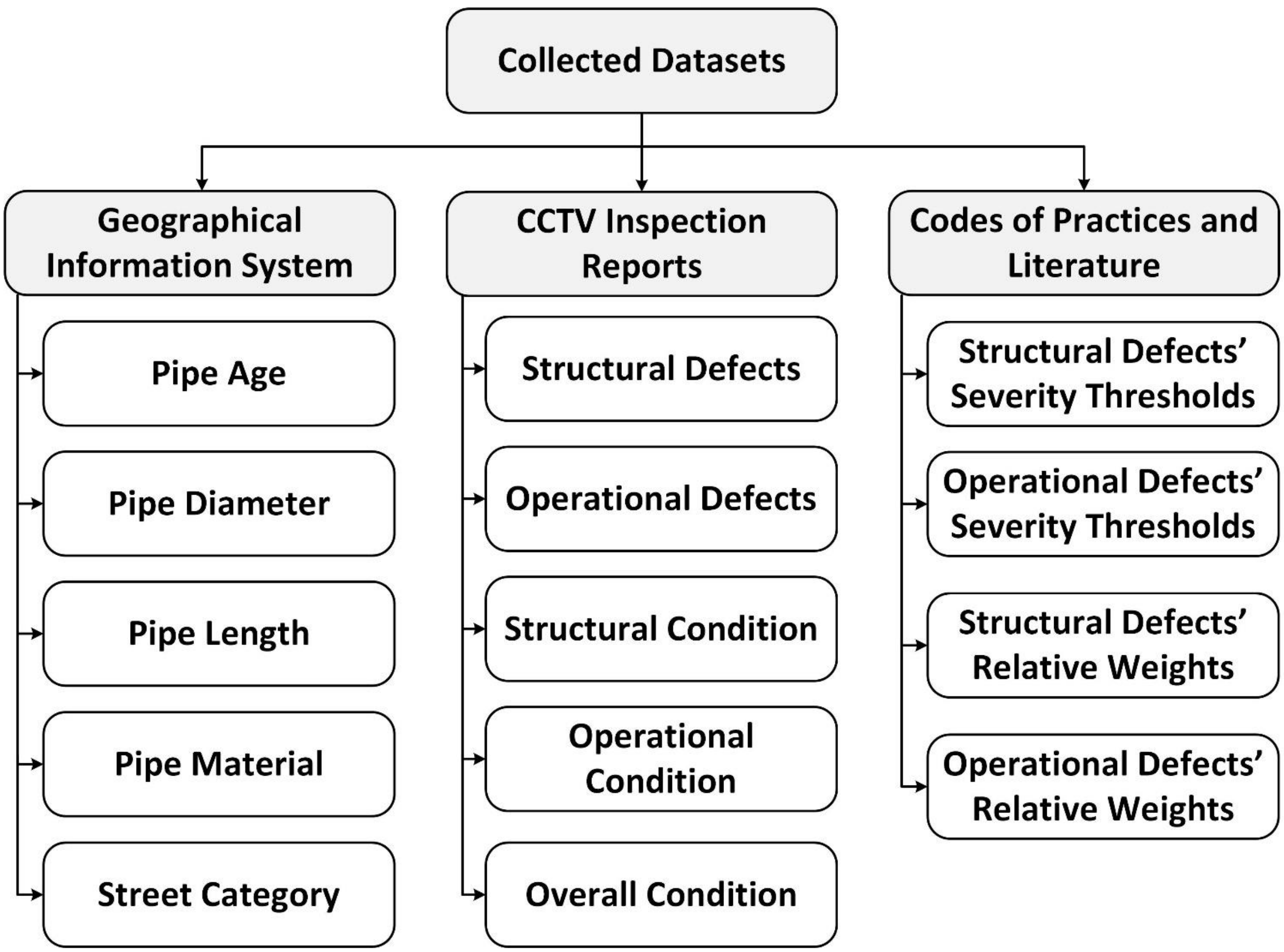


Figure 4.1: Description for Collected Data Used in Modes' Development

4.2. CCTV Inspection Reports

The dataset used in the BBN model development was chosen from an inventory of CCTV inspection reports for an existing network in Doha, Qatar. The data comprised records for more than 1900 sections with a total length of 77 kilometers, all consisting of different materials and diameters. Figures 4.2 and 4.3 show the distribution of diameters and materials of the pipes among the collected CCTV inspection reports. In order to conform to the characteristics for data quality presented by Davies (2001), only 1677 sections were considered with a total inspected length of 38 kilometers. The condition rating for these sections followed the EN13508 (British Standards Institution (BSI), 2012), and Class method DWA-M 149-3 (German Association for Water, Wastewater and Waste (DWA), 2015).

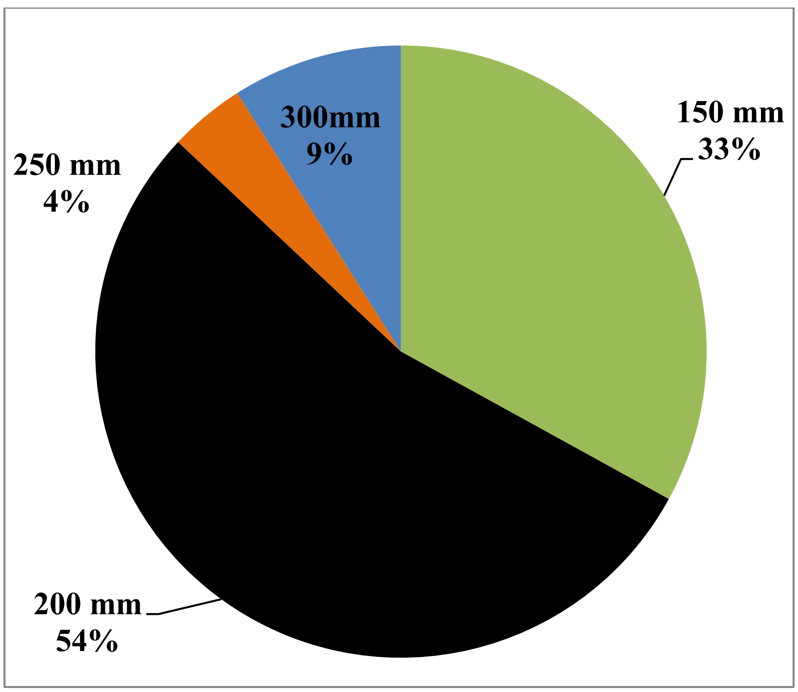


Figure 4.2*:* Distribution of Pipes' Diameters in Collected Data (Doha- Qatar)

The defects in these standards are given acronyms of three letters and an additional letter to represent the sub category of that defect. These sections were found acceptable in terms of completeness, and accuracy. To ensure the consistency of data and to minimize variation, all inspection reports used, were gathered from the same source (the same contractor performing the inspections) (i.e. different sources could make the data subject to variation). Table 4.1 shows a sample for the different defects in the sections found in the gathered CCTV inspection reports. In this table the different defect acronyms are followed by a description of each, with all the relevant data such as pipe diameter, length, material, structural, operational and overall condition rating for this section.

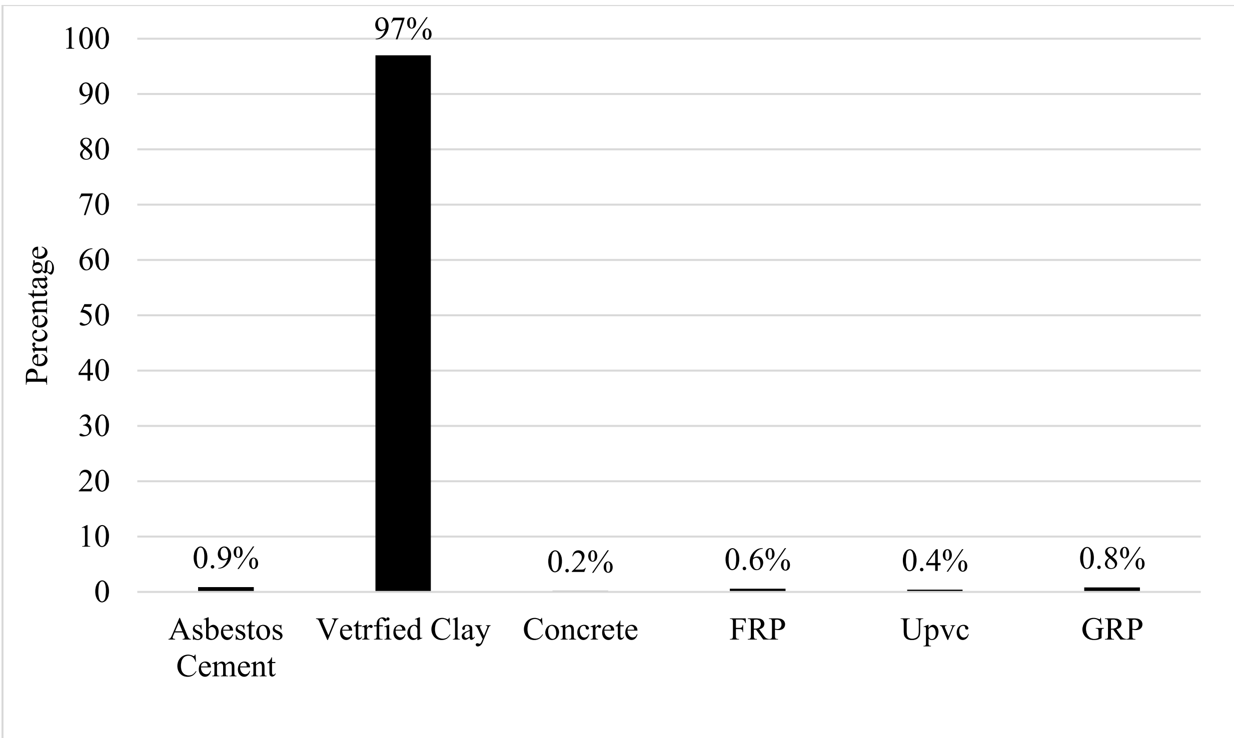


Figure 4.3*:* Distribution of Pipes' Material in Collected Data (Doha- Qatar)

By analyzing the different types of defects found in the collected CCTV inspection reports, it was discovered that structural defects form 47% of the total defects found in the inspected sections, while the operational defects make up the remaining 53%. In the structural defects, fractures and cracks formed 27% of those defects, whereas the remaining 20% were divided by a 1:2 proportion. Attached deposits and infiltration had the highest share in the operational defects with 22% and 17%, respectively.

Table 4.1: Sample for Defects from CCTV Inspection Reports (Doha – Qatar)

Section	Defect	Length	Diameter	Material	Description	SC	OC	Overall
	BBBB				Attached deposits-grease- cross section reduction = 1%			
	BAF B				Surface damage- spalling			
	BBDA				Ingress of soil – sand- cross section reduction = 1%			
	….				….			
1	BABA	22	150	AE	Fissure, surface crack, longitudinal, Width = 0.30mm	3	3	3
	BAF B							
	BBDA				Soil Intrusion, sand, cross section reduction = 2%			
	⋮				⋮			
	BBDD				Soil Intrusion, gravel, cross section reduction = 5%			

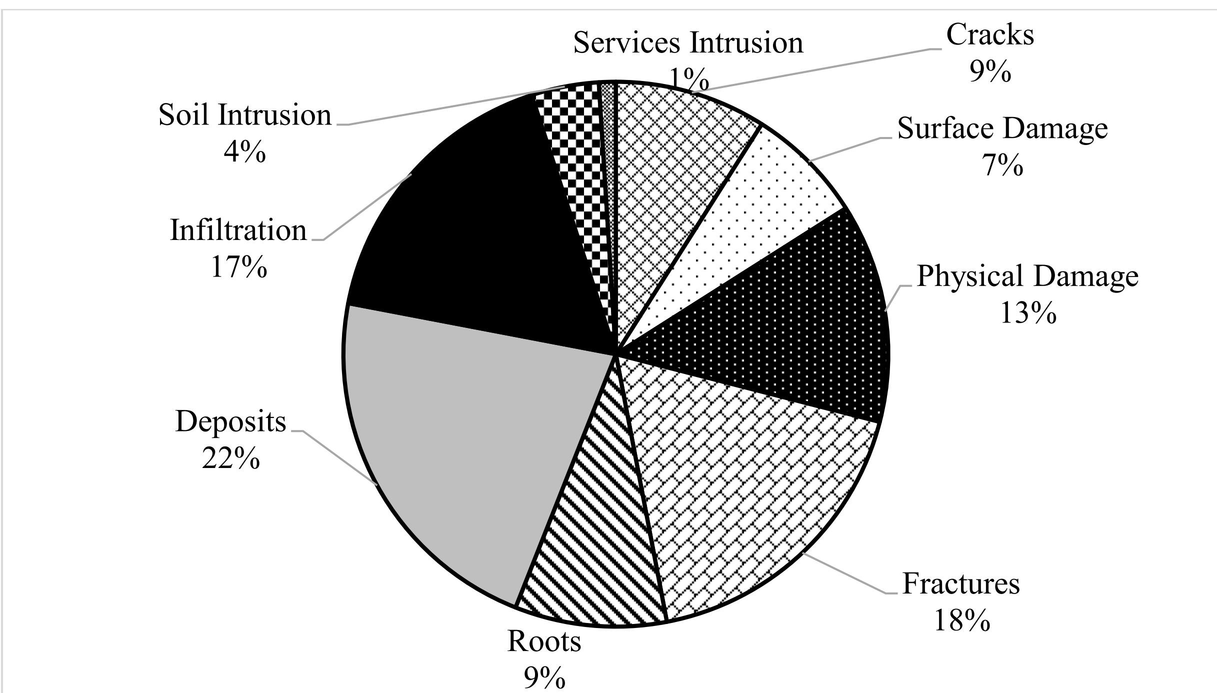


Figure 4.4*:* Distribution of Different Defect Types in Collected Data (Doha- Qatar)

The remaining 14% was distributed among roots, soil, and services intrusion. The distribution of different defects is depicted in Figure 4.4. Figure 4.5 shows the structural and operational defects in the pipelines in Qatar dataset. The majority of the sections (73%) had structural condition ratings between 3 and 4 (poor and critical conditions). Similarly, three quarters of the sections had an operational condition of 2, 3 and 4.

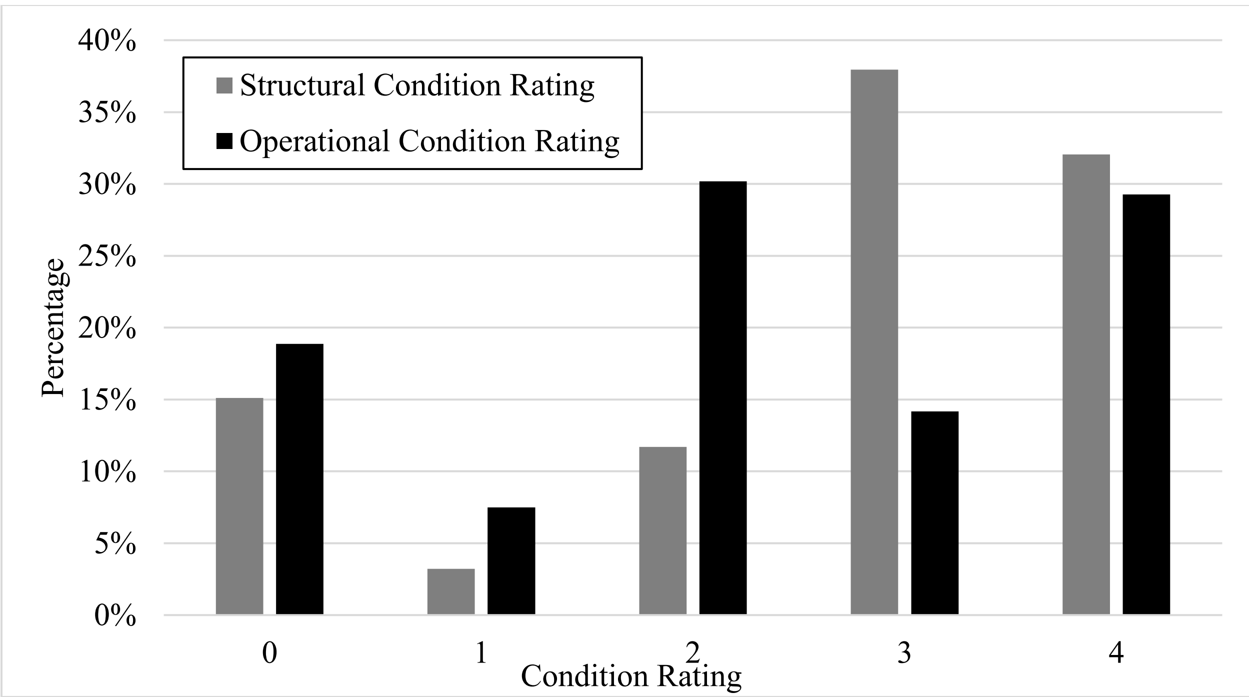


Figure 4.5*:* Distribution of Condition Rating in Collected Data (Doha- Qatar)

As shown in Figure 4.3, more than 50% of the pipeline sections are 200 mm in diameter and more than 95% of their total lengths are vitrified clay pipes. As such, another dataset was used in an attempt to increase the diversity of data available and to make it more descriptive. The defects found in the CCTV inspection reports for another existing sewage network in the city of Laval, Quebec, Canada were also used. The data comprised more than 260 inspected sections of a total length of approximately 5 kilometers. Figures 4.6 and 4.7 show the distribution of different pipe diameters and materials in these inspected sections.

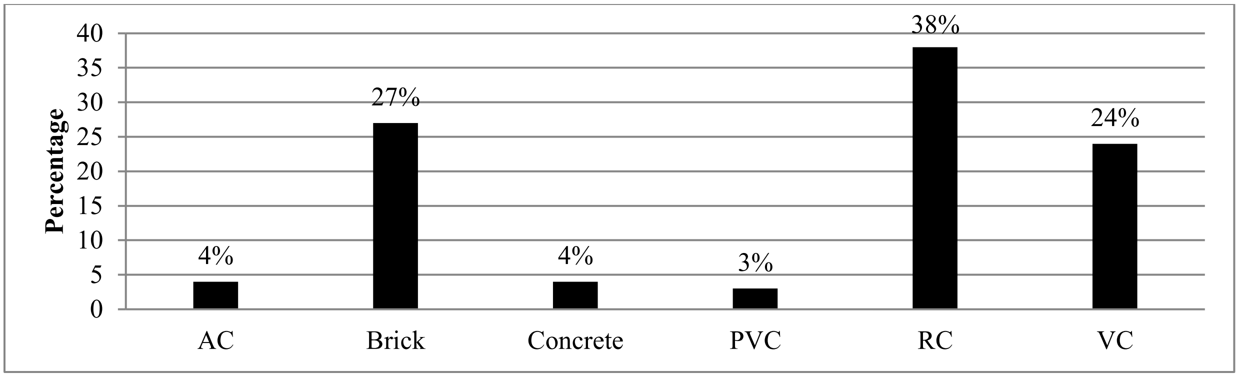


Figure 4.6: Distribution of Pipes' Material in Collected Data (Quebec- Canada)

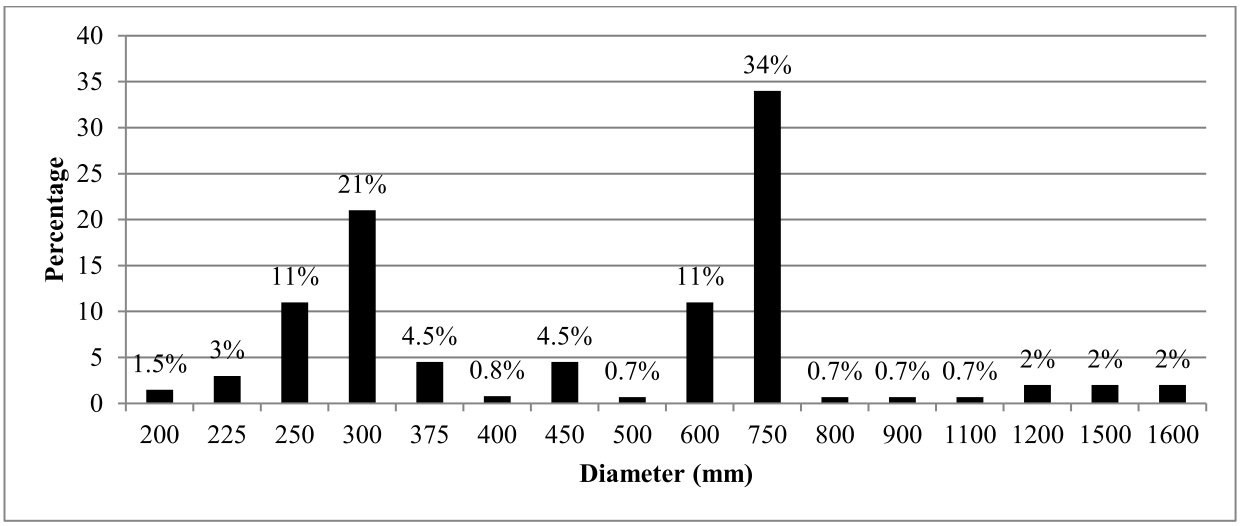


Figure 4.7: Distribution of Pipes' Diameters in Collected Data (Quebec- Canada)

Similar to the first dataset, the CCTV inspection reports were tabulated in the form shown in Table 4.2. Information such as diameter, material, length and different defect types with the location of these defects in the section were given in addition to the structural and operational conditions. Figure 4.8 shows the distribution of defects found in the city of Laval CCTV inspection reports. As depicted in the figure, the highest share of defects belonged to the structural category, where 53% of the defects were divided into cracks, fractures, physical damages and surface damages. The rest of the defects were distributed between infiltration with 44% and roots with a value of 3%. Figure 4.9 shows the distribution of the condition ratings in the same dataset. The figure shows that the operational conditions of the pipelines is better that that of the dataset in Doha, Qatar. Sixty-five percent of the pipes were in an excellent or very good condition (i.e. operational condition rating of 1 and 2). On the other hand, the structural condition was evenly distributed over the different condition ratings. Almost 22% of the structural condition ratings were 4 and the rest were distributed between condition ratings 1, 2, 3 and 5.

Table 4.2: Sample for Defects from CCTV Inspection Reports (Quebec- Canada)

Section	Diameter (mm)	Material	Length	@	Defect Type	SC	OC	Infiltration type
1	375	RC	68.7	2.3	Circular crack	2	2	No inf.
				20.5	Longitudinal crack			
2	450	RC	76.5	9.81	Visible aggregate, wall connection	2	5	No inf.
				10	Intrusion of the sealant filling, 40%,			
				10.81	Visible aggregate, wall connection			
				13.42	Visible aggregate, wall connection			
				15	Medium roots attached, 10%			
				⋮	⋮			
5	255	RC	52.5	17.21	Visible aggregate, wall connection	5	2	No inf.
				43.41	Visible aggregate, wall connection			No inf.
				45	Breakage in sewer pipe			
	255	RC	55.2	47.22	Continuous infiltration	3	4	Ir
				47.23	Visible aggregate, wall connection			No inf.

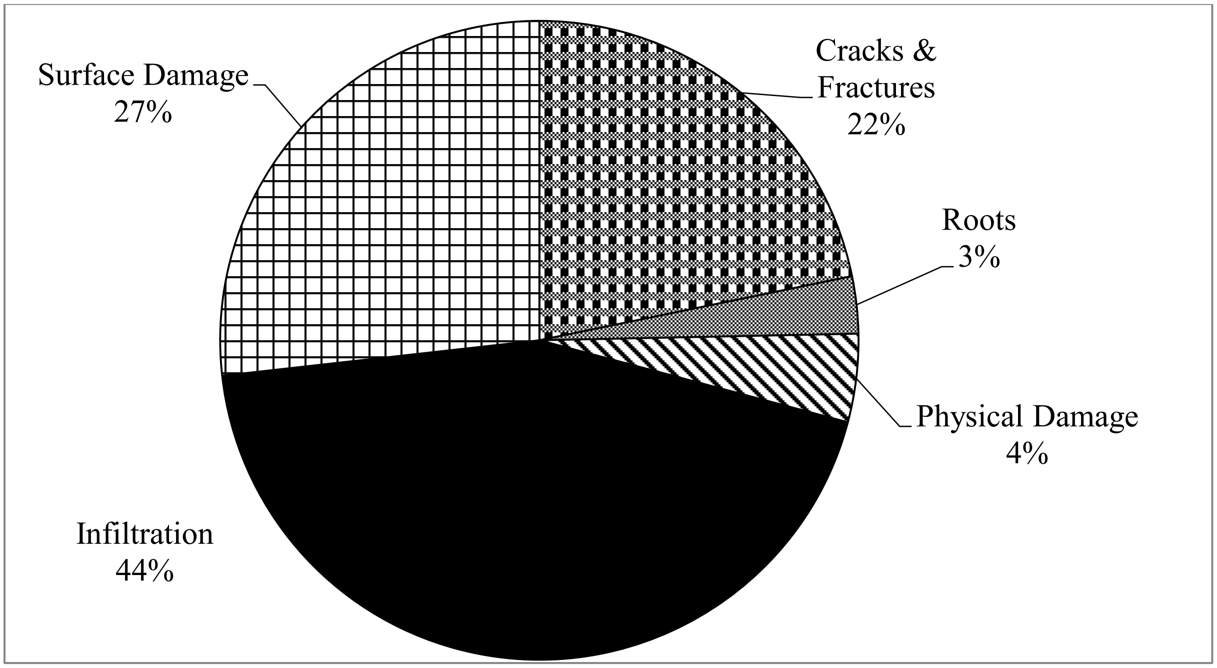


Figure 4.8*:* Distribution of Different Defect Types in Collected Data (Quebec- Canada)

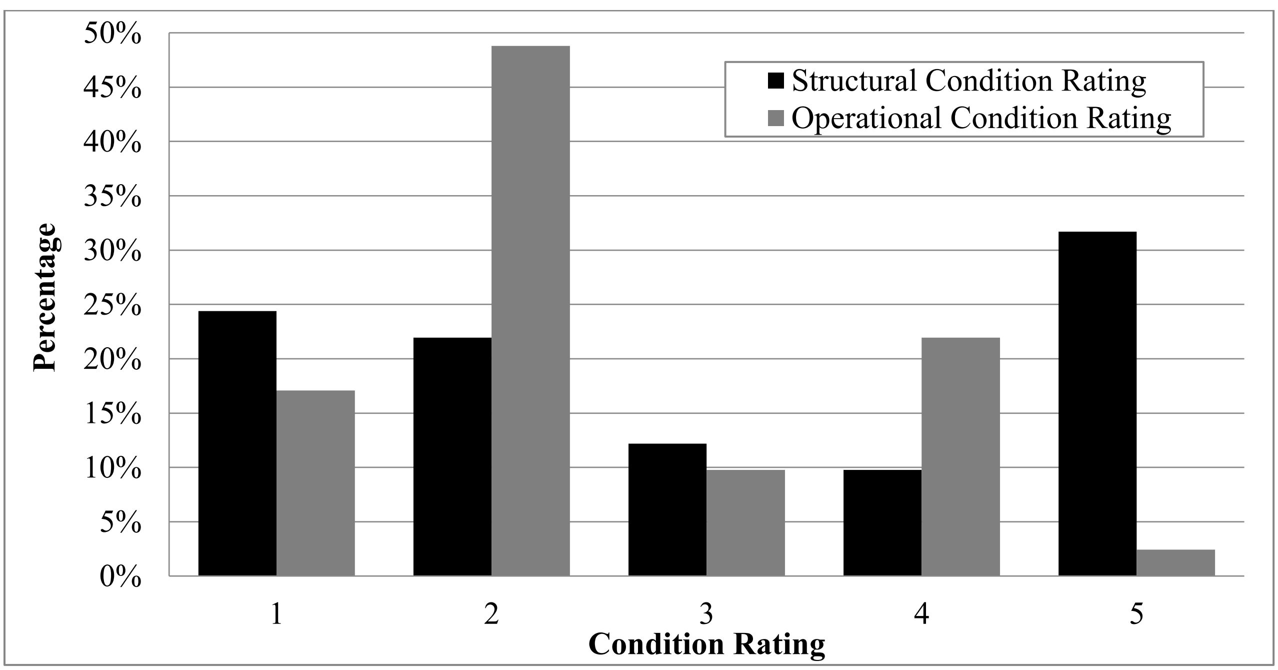


Figure 4.9*:* Distribution of Condition Rating in Collected Data (Quebec – Canada)

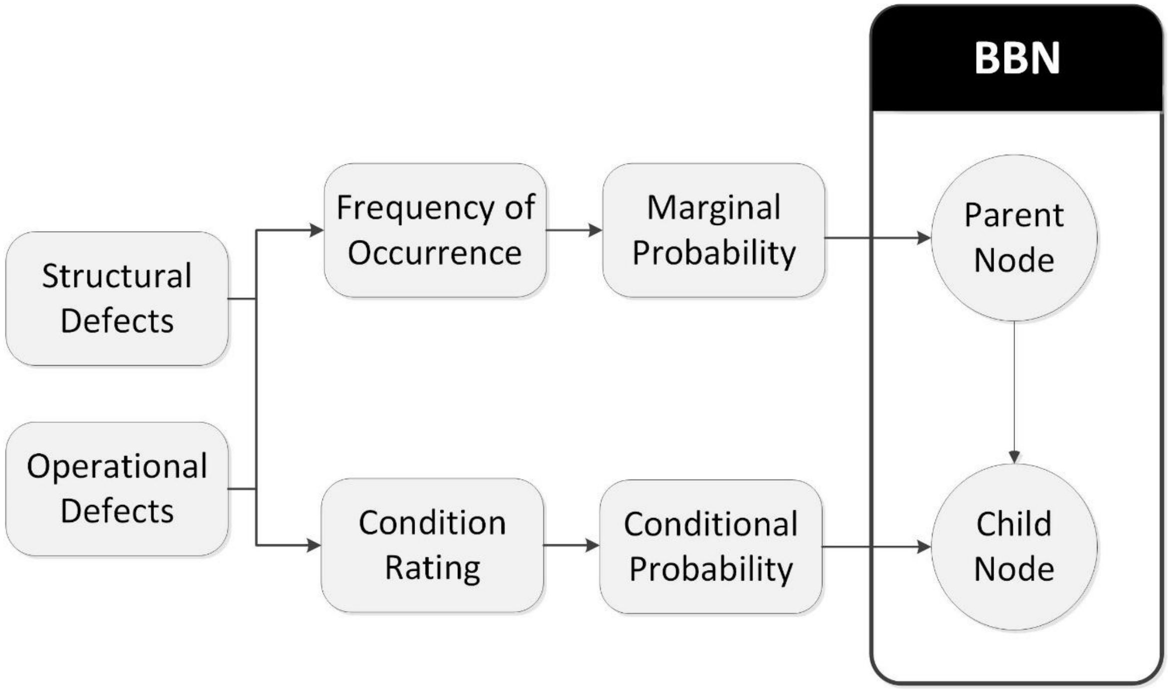


Figure 4.10*:* Data used to Develop BBN

The different defects found in the CCTV inspection reports were used to build the BBN required to determine the likelihood of failure as shown in Figure 4.10. The frequency of occurrence of these defects was used to determine the marginal probabilities of parent nodes. Additionally, the different structural, operational and overall condition ratings were used to determine the conditional probability of the child node, provided that a certain defect occurred.

4.3. Geographic Information System (GIS) Files

The second type of data was the GIS shape files in which similar information for the pipelines was found. Table 4.3 shows a sample for the data found in the GIS shape files. As shown in the table, data similar to that found in the CCTV inspection reports are displayed, such as the length, diameter, material, year of installation, start and end manholes. In addition to this information, whether the pipeline was connected or disconnected, data on flow, and invert levels of the upstream and downstream from which depth could be calculated, were also included.

Table 4.3: Sample for GIS Shapefiles for Sewer Pipelines (Doha- Qatar)

Id	Length (m)	Diameter (mm)	Material	fm_inv_lvl	to_inv_lvl	Flow	Year_laid	status	f_mh	t_mh
2293	61.0	250	VC	38.54	36.61	82	1992	Connected	S1/A8/9/2/1	S1/A8/9/2
3796	48.03	200	VC	-4.18	-4.50	27	1993	Connected	25/9A/2	25/9A/1
4120	26.85	300	VC	0.59	0.48	62	1986	Connected	25/5/16	25/5/15
4176	53.01	150	VC	0.57	0.22	13	1985	Connected	25/7/B4/5	25/7/B4/4
4255	49.76	150	VC	0.22	-0.10	13	1985	Disconnected	25/7/B4/4	25/7/B4/3
4451	45.38	150	VC	-0.81	-1.10	12	1985	Connected	25/7/B4/1	25/7/B4

Similar to Table 4.4, information regarding the streets were also extracted from the GIS files. This information comprised data regarding the class of the road, the number of lanes, and whether the street ran one-way or not. Figure 4.11 shows the superimposed layers of the streets and the pipelines. Each layer had an attribute table in which the user could view and choose the required data. Multinomial logistic regression was used to determine the probability by which the parent node would transfer from one state to the other. The categorical equations of multinomial logistic regression require two types of inputs which are the independent and dependent variables as shown in Figure 4.12. Information found in the GIS files was used as the explanatory variables. The names of the manholes were cross referenced with the CCTV dataset to determine the condition rating of the different sections to determine the dependent variables.

Table 4.4: Sample for GIS Shapefiles for Streets (Doha- Qatar)

FID	Type	One Way	Lanes
0	primary	Y	1
1	primary	Y	1
2	residential	Y	2
3	primary	N	3
4	primary	Y	2
6	residential	N	3
7	residential	N	2
8	residential	N	3

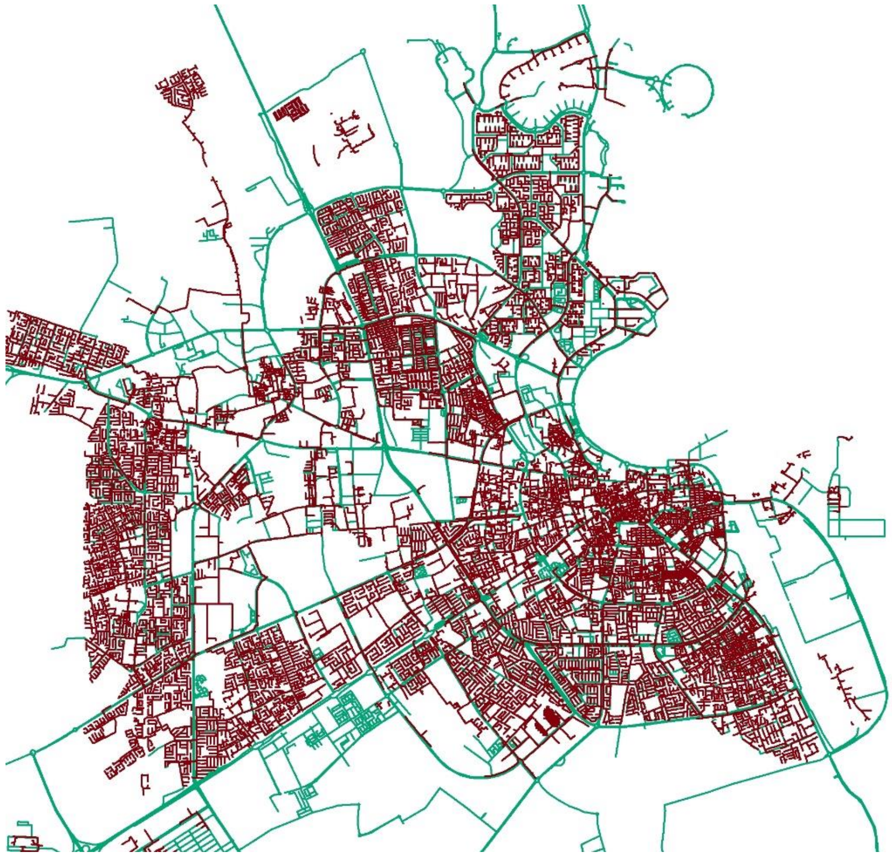


Figure 4.11*:* GIS Shapefiles for Sewer Pipelines and Streets (Doha-Qatar)

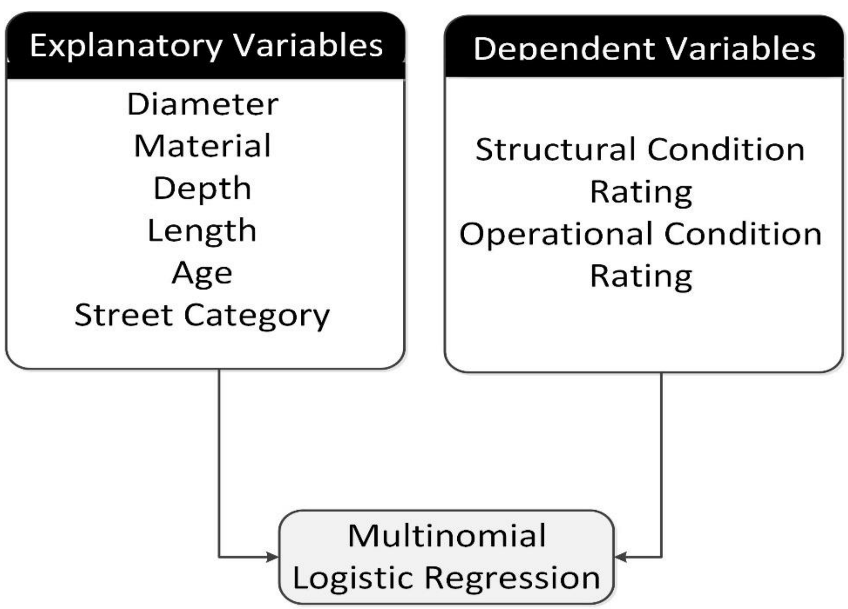


Figure 4.12*:* Data used to Develop Multinomial Logistic Regression

4.4. Codes of Practice and Literature

To determine the linguistic values for different defects in the BBN model, thresholds were collected from codes of practices to determine the corresponding linguistic variable to the different defect values. Tables 4.5 and 4.6 show the threshold values for the severity of different defects which are adopted from Rahman and Vanier (2004). As shown in the tables, different thresholds are specified for each defect from which the user can determine the severity of the defect and whether this defect is light, medium, or high.

Table 4.5: Different Structural Defect States and Corresponding Severity Threshold Values

Defects	Description	Distress Level	Thresholds
Deformation	Light		<5% change in diameter
	Moderate		5%–10% change in diameter
	Severe		11%–25% change in diameter
Crack and Fractures	Longitudinal	Light	Up to 3 cracks, no leakage or width = 10 mm
		Moderate	>3 cracks, leakage or 10 mm < width <=25 mm
	Circumferential	Light	Up to 3 cracks, no leakage or width = 10 mm
		Moderate	>3 cracks, leakage or 10 mm < width <=25 mm
	Complex	Light	Up to 3 cracks, no leakage or width = 10 mm
		Moderate	>3 cracks, leakage or 10 mm < width <=25 mm
	Severe		Multiple cracks, leakage or width >25 mm
Surface Damage	Light		<5 mm wall thickness lost, slight spalling or wear, pitting on metal pipe
	Moderate		5 to 10 mm wall thickness lost, exposed reinforcement or aggregates
	Severe		>10 mm pipe wall thickness lost, corroded reinforcement.
Sag	Light		< 50 mm
	Moderate		50 to 100 mm
	Severe		> 100 mm

Table 4.6: Different Operational Defect States and Corresponding Severity Threshold Values

Defects	Description	Distress Level
Root	Light	Fine roots, reduction in diameter <10%, F- fine roots, J-joint
	Moderate	Reduction in diameter 10% – 25%
	Severe	Reduction in diameter >25%, M-mass, J- joint
Encrustation	Light	Reduction in diameter <10%, J- joint
	Moderate	Reduction in dia.10% – 25%, J- joint
	Severe	Reduction in diameter >25%, H- heavy, J- joint
Protrusion	Light	Reduction in diameter <10%
	Moderate	Reduction in diameter 10%-25%
	Severe	Reduction in diameter >25%
Infiltration	Light	Seeping, dripping
	Moderate	Running, trickling
	Severe	Gushing, spurting

The relative weights used in the development of the BBN were adopted from another study (Daher et al. 2017). In this research, experts were sought to determine the relative weights of the different components in a segment (i.e. the weight of pipes to manholes in a sewage network) in addition to the relative weights of each defect and its impact on the structural and operational condition of the segment components. Figures 4.13, 4.14 and 4.15 show the different relative global weights of each defect with respect to the structural and operational condition in sewer pipelines. These weights were derived using Analytical network process where pairwise comparison was carried out based on relative importance determined by the experts using Saaty's nine-point scale (Saaty, 1996).

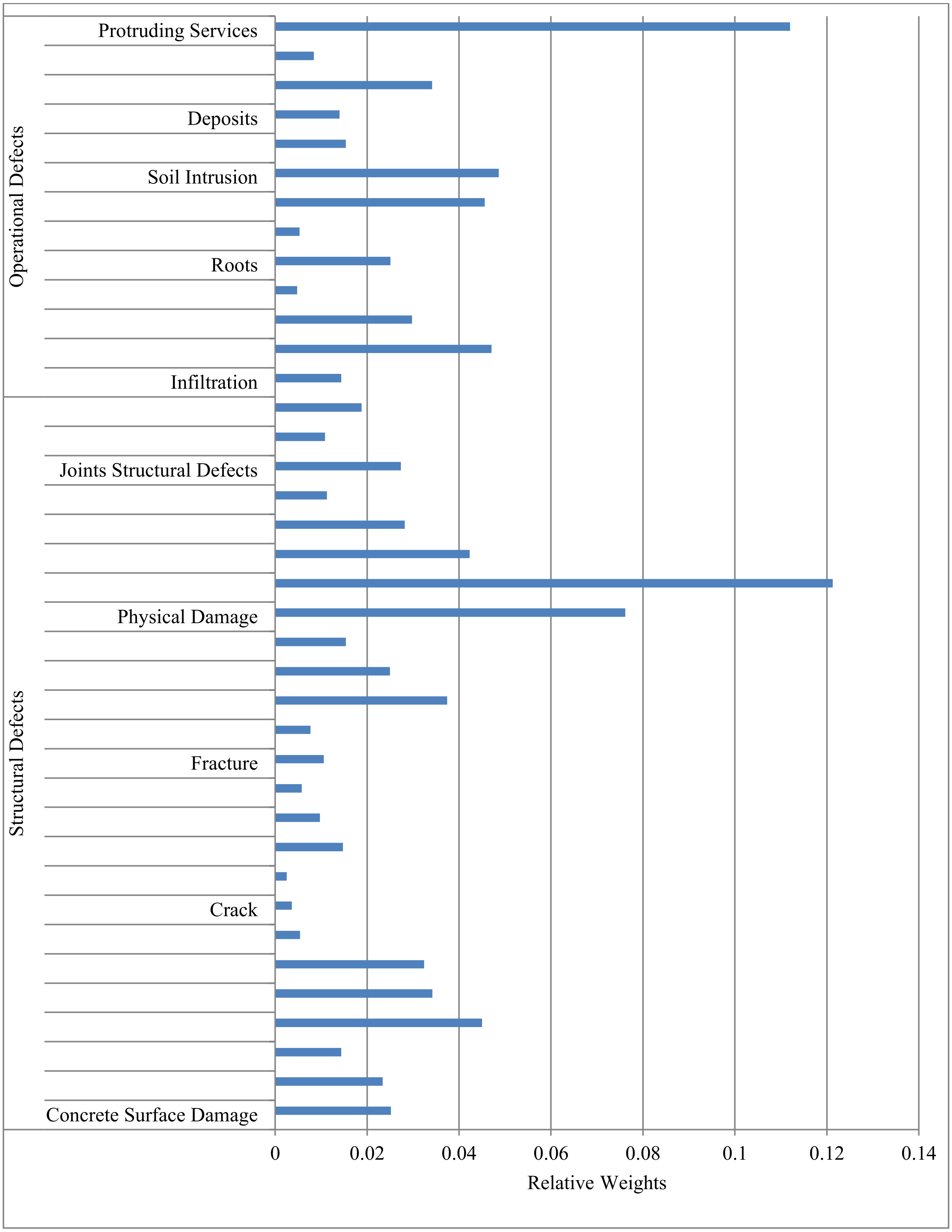


Figure 4.13: Sewer Pipelines Defects Relative Weights (Daher et al. 2017)

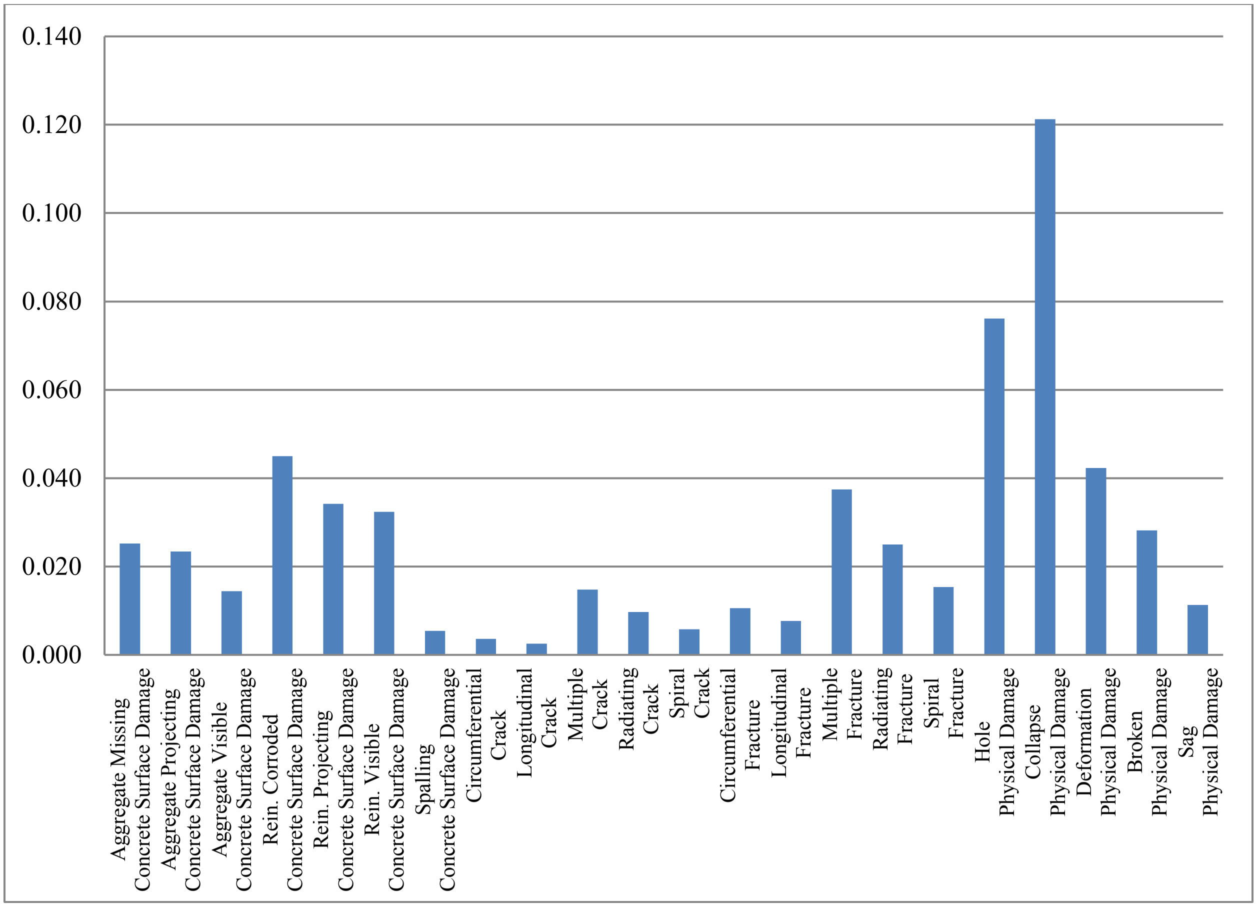


Figure 4.14: Structural Defects Relative Weights in Sewer Pipelines (Daher et al. 2017)

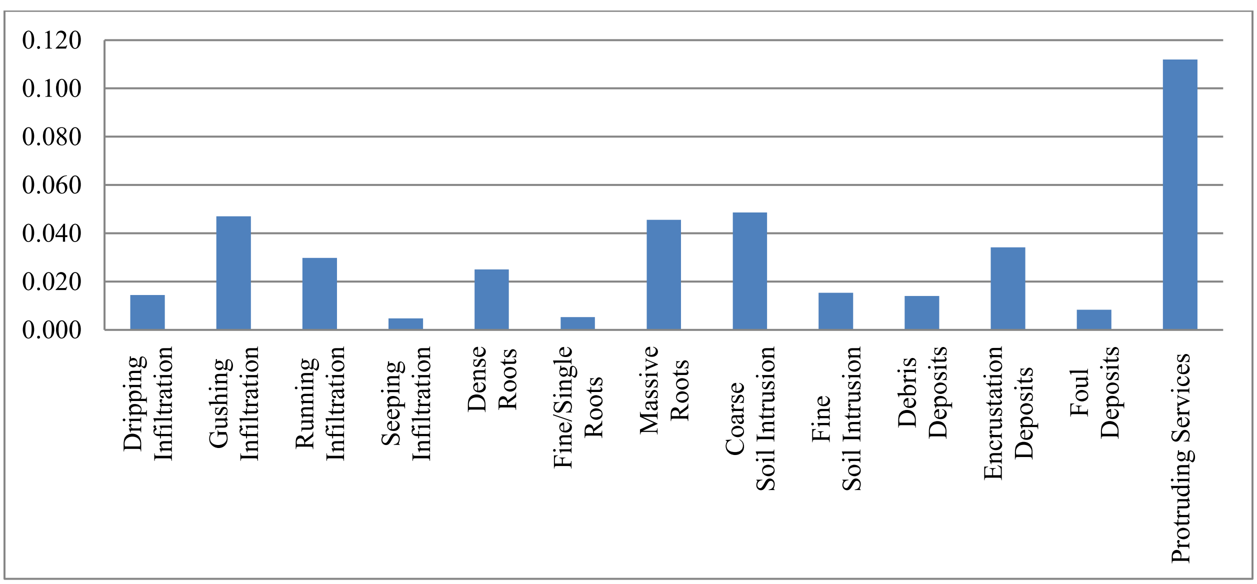


Figure 4.15: Operational Defects Relative Weights in Sewer Pipelines (Daher et al. 2017)

4.5. Recap

In this chapter, the different datasets used to develop the proposed models were presented. The datasets comprise three types, namely: CCTV inspection reports, GIS shape files, and data from literature and codes of practice. The defects found in the CCTV inspection reports were used to develop the BBN model by determining the marginal and conditional probabilities based on the frequency of occurrence of defects. Additionally, information found in GIS shape files were used in the development of DBN by identifying the transitional probabilities using pipe length, material, diameter, depth and street category. The last and third data type was the severity thresholds for the defects found in the current codes and practices. These thresholds were used to convert the defects numeric values into linguistic variables, as required by the BBN model. Additionally, relative weights for the different defects found in sewer pipelines were used to reduce the cumbersome nature of the developed BBN model.

Chapter 5: Models' Implementation and Validation

5.1. Introduction

In this chapter, the implementation of different developed models is presented. Actual data is used to examine the validity of the developed models and examine their robustness through different case studies as shown in Figure 5.1. Data from CCTV inspection reports is filtered to model the deterioration of sewer pipelines using BBNs. To capture the dynamic nature of the deterioration process, the gathered data from GIS files is analyzed and filtered to develop multinomial logistic regression, representing the transitional probabilities required for creating DBNs. Additionally; the implementation of the economic loss model for failure of sewer pipelines is presented. Sugeno Fuzzy Inference System is used to combine both the likelihood and consequences of failure, carried out using actual data and compared with current inspection practices. At the end of this chapter an evaluation of the formulated optimization problem is also presented.

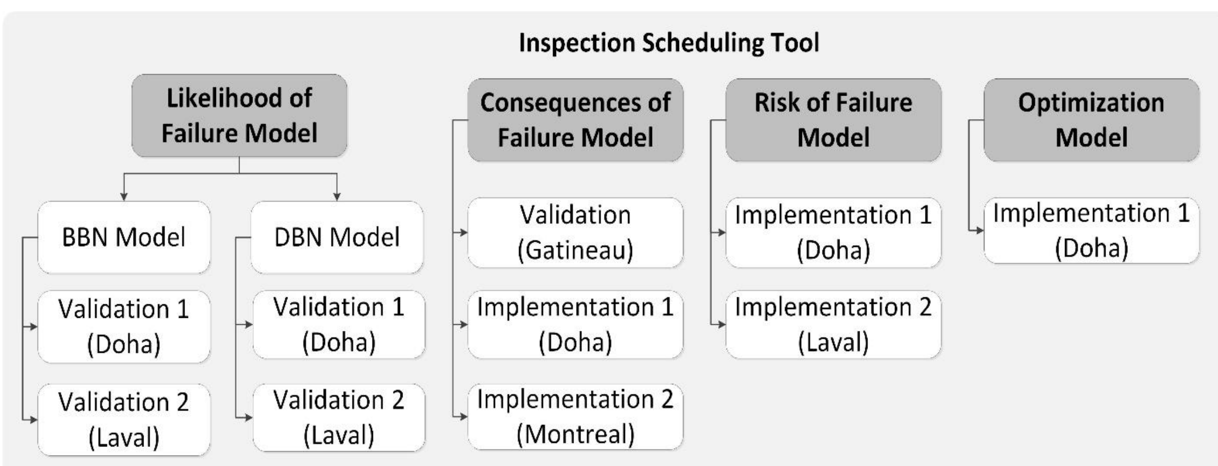


Figure 5.1: Developed Models' Implementation and Validation on Different Case Studies

5.2. Likelihood of Failure Model Implementation

As previously discussed in sections 3.2.3., the likelihood of failure model is implemented in two steps. The first is the BBN, while the second is the DBN. In the following section, the implementation of the two models is presented.

5.2.1. Static BBN Model for Sewer Pipelines

To determine marginal and conditional probabilities for each defect, CCTV inspection reports were analyzed and data mining was performed to learn the patterns of the probability of occurrence of certain defects, and the structural and operational condition of the pipeline. Table 5.1 shows the marginal probabilities for the different defects in sewer pipelines to be in a given state. The values shown in the table were determined using Monte Carlo Simulation. Figure 5.2 shows a sample for spalling marginal probability determination using MCS. The occurrence of independent events (defects) was sampled based on their probability distributions. The occurrence of independent events was evaluated, and was then propagated through the BBN to assess the posterior probabilities (probabilities of structural and operational conditions, and eventually the overall likelihood that a pipeline will be in a particular condition containing certain defects) of dependent events (family of defects and conditions) to sample their occurrence.

MSBNX (Microsoft Corporation 2001), was used to create the BBN, whereas MS Excel (Microsoft Corporation 2007) and Visual Basic 6 were used to iterate the developed BBN. Table 5.2 shows the conditional probabilities in case of fractures having different severities. Tables 5.3 and 5.4 show a sample for the conditional probabilities for a sewer pipeline's overall condition, including the structural and operational conditions. After the network was constructed, Monte Carlo simulation was used to eliminate uncertainties by propagating the network several number of iterations.

Table 5.1: Marginal Probabilities Used in BBN Model Development

Category	Light	Medium	Severe	Sub-Category	Light	Medium	Severe
Surface Damage	0.429	0.284	0.287	Break	0.6295	0.2516	0.1189
				Collapse	0.1140	0.6820	0.2040
				Corroded Surface	0.1140	0.6820	0.2040
				Holes	0.1138	0.6824	0.2036
				Horizontal Deformation	0.6505	0.1126	0.2368
				Vertical Deformation	0.1138	0.6824	0.2036
Physical Damage	0.701	0.15	0.15	Missing Aggregate	0.9506	0.0373	0.0121
				Projecting Aggregate	0.8179	0.1660	0.0160
				Spalling	0.8179	0.1660	0.0160
				Visible Aggregate	0.8179	0.1660	0.0160
Fracture	0.651	0.113	0.237	Circumferential	0.8500	0.1471	0.0029
				Longitudinal	0.6506	0.1126	0.2368
				Complex	0.6506	0.1126	0.2368
Cracks	0.185	0.0546	0.76	Circumferential	0.7721	0.2276	0.0003
				Longitudinal	0.1850	0.0546	0.7604
				Complex	0.1850	0.0546	0.7604
Settled Deposits	0.462	0.267	0.271	----	0.6816	0.2629	0.0555
Soil Intrusion	0.059	0.518	0.422	Sand	0.6295	0.2516	0.1189
				Gravel	0.9506	0.0373	0.0121
Attached Deposits	0.951	0.0373	0.0121	Grease	0.9506	0.0373	0.0121
				Encrustation	0.9506	0.0373	0.0121
				Foul	0.6267	0.1147	0.2587
Roots	0.253	0.49	0.256	Fine	0.6267	0.1147	0.2587
				Dense	0.1263	0.5505	0.3232
Protruding Services	0.714	0.126	0.159	----	0.1263	0.5505	0.3232
Infiltration	0.126	0.551	0.323	Dripping	0.1263	0.5505	0.3232
				Flowing	0.1263	0.5505	0.3232
				Gushing	0.1139	0.6825	0.2036
				Sweating	0.1140	0.6820	0.2040

Table 5.2: Sample for Marginal Probabilities Used in BBN Model for Different Fracture Types

Type of Fracture / Severity	Light	Medium	Severe
Circumferential	0.8499	0.1470	0.0029
Longitudinal	0.6505	0.1126	0.2367
Complex	0.6505	0.1126	0.2367

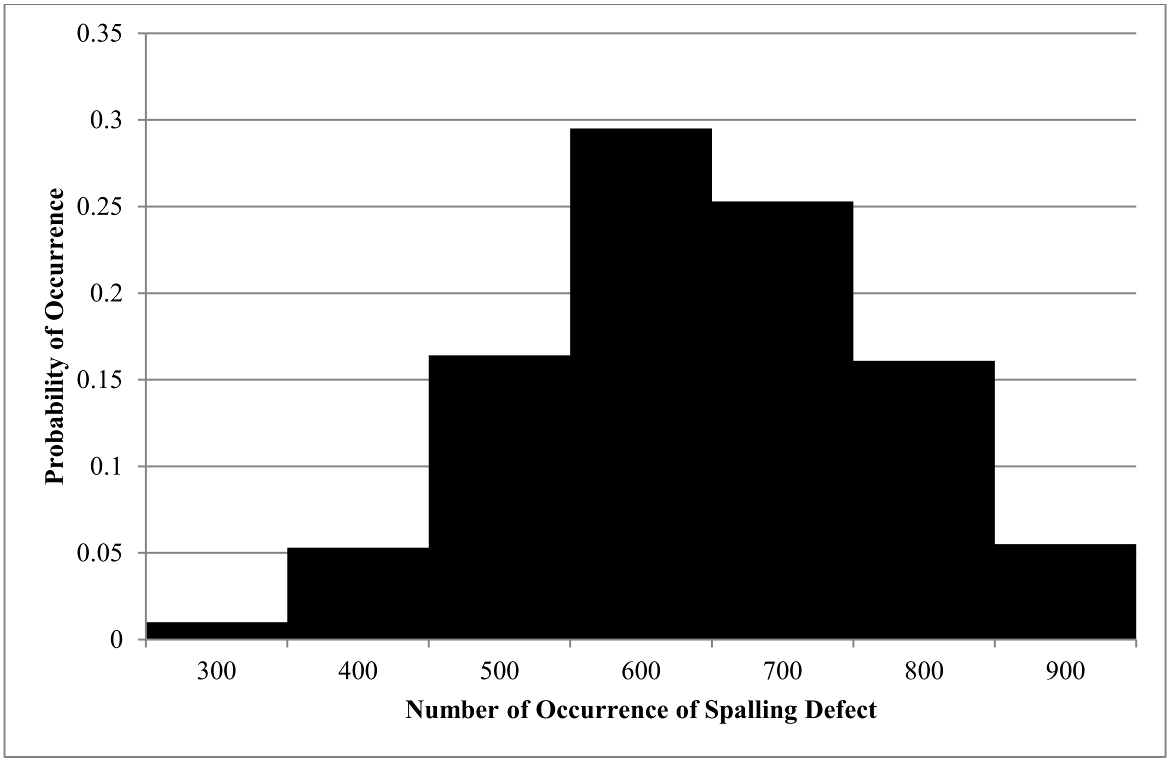


Figure 5.2: Sample for Monte Carlo Simulation Output in Case of Light Spalling Defects

To determine the conditional probabilities for child variables a 10-90 test was performed, in which conditional probabilities were computed from 10% of the data and testing was carried out on the remaining 90%. In the 10 – 90 tests, a classifier is trained using a training set and then the parameters are tuned using a validation test. The algorithm used for parameter learning was likelihood sampling with the log likelihood method with 100 iterations. In the likelihood sampling algorithm, multiple observations are sampled based on the weights of each observation node. These weights are derived from the accumulation of the evidences' likelihood. Figure 5.3 shows the plot for the parameter learning process with the different values of log likelihood and change in delta until convergence was achieved on the vertical axis and the number of iterations on the horizontal axis. In each iteration parameters were calculated to maximize the log likelihood of the observed data by using a stopping criteria of 0.1 logits which is the largest absolute change in the estimated logit measurement calculated based on previous iterations until convergence is achieved indicating that the data fit the model.

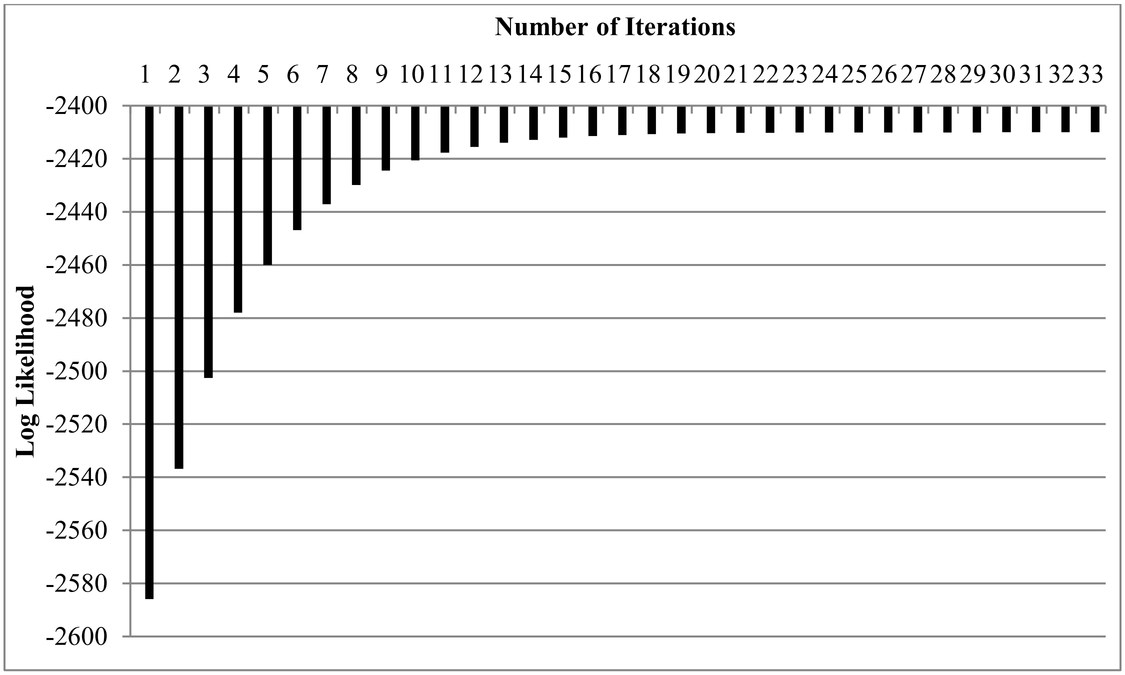


Figure 5.3: Parameter Learning for 10 – 90 Test in Case of Roots Operational Defects

Table 5.3: Sample for Conditional Probabilities used in BBN model for different fracture types with different severities

Circumferential	**Longitudinal**	**Complex**	**Severity**		
			Light	**Medium**	**Severe**
Light	Light	Light	0.3194	0.4632	0.217
Light	Light	Light	0.2792	0.4377	0.2830
Light	Light	Light	0.2905	0.2384	0.4712
Light	Light	Medium	0.3333	0.3333	0.3333
⋮	⋮	⋮	⋮	⋮	⋮
Severe	Severe	Medium	0.3333	0.3333	0.3333
Severe	Severe	Severe	0.4276	0.4328	0.1394
Severe	Severe	Severe	0.4270	0.4321	0.1408
Severe	Severe	Severe	0.4284	0.4338	0.1376

Table 5.4: Sample for Conditional Probabilities Used in BBN Model for Structural, Operational and Overall Condition Ratings

SC	OC	Overall Condition				
		0	**1**	**2**	**3**	**4**
0	0	0.986	0.0001	0.0001	0.0127	0.0001
0	1	0.9967	0.0007	0.0007	0.0007	0.0009
0	2	0.9995	0.0001	0.0001	0.0001	0.0001
0	3	0.9390	0.0102	8.03E-05	0.0504	0.0001
0	4	0.4177	0.0008	0.0007	0.00071	0.5798
1	0	0.7856	0.2087	0.0016	0.0016	0.002
:	:	:	:	:	:	:
4	3	0.0126	0.00738	0.3663	0.6135	0.0001
4	4	0.0001	0.0001	0.2301	0.1077	0.6617

5.2.2. Dynamic Deterioration model for sewer pipelines

The data used in building the multinomial logistic regression model from which transitional probabilities are determined, required for the DBN, is information about pipeline characteristics, such as pipe age, diameter, length, material, etc. This information was all in the form of shape files that are part of the GIS database for an existing sewage network in Doha, Qatar. Figure 5.4 shows the different information found in the GIS datasets.

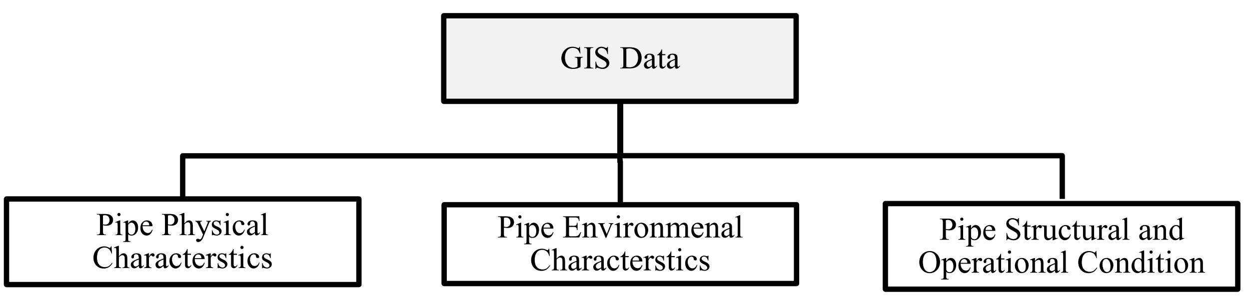


Figure 5.4: Collected GIS Data Categorization

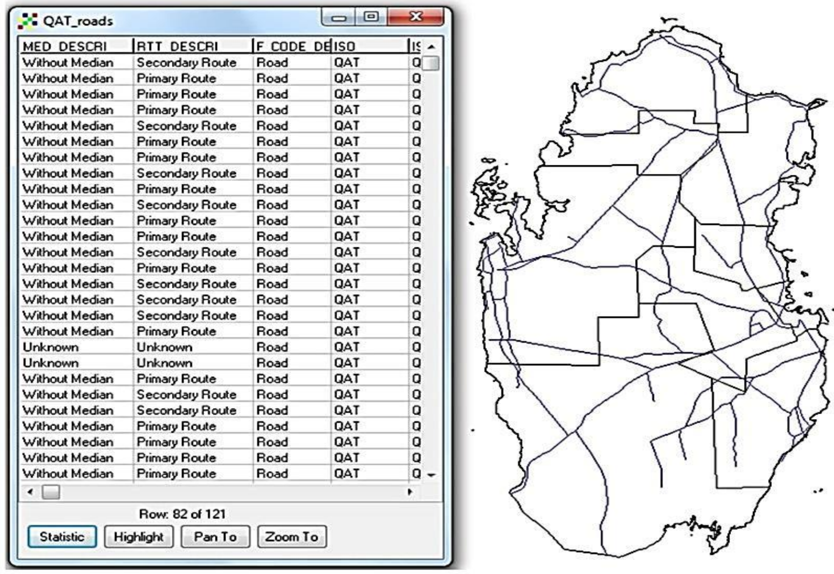


Figure 5.5: GIS data Shape files Output for Road Categories in Doha-Qatar

Figure 5.5 shows a snapshot for the dataset of GIS shape files for the roads category in Doha, Qatar. The information was an output in table form that categorizes the different roads based on their importance, divided into primary, secondary and local roads. Such information is useful when assessing the condition rating of pipelines as a result of environmental factors and in assessing the consequences of failure for a pipeline. Street categories were determined based on the importance of the road. Arterial roads such as express ways and "two ways" with more than two lanes, were given a value of "1", while collector roads having two ways and less than two lanes were given a value of "2," and the local roads with features less than the other two classes were given a value of "3." Table 5.5 shows a summary for the criteria adopted in that conversion.

Table 5.5: Street Categorization Based on Their Types

Road/Street Type	Category
One way - One lane roads OR Local	3
Two way - Two lane roads OR Secondary	2
Two Way - > Two lane roads OR Primary	1

Table 5.6 shows the condition ratings used in the logistic regression model. Three possible states, 1 for excellent and very good conditions, 2 for good conditions and 3 for poor and critical conditions, were used. Therefore, two multinomial logistic regression equations were generated using Maximum Likelihood Estimation (MLE) to estimate the parameters of these two equations. The general form of the multinomial logistic regression equations are shown in Equation 5.1.

Table 5.6: Equivalent Condition Ratings Used in Multinomial Logistic Regression Model

Condition Rating as per European Standards	Condition Rating used in Multi-nominal Logistic Regression
0 and 1	1
2	2
3 and 4	3

$$Ln\left(\frac{P(CR=j)}{P(CR=3)}\right) = \alpha_j + \beta_{j1} * Age + \beta_{j2} * Diameter + \beta_{j3} * Length + \beta_{j4} * Buried\ Depth + \beta_{j5} * Z_{Road\ Class=1} + \beta_{j6} * Z_{Road\ Class=2} + \beta_{j7} * Z_{Road\ Class=3} + \beta_{j8} * Z_{Mat=AC} + \beta_{j9} * Z_{Mat=VC} + \beta_{j10} * Z_{Mat=PVC} + \beta_{j11} * Z_{Mat=RC} + \beta_{j12} * Z_{Mat=Brick} + \beta_{j13} * Z_{Mat=Con} + \beta_{j14} * Z_{Mat=GRP} \quad (5.1)$$

Where j: is 1, 2 indicating the structural and operational condition ratings.

α_j: is the intercept term for condition rating *(j)*

$\beta_{j1}, \beta_{j2}, \ldots\ldots \beta_{j14}$: are the regression coefficients estimated by the maximum likelihood method for condition rating (j).

(Z_i) is a variable defined for different values of the categorical variables which is assigned a value of either 0 or 1 based on the following:

$Z_{Road\ Class=1}$ = 1, If road class = 1, otherwise 0

$Z_{Road\ Class=2}$ = 1, If road class =2, otherwise 0

$Z_{Road\ Class=3}$ = 1, If road class = 3, otherwise 0

$Z_{Mat=AC}$ = 1, if pipe material is Asbestos Cement, otherwise = 0

$Z_{Mat=VC}$ =1, if pipe material is Vitrified Clay, otherwise = 0

$Z_{Mat=PVC}$ = 1, if pipe material is PVC, otherwise = 0

$Z_{Mat=RC}$ = 1, if pipe material is Reinforced Concrete, otherwise = 0

$Z_{Mat=Brick}$ = 1, if pipe material is Brick, otherwise = 0

$Z_{Mat=Con}$ = 1, if pipe material is Concrete, otherwise = 0

$Z_{Mat=GRP}$ = 1, if pipe material is GRP, otherwise = 0

Table 5.7 shows the different variables used in the analysis. The calibration of the multinomial logistic regression was done using SPSS statistical analysis software. The diameter, length, age and buried depth for the pipeline were entered as the covariates, whereas material and street category were considered factors. Structural and operational condition ratings were the dependent variables.

Table 5.7: Sample from Dataset Used in Calibrating Multinomial Logistic Regression Model

Section	Length (m)	Diameter (mm)	Material	Street Category	Age (Years)	Depth (m)	SC	OC
1	54.73	150	VC	3	52	1.35	3	3
2	29.33	150	VC	3	52	1.35	3	3
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1486	22.6	450	RC	3	65	1.5	1	1
1489	61.7	450	RC	3	65	1.5	3	1
1490	72.6	400	VC	2	65	3	3	1
1491	9.4	600	C	3	65	3.5	1	1
⋮ 1719	⋮ 63	⋮ 750	⋮ C	⋮ 3	⋮ 65	⋮ 1.5	⋮ 1	⋮ 1

5.2.2.1. Significance of the Logistic Regression model

Significance of the model was evaluated based on the likelihood ratio of the full model to the intercept only model as shown in Table 5.8. According to the output, the difference between –2 log likelihood values of the multinomial logistic model and intercept only model was 206.647 and 194.214, which corresponds to an improvement (i.e. the added variables statistically improve the model when compared to the intercept alone). Tables 5.9 and 5.10 show the parameter estimates for condition ratings where (β) represents the coefficient for the various independent variables. The criteria chosen to test the statistical significance of the variables set at ≤ 0.05 . As such, variables having a (p) value greater than 0.05 were considered statistically insignificant.

Table 5.8: Results of Significance Test for Multinomial Logistic Regression Analysis

Model		-2 Log Likelihood	Chi-Square	df	p
Structural Condition Rating Model	Intercept Only	1926.182			
	Full Model	1719.535	206.647	32	.000
Operational Condition Rating Model	Intercept Only	2137.053			
	Final	1942.839	194.214	30	.000

5.2.2.2 Significance of the Logistic Regression Model Parameters

The differences between the -2 Log Likelihood value of the full model and -2 Log Likelihood values of the reduced models in which one of the parameters is excluded are calculated. The differences between -2 Log Likelihood values and significance of each model parameter are shown in Table 5.11. According to the output and as shown in Table 5.11, excluding the variable "Material" from the model causes the highest difference in the -2 log likelihood value; while, the lowest difference in the -2 log likelihood value corresponds to the exclusion of "Age" from the overall model.

After checking the accuracy of the developed logistic regression model, different years were plugged in the equation for a vitrified clay, 200 mm diameter pipeline. Both probabilities for structural and operational condition ratings versus time were plotted, from which deterioration curves were plotted as shown in Figures 5.6 and 5.7.

Table 5.9: Multinomial Logistic Regression Parameter Estimates for Structural Condition Ratings

Structural Condition Rating	**1**				**2**			
Variables	**β**	**Std. Error**	**Wald**	**p**	**β**	**Std. Error**	**Wald**	**p**
Intercept	6.348	1.525	17.336	0	-4.296	1.583	7.368	0.007
Length	-0.019	0.003	42.82	0	-0.009	0.005	3.903	0.048
Diameter	0.001	0.001	0.083	0.077	-0.002	0.001	4.39	0.036
Age	-0.085	0.03	8.017	0.005	0.072	0.032	5.158	0.023
Depth	-0.44	0.15	8.624	0.003	0.16	0.216	0.544	0.461
Street=1	0.428	0.186	5.309	0.021	-0.975	0.456	4.576	0.032
Street=2	-0.234	0.128	3.346	0.067	-0.645	0.246	6.853	0.009
Street=3	Reference Level							
Material: AC	-0.34	0.54	0.395	0.053	-0.06	0.645	0.009	0.925
Material: Brick	0.847	0.56	2.283	0.131	-0.539	0.822	0.429	0.512
Material: C	1.167	0.712	2.688	0.101	0.526	0.839	0.393	0.531
Material: GRP	0.34	0.514	0.439	0.308	-15.749	2377.61	0	0.995
Material: PVC	17.583	1647.21	0	0.291	-0.349	3296.92	0	1
Material: RC	1.653	0.443	13.906	0	0.432	0.477	0.822	0.365
Material: VC	Reference Level							

In both figures, it can be observed that the probability of structural or operational condition rating to be 1 decreases exponentially with age. As for the condition rating 2, the probability increases at first until the approximate mid-age of the pipeline and then decreases with a lower rate than that of 1, while the condition rating of 3 increases exponentially with time approaching a probability of 1 overtime.

Table 5.10: Multinomial Logistic Regression Parameter Estimates for Operational Condition Ratings

Operational Condition Rating	1				2			
Variables	**β**	**Std. Error**	**Wald**	**p**	**β**	**Std. Error**	**Wald**	**p**
Intercept	-7.431	1.749	18.055	0	-5.052	2.116	5.703	0.017
Length	-0.016	0.003	28.537	0	0.001	0.004	0.093	0.761
Diameter	0.001	0.001	0.602	0.238	-0.002	0.002	2.574	0.109
Age	0.167	0.035	22.679	0	0.089	0.042	4.469	0.035
Depth	-0.405	0.17	5.655	0.017	0.193	0.193	1	0.317
Street=1	0.347	0.188	3.397	0.065	-0.333	0.277	1.441	0.23
Street=2	-0.476	0.132	12.998	0	-0.831	0.191	18.99	0
Street=3	Reference Level							
Material: AC	-0.383	0.566	0.457	0.499	-0.16	0.678	0.056	0.813
Material: Brick	-2.267	0.666	11.573	0.001	-0.379	0.859	0.195	0.659
Material: C	0.313	0.904	0.12	0.072	-0.239	1.313	0.033	0.856
Material: GRP	-0.409	0.528	0.601	0.038	-0.231	0.692	0.112	0.738
Material: PVC	-1.123	0.77	2.124	0.145	0.424	0.733	0.334	0.563
Material: RC	0.083	0.525	0.025	0.174	0.411	0.632	0.423	0.515
Material: VC	Reference Level							

Table 5.11: Model Fitting Criteria, Likelihood Ratio Test and Significance Test Results for Independent Variables

Model		**-2 Log Likelihood**	**Chi-Square**	**Degrees of freedom**	**p**
Structural Condition Rating Model	Full Model	1719.535			
	Length	1764.325	44.790	2	.000
	Diameter	1725.528	5.993	2	.050
	Age	1719.535	**0.000**	0	
	Depth	1731.367	11.832	2	.003
	Street	1744.094	24.559	4	.000
	Material	1798.965	**79.430**	16	.000
Operational Condition Rating Model	Intercept	1942.839			
	Length	1981.203	38.364	2	.000
	Age	1942.839	**0.000**	0	
	Depth	1954.595	11.756	2	.003
	Diameter	1949.972	7.132	2	.028
	Material	1998.035	**55.196**	16	.000
	Street	1977.733	34.894	4	.000

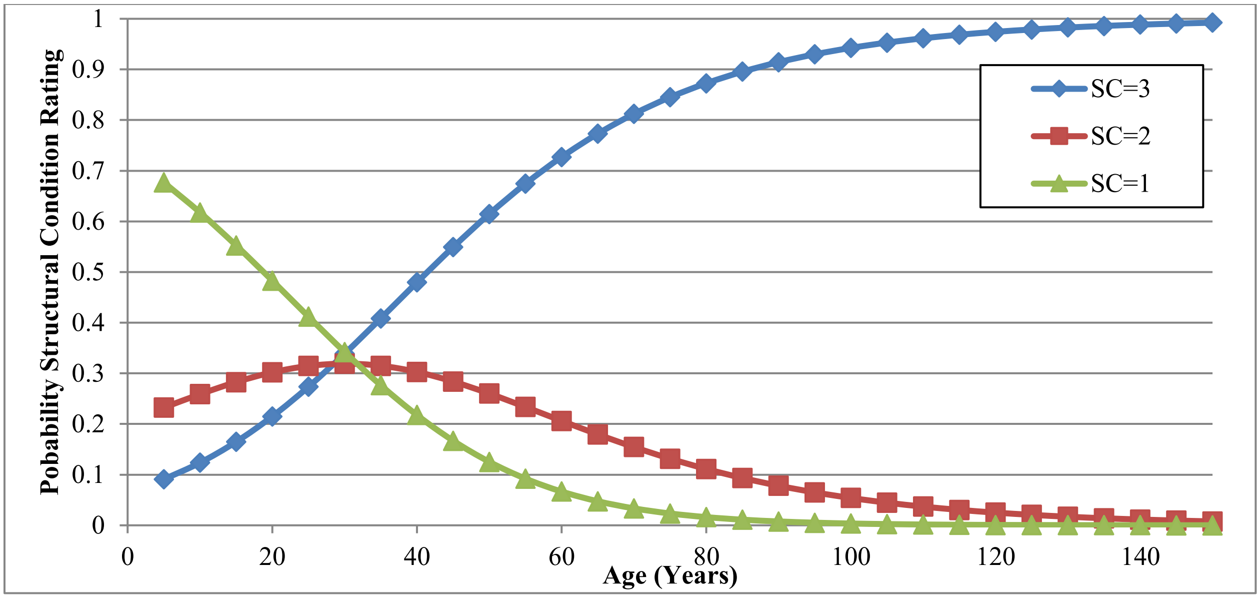


Figure 5.6: Sample for Structural Deterioration Curves of Vitrified Clay - 200 mm Sewer Pipeline (Probability of Structural Condition Rating Versus Age)

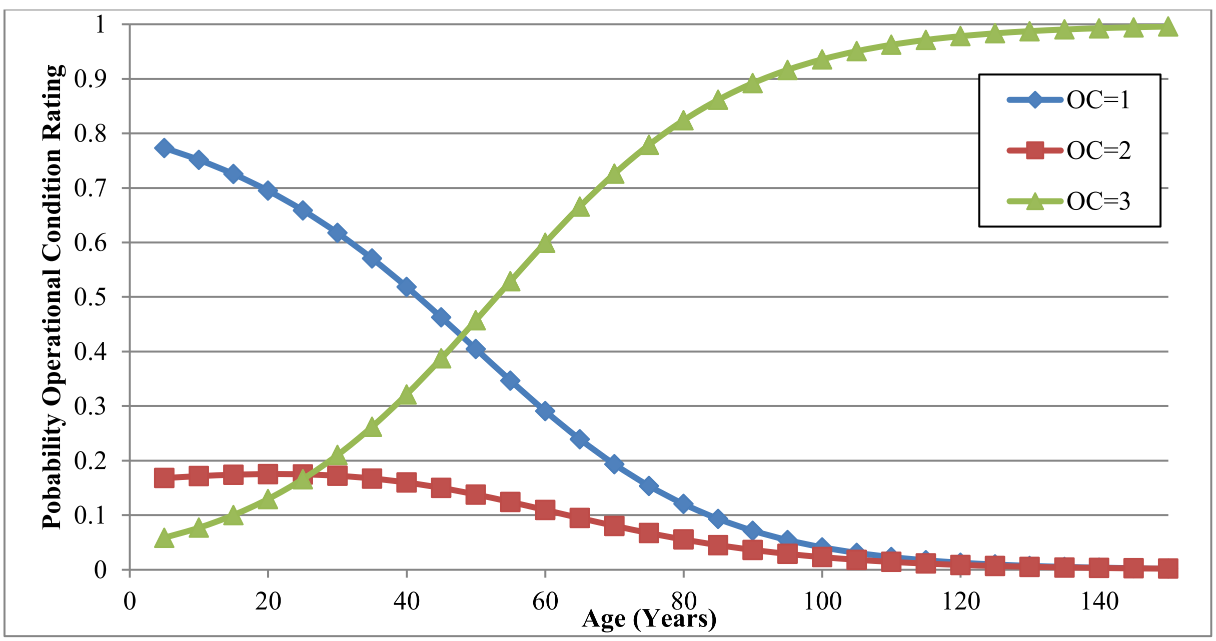


Figure 5.7: Sample for Operational Deterioration Curves of Vitrified Clay - 200 mm Sewer Pipeline (Probability of Operational Condition Rating Versus Age)

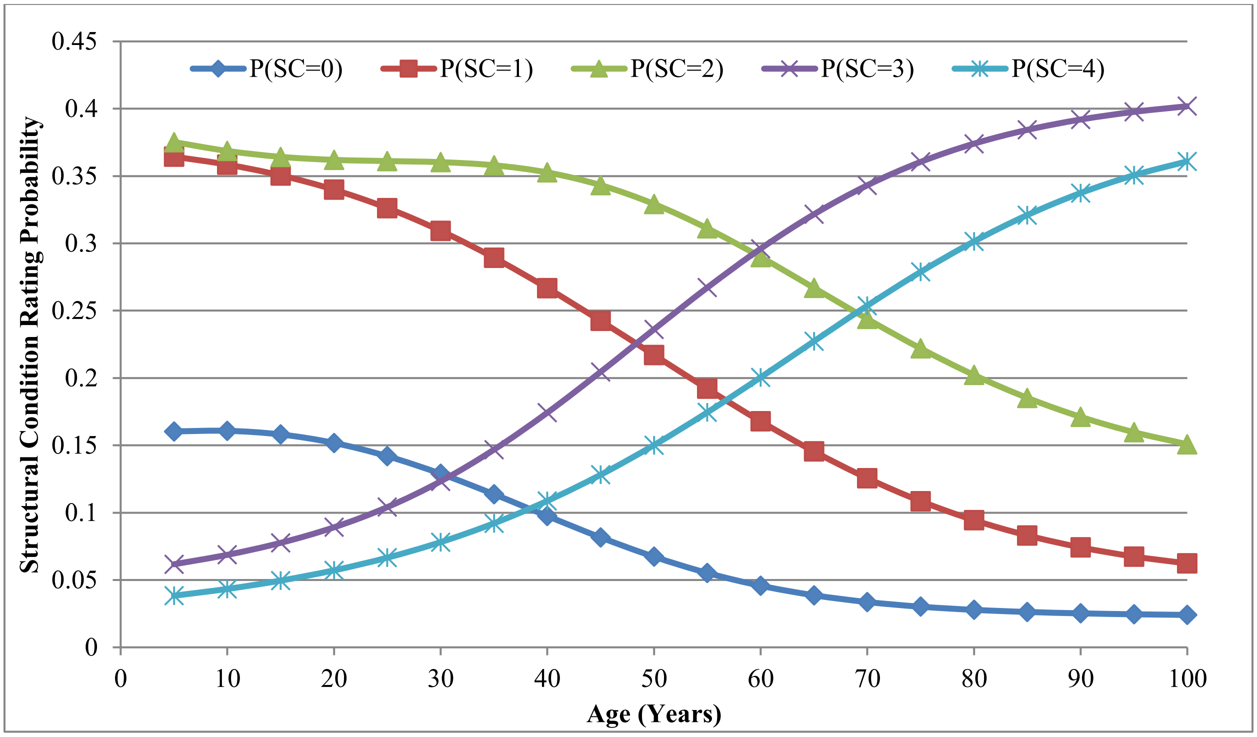


Figure 5.8: Sample for Deterioration Model Output for Probabilistic Structural Condition Rating

After obtaining transitional probabilities using multinomial logistic regression, a time step of 5 years was used to determine the different structural and operational condition rating probability. Figure 5.8 shows the probability of structural condition rating to be 0, 1,2,3, or 4 with respect to time as a result of feeding the transitional probabilities to the BBN model.

5.2.3. Likelihood of Failure Case Study 1 – City of Doha, State of Qatar

The validation of the developed deterioration model was performed in two stages; the first stage was validating the accuracy of prediction for the developed BBN model. This was done using 3.5 kilometers of pipeline consisting of 94 sections that were chosen randomly from the original collected data and set aside for the purpose of validation only. The second stage of model validation was to examine the deterioration model capabilities and to determine the accuracy of predicting the age at which a pipeline would enter a certain condition. Seven sections were used for that purpose, which were chosen randomly from the validation dataset (i.e. the 94 sections) representing 10% of the validation dataset's total length.

To choose these sections randomly, a random number generator was used to generate random numbers and the corresponding sections for the generated numbers were selected. The selected set of sections had different structural and operational defects and their condition ratings ranged between 2 and 4. Structural, operational, and overall condition ratings were determined using the developed BBN model. The number of sections for each condition rating were compared with the actual number of sections' condition ratings as shown in Figure 5.9. The figure shows that for the structural and overall condition ratings, the model tends to predict a higher number of sections in cases of good condition ratings (0,1 and 2) while it predicts a lower number of sections in poor condition ratings (3 and 4).

This could be attributed to the absence of the human judgment dimension, which could lead to biased or erroneous decisions, and the ability of the model to predict the condition rating based on the conditional probabilities only and the defect severity (i.e. some sections in the validation set showed low severity of defects and were given poor condition ratings). To determine the accuracy of the model in predicting condition ratings, Mean Absolute Error (MAE) and Root Mean Square Error were calculated as shown in Table 5.12. The MAE and RMSE were calculated between the predicted condition rating resulting from the BBN model and the actual ones. The table shows that the model can predict the condition ratings with an error less than unit (1) condition rating, however for the operational condition ratings, the model could over or under predict the actual value by a unit (1) condition rating.

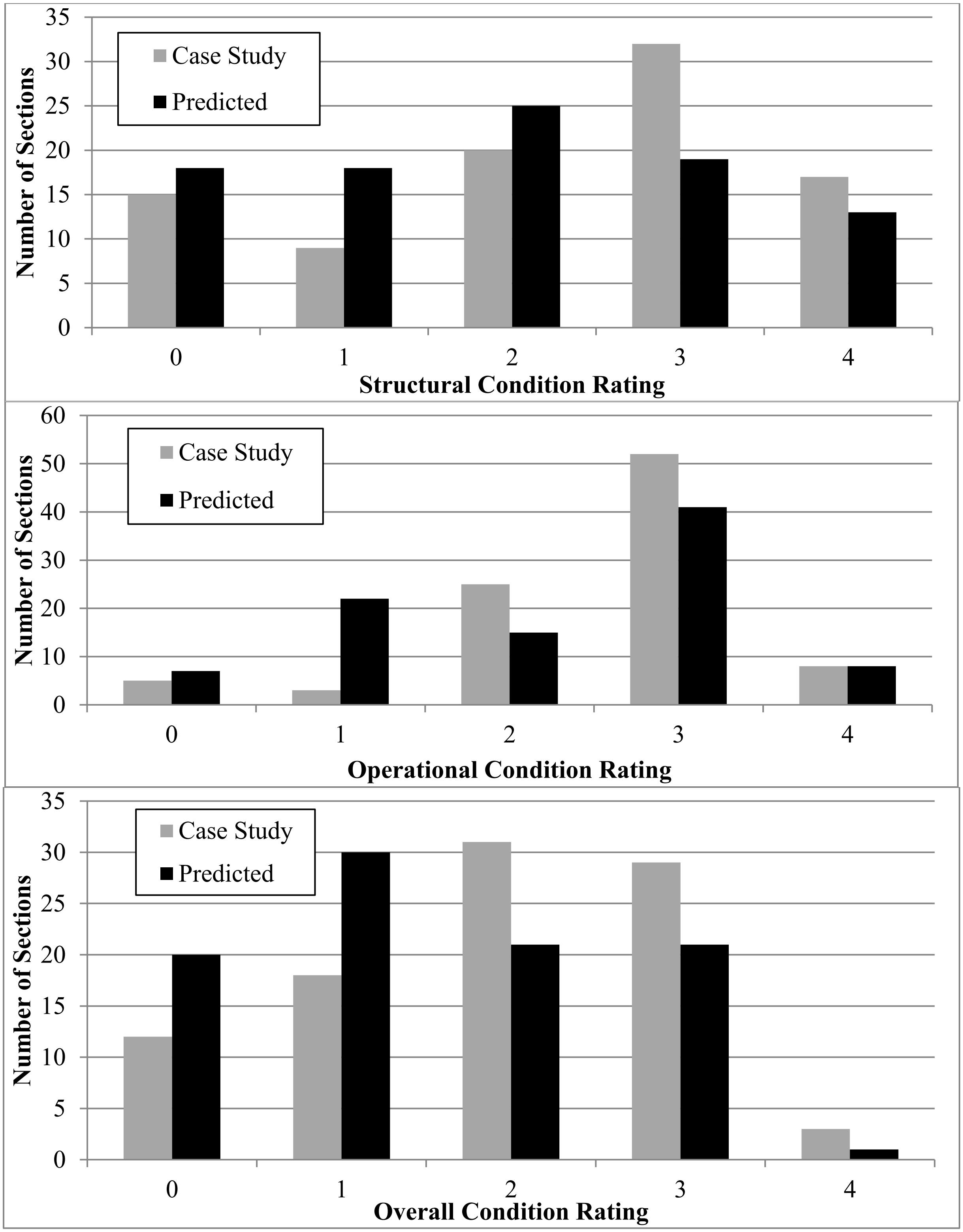


Figure 5.9: Prediction Accuracy for Likelihood of Failure Case Study 1

Table 5.12: BBN Model Prediction Accuracy for Case Study 1

	Structural Condition	Operational Condition	Overall Condition
MAE	0.67	1.06	0.56
RMSE	1.05	1.30	0.95

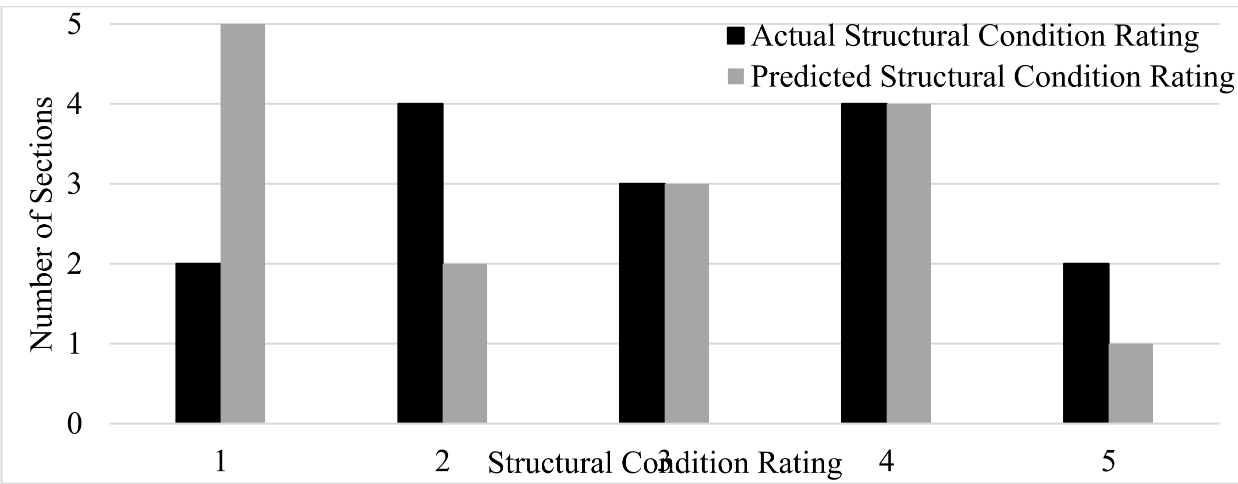
After determining the accuracy of prediction of the BBN model, the DBN model's accuracy was examined. As shown in Table 5.13, the selected pipelines characteristics were entered in the model and the highest corresponding condition rating was set as the stopping criteria for the model, to determine the age at which this condition rating would be achieved. The last two columns in the table show the actual time at which the condition of the pipeline was assessed versus the predicted time at which the highlighted condition would be achieved. Most of the results yielded periods that were around 65 years (i.e. 65, 70, 75). It is worth noting that the error in determining the exact periods of time could be attributed to the fact that the time slices in the developed DBN was taken 5 years steps; as such the error in 1 year could be shifted to 5 years.

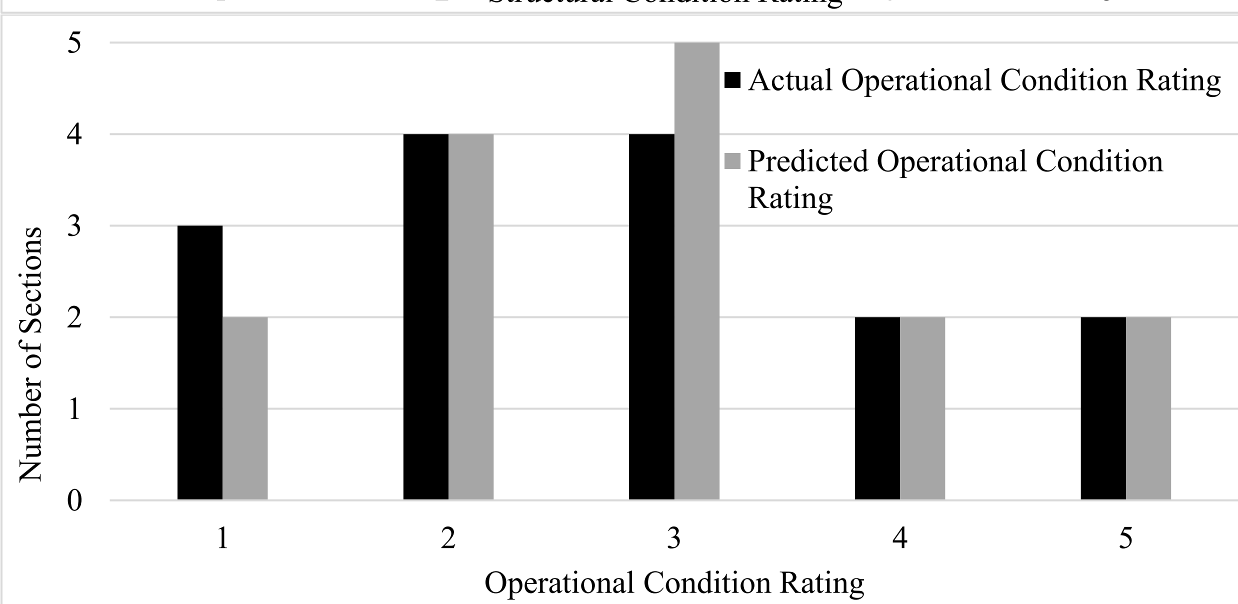
Table 5.13: DBN Model Prediction Accuracy for Case Study 1

Section	**Length (m)**	**Diameter (mm)**	**Depth (m)**	**Street**	**Material**	**Structural Condition**	**Operational Condition**	**Overall**	**Condition Assessment Time (Years)**	**Age at which Condition Rating is Achieved (Years)**
1	50	150	1.35	3	VC	2	**3**	2	65	70
2	70	300	1.6	1	GRP	**4**	3	3	65	80
3	60	300	2	3	GRP	0	**2**	0	65	65
4	50.3	200	1.5	3	VC	**4**	3	3	65	75
5	40	200	1.5	3	VC	**4**	2	2	65	90
6	37.7	300	1.5	2	GRP	0	**2**	0	65	65
7	59.8	150	1.35	3	VC	**4**	2	2	65	70

5.2.4. Likelihood of Failure Case Study 2 – City of Laval, Quebec Province, Canada

The second case study used for validation purposes of the developed model comprised 15 sections from the city of Laval with a total length of 500 meters of pipeline in Quebec, Canada. Structural, operational, and overall condition ratings were determined using the developed BBN model. The number of sections for each condition rating were compared with the actual number of sections' condition ratings as shown in Figure 5.10. To determine the accuracy of the model in predicting condition ratings, Mean Absolute Error (MAE) and Root Mean Square Error were calculated as shown in Table 5.14. The MAE and RMSE were calculated between the predicted condition rating, as determined by the BBN model and the actual ones. The table shows that the model can predict the condition ratings with an error less than unit (1) condition rating, however, for the operational condition ratings the model could over or under predict the actual value by a unit (1) condition rating.





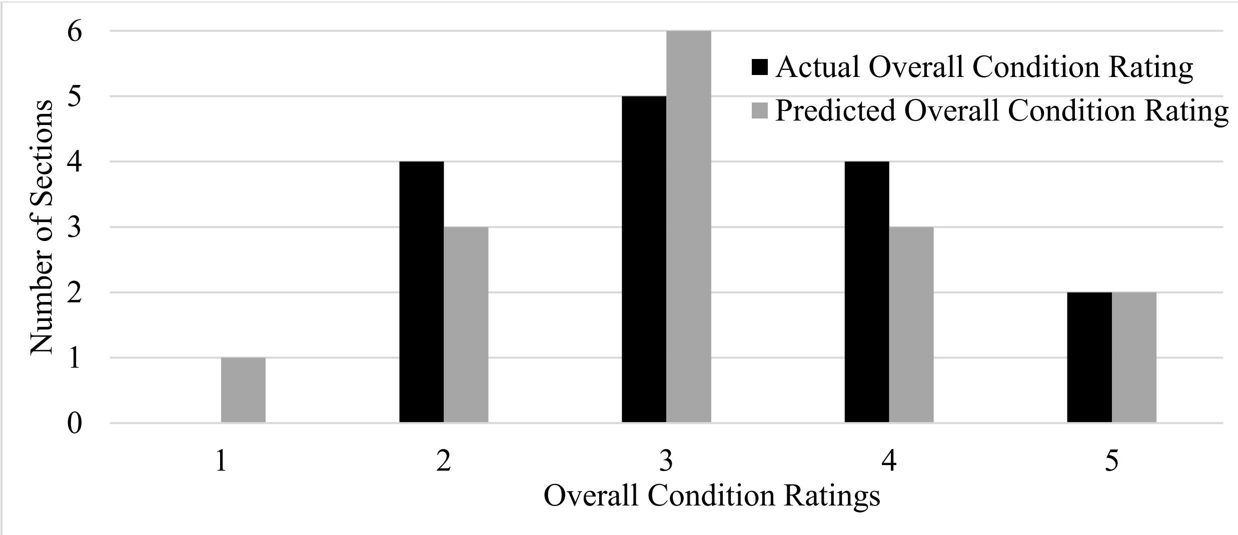


Figure 5.10: Prediction Accuracy for Likelihood of Failure Case Study 2

Table 5.14: BBN Model Prediction Accuracy for Case Study 2

	Structural Condition	**Operational Condition**	**Overall Condition**
MAE	0.67	0.80	0.53
RMSE	0.65	1.07	0.61

After determining the accuracy of prediction of the BBN model, the DBN model's prediction accuracy was examined. As shown in Table 5.15, the selected pipelines characteristics were entered in the model and the highest corresponding condition rating was set as the stopping criteria for the model, to determine the age at which this condition rating would be achieved. The last two columns in the table show the actual time at which the condition of the pipeline was assessed versus the predicted time at which the highlighted condition would be achieved. Most of the results yielded times that were around +5 years. It is worth noting that the error in determining the exact times could be attributed to the fact that the time slices in the developed DBN was 5 years and as such the error in 1 year could be shifted to 5 years.

Table 5.15: DBN Model Prediction Accuracy for Case Study 2

Section	Length (m)	Diameter (mm)	Depth (m)	Street	Material	Structural Condition	Operational Condition	Overall	Condition Assessment Time (Years)	Age at which Condition Rating is Achieved (Years)
1	62.1	300	1.75	2	RC	**5**	2	4	38	40
2	65.1	250	1.6	2	AC	3	**4**	3	39	45
3	71.8	250	1.55	3	AC	**5**	2	4	63	65
4	56.2	300	1.5	3	AC	**2**	**2**	2	63	70
5	37.1	400	1.5	3	AC	**1**	**1**	1	52	55
6	53.3	900	2.9	2	RC	**5**	1	4	52	55
7	64.2	300	1.5	3	AC	**2**	1	2	41	50

5.3. Consequences of Failure Model Implementation

To validate the economic loss model presented in section 3.2.4, real data from an actual break incident for a 200mm sewer pipeline with a total length of 50 meters in city of Gatineau in the province of Quebec, Canada, was compared with the output of the model. No services were required from police or fire men, because the situation didn’t entail danger to the public. Some tests related to groundwater and surface water qualities were necessary following the break incident. These tests were intended to detect the presence or absence of several bacteria, including coliform bacteria (total or fecal), bacteria Escherichia coli or the bacteria enterococci. The various laboratory costs and treatment costs of soil and groundwater were $ 8205. Traffic was diverted from the location of the break to a longer route which had impact on the traffic. The detour distance for this diversion was approximately 800 m causing an increase in the journey travel time of 90 seconds. Actual versus calculated direct and indirect costs are shown in Table 5.16.

Table 5.16: Different Actual and Calculated Direct and Indirect Costs for Model Validation

Resource	Cost	Quantity	Calculated	Actual	Deviation (%)
Hourly rate of heavy equipment operator ($/hr)	70	3			
Grade Man ($/hr)	60	1			
Compactor ($/hr)	200	1			
Excavator Cat 325 CL ($/hr)	130	1			
Ripper ($/hr)	250	1			
Pipe Material ($/m)	41	50			
Sand Bedding Material ($/Cu.m)	18	38			
Gravel Bedding Material ($/Cu.m)	42	10			
Number of Vehicles /day	1400				
Total Direct Costs ($)			4250	3841	-10
Total Indirect Costs ($)			3154	3621	12
Number of Buses /day	50				
Occupancy Ratio Vehicles	1.25				
Occupancy Ratio Buses	20				
Traffic disruption ($)			2253	1774	-27
Overconsumption of fuel ($)			180	233	22
Increased running costs ($)			2126	2980	28
Water Contamination Costs ($)			8205	6230	-31

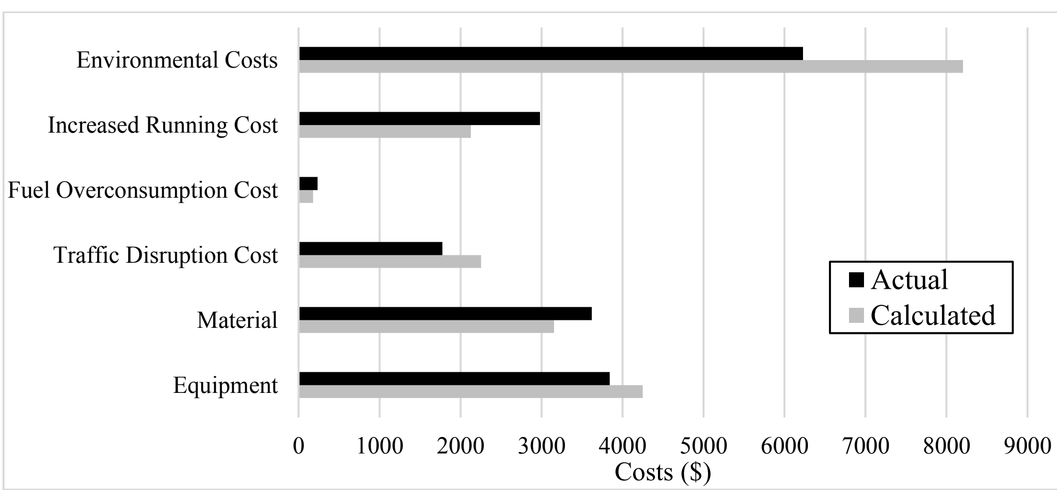


Figure 5.11: Calculated Versus Actual Costs of Failure for Economic Loss Model

5.3.1 Effect of Parameters' Uncertainty on Model Prediction

It is obvious that the parameters included in calculating the benefit to cost ratio cannot be estimated with much precision, especially when it is implemented in locations with significant cultural and social differences. To account for the effect of the parameters' uncertainties on the model prediction, probabilistic approach analysis using Monte Carlo simulation in conjunction with the output of the proposed economic loss model was used. Each parameter was represented by PERT distribution, which was chosen as the sampling procedure in Monte Carlo simulation. PERT distribution was employed because it can be used to provide a close fit to the normal or lognormal distributions and its bounds can be modified systematically to investigate the effects on the model output. PERT distribution is considered a special case of Beta distribution in which minimum, maximum, and most likely, values are assigned to the probability density function. Equation 5.2 (Vose, 2000) shows how the mean value in PERT distribution is calculated.

$$x_{mean} = \frac{(x_{min}+\alpha x_{mode}+x_{max})}{\alpha+2} \tag{5.2}$$

Where, x_{mode}: is the parameter to be simulated and

α: is the scale parameter for the height of the distribution and is usually equal to 4 (Vose, 2000).

The mean value is used to calculate the shape parameters as shown in Equations 5.3 and 5.4 (Croarkin and Tobias, 2006).

$$v = \frac{(x_{mean}-x_{min})(2x_{mode}-x_{min}-x_{max})}{(x_{mode}-x_{mean})(x_{max}-x_{min})} \tag{5.3}$$

$$w = \frac{v(x_{max}-x_{mean})}{(x_{mean}-x_{min})} \tag{5.4}$$

Using shape parameters v and w, the probability density function for Beta distribution can be calculated using Equations 5.5 and 5.6 (Vose, 2000 and Croarkin and Tobias, 2006).

$$f(x) = \frac{x^{v-1}(1-x)^{w-1}}{U(v,w)} \tag{5.5}$$

$$U(v,w) = \int_0^1 y^{v-1}(1-y)^{w-1}dy \tag{5.6}$$

PERT distribution was used to simulate normal distribution, then it was adjusted so as to investigate the effect of width of the parameter distributions on the variance and uncertainty in the economic loss model predictions. A series of perturbations were used to study the effect of parameter uncertainty on the model's output. The four parameters were namely: occupancy ratio, number of vehicles, % of workers, and number of people infected, were replaced with symmetrical PERT distributions. Using four consecutive Monte Carlo simulation runs, the widths (ranges) of the probability distributions were incrementally changed. The mean (mode) values were changed by $\pm$25%, $\pm$50%, $\pm$75%, and $\pm$100%. The base values for the four parameters set before perturbation and simulation, were the elements of the parameter vector x_0 = [1.5, 1800, 65, 11]. Output uncertainty was represented by variance (σ^2) and 90% Confidence Interval (CI) which is the difference between the 95th and the 5th percentiles under the cumulative distribution curve of the output.

Both σ^2 and 90% CI were evaluated for comparison. The gain factor called hereinafter G.F., which is the ratio of the output's Coefficient of Variation (CV) to input's (parameter) CV, was used as a measurement of the increase or decrease in the perturbation transferred between parameter and model output. It was found that the model predictions were quite tolerant to significant variation in parameter values. This can be shown in Figures 5.12 and 5.13, in which it is evident that the 95th percentile predictions of the model (benefit to cost ratio) varies little in response to significant changes in the CV for the four parameters represented by symmetric probability density functions simulated by PERT distributions.

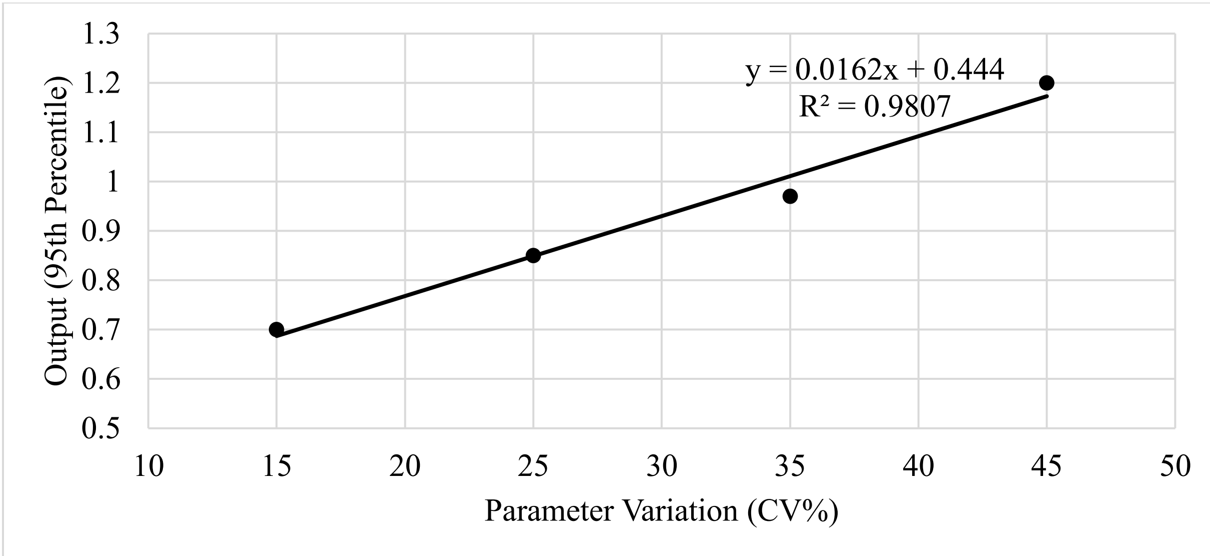


Figure 5.12: 95th Percentile Results for Predicted Benefit to Cost Ratio

For instance, 95th percentile results increased by less than 2%, although there was an increase in the CV for the four parameters jointly from approximately 10% to 40% which is a significant change in the width of the parameter distribution resulting in only a small change in the 95th percentile value of the output.

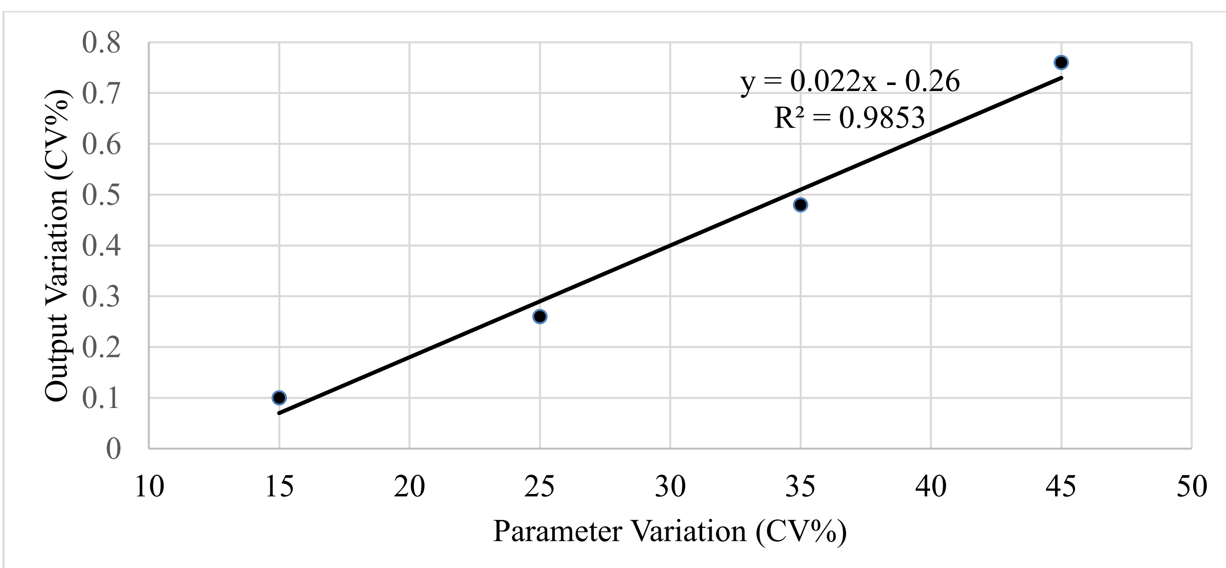


Figure 5.13: Gain Factor as a Result of Perturbation on Economic Loss Model Parameters

5.3.2. Weighing Risk Using Risk Benefit Analysis (RBA)

Risk Benefit Analysis (RBA) can be considered a decision rule in which it can take one of two forms. In the first form, RBA relates benefits, costs, and risk, where the risk component is treated as cost (i.e. represented in monetary amount) (Pearce et al. 2006). In the second form, benefits in the RBA are standardized, and the goal is to minimize the risk component that would describe the standardized benefit component (i.e. benefits would be costumer-linear meter of pipelines and the risk in that case would be illnesses per customer-linear meter of pipeline). In order to use this concept in determining whether the utility would outweigh the risk of doing nothing versus conducting repairs, the first form of RBA is used. Table 5.17 shows the proposed different levels of risk of failure corresponding to the B/C. Using these levels, a user can weigh the risk of making decisions (do repairs versus do nothing) with respect to the consequences of failure levels.

Table 5.17: Consequences of Failure Levels and Corresponding Risk Levels

Consequences of Failure	B/C Ratio	Associated Risk Values (%)
Catastrophic Failure	≤ 0.35	90 - 100
Very High Impact	> 0.35 - ≤0.5	76 - 90
High Impact	> 0.5 - ≤ 0.7	66 - 75
Moderate Impact	> 0.7 - ≤1	50 - 65
Low Impact	>1 - ≤1.3	34 – 50
Very Low Impact	>1.3 - ≤1.8	16 – 33
Insignificant Impact	>1.8	0 – 15

The economic loss model was implemented on four pipelines and a comparison was made between repairing the pipeline in question, or doing nothing. Table 5.18 shows different pipelines with the B/C and the corresponding risk of failure level from which a decision can be made. For pipelines with high B/C, a repair would not be as crucial as in the cases of pipelines with B/C less than 1, which indicates catastrophic levels of failure.

Table 5.18: Risk Benefit Analysis as a Decision Support Tool

Pipe Number	**B/C**	**Risk of failure**	**Action**
Pipe 1	0.34	90-100	Do Repairs
Pipe 2	0.5	76-90	Do Repairs
Pipe 3	6.9	16-33	Do Nothing
Pipe 4	1.44	0-15	Do Nothing

5.3.3. CBA for Investment Decisions

The proposed economic loss model focuses on the repair costs spent at the moment of an asset failure, however it does not take into consideration that these expenditures would have positive benefits on the life span of the pipeline. It should be noted that large repair costs spent on rehabilitation of sewer pipelines would generate benefits over longer periods of time (as a result of elongating the life span of the pipeline). In cases of smaller repairs which could be carried out repeatedly at shorter intervals, there would also be benefits and the lifetime of the pipeline would increase, though not necessarily as much as in the case of larger investments. In order to compare these two strategies, the extension of service-life of a rehabilitated pipeline can be taken into account using annual equivalent approach, as shown in Equation 5.7. Figure 5.14 shows the different investments and costs over the pipeline's service-life, data to which a decision maker can apply the proposed economic loss model to convert the net present values into annual costs allowing them to compare the different investments paid in repairs.

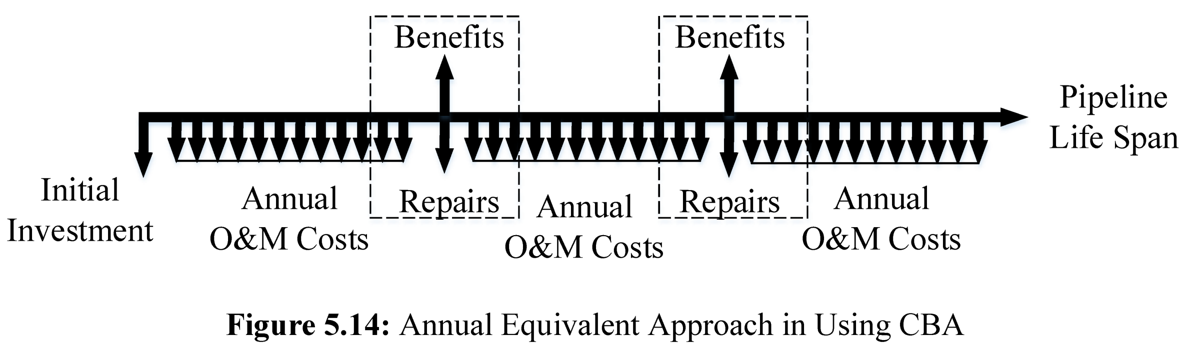


Figure 5.14: Annual Equivalent Approach in Using CBA

$$AC = \frac{I}{A_{t,c}} + OC + \frac{R_c - B}{A_{t,c}} \tag{5.7}$$

Where AC: Annual equivalent cost,

I: Initial Investment,

OC: Operation and maintenance costs,

R_c: Repair costs (Costs paid in case of failure),

B: Health benefits in case of avoiding failure,

$A_{t,c}$:Present value of the annuity factor,

t: is the lifetime span of the pipeline and

c: is the capital cost ($A_{t,c} = \frac{1-\frac{1}{(1+c)^t}}{c}$).

5.3.4. Consequences of Failure Case Study 1 – City of Doha, State of Qatar

To determine the applicability of the proposed methodology in determining the economic loss as a result of the sewer pipelines' failure, a sewer pipeline in the field is used in the CBA implementation. The 200 mm vitrified clay sewer pipeline with a total length of 27.8 meters located in Doha, Qatar, is the one used here. Table 5.19 shows the relevant data for the pipeline used in calculating the costs and benefits derived from avoiding pipeline failure, with (QALYs) representing the marginal utility for customers in cases of better sanitation. Figure 5.15 shows the ratio of direct to indirect costs of failure. As illustrated, indirect costs comprise 94%, which indicates that the indirect costs are as important as direct costs and cannot be neglected when estimating the consequences of failure.

5.3.5. Consequences of Failure Case Study 2 – City of Montreal, Quebec, Canada

A 1600 mm brick sewer pipeline with a total length of 80 meters located in Montreal, Canada, is used as a second case study to reflect the generality of the developed economic loss model. Table 5.20 shows the relevant data for each of the pipelines used in calculating the costs and benefits derived from avoiding pipeline failure, with (QALYs) representing the marginal utility for customers in cases of better sanitation. Figure 5.16 shows the ratio of direct to indirect costs of failure.

The different costs were compared in the two case studies as shown in Figure 5.17. Groundwater and soil remediation costs represent the highest share with almost 40% and 60% of the indirect costs for case study 1 and 2, respectively. The lower percentage in the first case study could be attributed to the significant difference in the pipelines' diameter which would result in lower flow rates and lower contaminated soil and ground water volumes, consequently. The costs as a result of delay and loss of productivity show higher values for case study 1 when compared to case study 2, because the average hourly rate for workers in Doha is higher than the average hourly rate in Montreal (i.e. $21/hr versus $14/hr).

Table 5.19: Parameter Values Used in Case Study 1

Parameter	**Qatar**		
Road Classification	Arterial (3 lanes 2 way)		
Ground Water Table Level	<2.5 m		
Year of Construction	1966		
Inspection Date	2013		
Length (m)	24		
Diameter (mm)	200		
Material	Vitrified Clay		
Depth (m)	1.4 m		
Structural: Operational: Overall Condition	4	4	4
Method of Ground Water Remediation	Pump and Treat		
Method of Pipeline Reinstatement	Open Cut Trenching		
Unit Cost of Material ($ /m)	25		
Unit Cost of Labor ($/hr)	3		
Unit Cost of Equipment ($/hr)	60		
Cost of Emergency Vehicle ($/hr)	90		
Number of Emergency Vehicles	3		
Number of Vehicles Impacted (Vehicles/Day)*	452	903	151
Fuel Price ($/liter)*	0.47	0.4	0.4
Running Cost Per Kilometer for Vehicle of Type ($/Km)*	0.7	0.8	1.1
Average Consumption of Vehicle Normal Cases (L/Km)*	0.15	0.28	0.33
Average Consumption of Vehicle During Disruption (L/Km)*	0.26	0.48	0.56
Detour Time (hr)	0.3		
Disrupted Distance (Km)	2.7		
Number of Inaccessible Parking Spaces	N.A.		
Hourly Cost Of Parking ($/hr)	N.A.		
Occupancy Ratio (%)	1		
Number of Operation Hours for Parking Lot (hr/Day)	N.A.		
Hourly Rate of Passengers ($/hr)	21		
Number of Workers Affected In Work Place	65		
Hourly Rate for Workers In Work Place ($/hr)	21		
Productivity Reduction Factor	0.65		
Number of Customers Affected	75		
Number of Probable Infections (14%)	11		
Costs Saved by Individuals ($)	1047		
Costs Saved by Avoiding Work Absence ($)	735		
Cost of Saved Opportunity (1 Year)	47040		
Quality Adjusted Life Years (QALYs) (Benefits)	49792		

*Values represent different types of vehicles namely light, medium and heavy

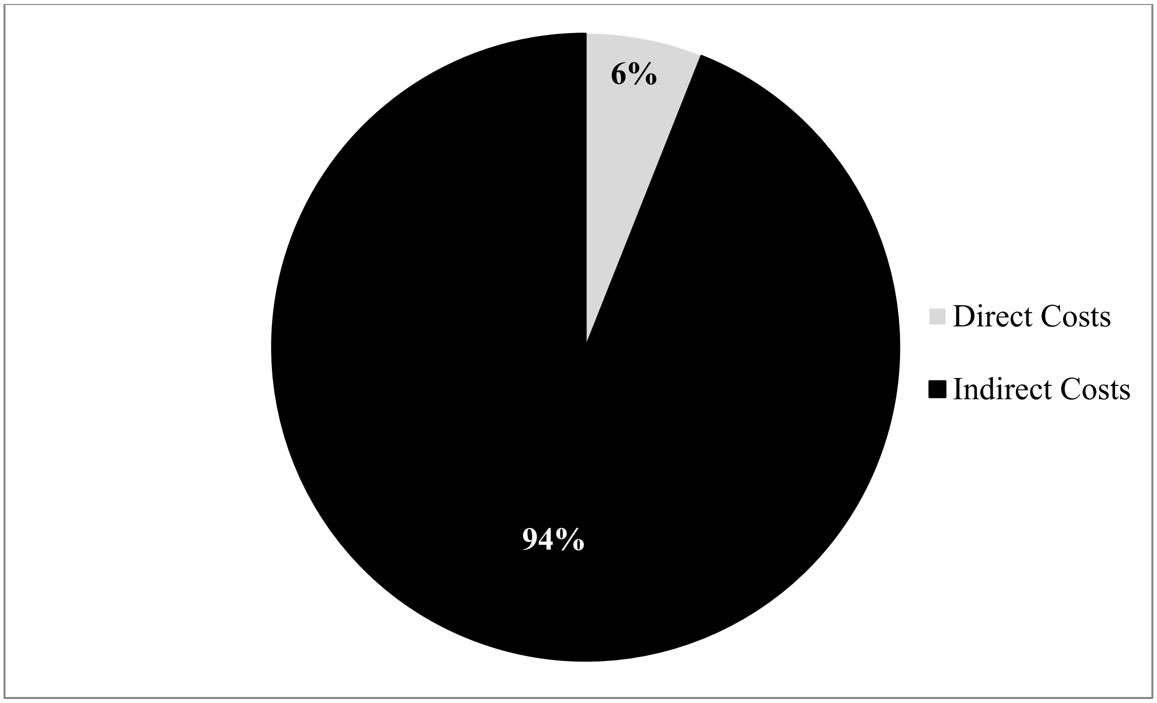


Figure 5.15: Direct Versus Indirect Costs Ratio for Consequences of Failure Case Study 1

The percentage of traffic disruption as a result of a sewer pipeline's failure in Montreal shows a value of 12% versus 1% in Doha of the total indirect costs. The length of the pipeline in the second case study is almost three times the length of the pipeline in the first case study. It can be seen from the above cost analysis, that the costs of failure could differ from one place to another due to the differences in people's daily commute, the behaviors, types of commuters, and the physical characteristics of the pipeline. Thus, determining the consequences using only costs could be misleading (i.e. the total costs for the two case studies are $97,925 and $98,508, however the impacts of each of the two pipelines' failure would be totally different). Therefore, benefit to cost ratio could be used to properly interpret the impact of failure using costs of that failure versus the benefits of avoiding it.

Table 5.20: Parameter Values Used in Case Study 2

Parameter	Quebec		
Road Classification	Arterial (2 lanes 2 way)		
Ground Water Table Level	<2 m		
Soil Type	Clayey Loam		
Year of Construction	1995		
Inspection Date	2009		
Length (m)	85		
Diameter (mm)	1600		
Material	Brick		
Depth (m)	4.3 m		
Structural: Operational: Overall Condition	5	5	5
Method of Ground Water Remediation	Pump and Treat		
Method of Pipeline Reinstatement	Open Cut Trenching		
Unit Cost of Material ($ /m)	650$ /1000 Brick		
Unit Cost of Labor ($/hr)	30		
Unit Cost of Equipment ($/hr)	90		
Cost of Emergency Vehicle ($/hr)	62		
Number of Emergency Vehicles	3		
Number of Vehicles Impacted (Vehicles/Day)*	1620	90	90
Fuel Price ($/liter)*	1.1	1	1
Running Cost Per Kilometer for Vehicle of Type ($/Km)*	0.7	0.8	1.1
Average Consumption of Vehicle Normal Cases (L/Km)*	0.1	0.28	0.33
Average Consumption of Vehicle During Disruption (L/Km)*	0.17	0.476	0.56
Detour Time (hr)	1.07		
Disrupted Distance (Km)	3.5		
Number of Inaccessible Parking Spaces	30		
Hourly Cost Of Parking ($/hr)	2.5		
Occupancy Ratio (%)	1.63		
Number of Operation Hours for Parking Lot (hr/Day)	12		
Hourly Rate of Passengers ($/hr)	14		
Number of Workers Affected In Work Place	17		
Hourly Rate for Workers In Work Place ($/hr)	14		
Productivity Reduction Factor	0.65		
Number of Customers Affected	195		
Number of Probable Infections (14%)	27		
Costs Saved by Individuals ($)	1180		
Costs Saved by Avoiding Work Absence ($)	490		
Cost of Saved Opportunity (1 Year)	31360		
Quality Adjusted Life Years (QALYs) (Benefits)	33805		

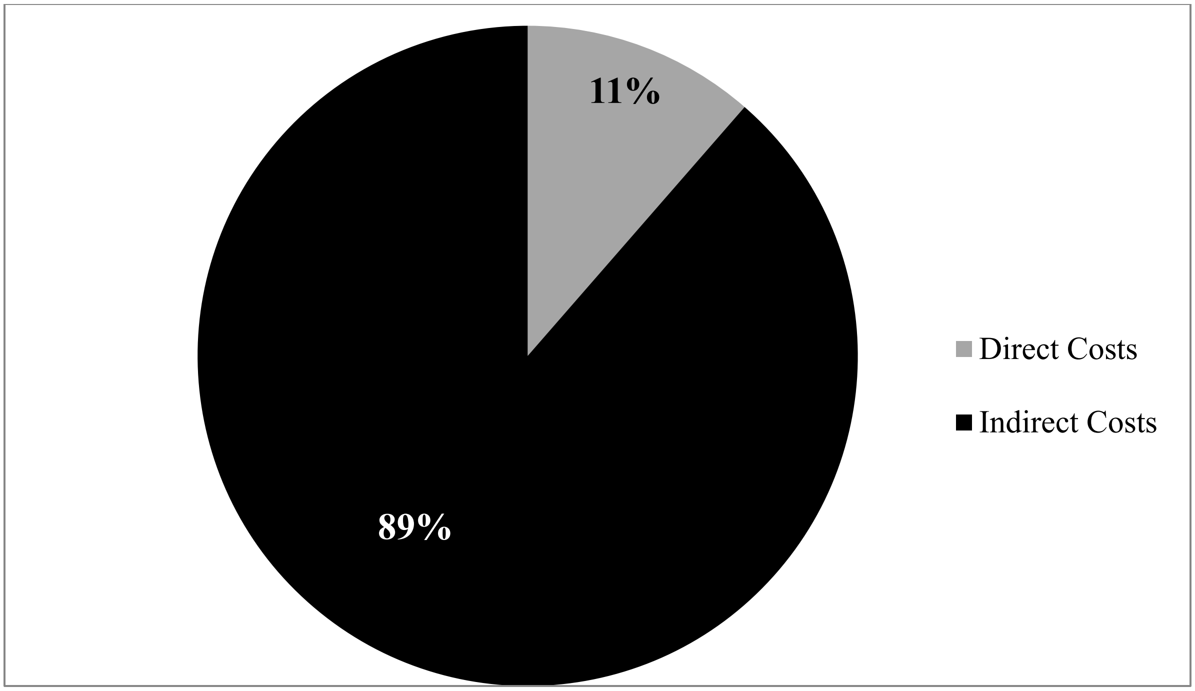


Figure 5.16: Direct Versus Indirect Costs Ratio for the Case Study 2

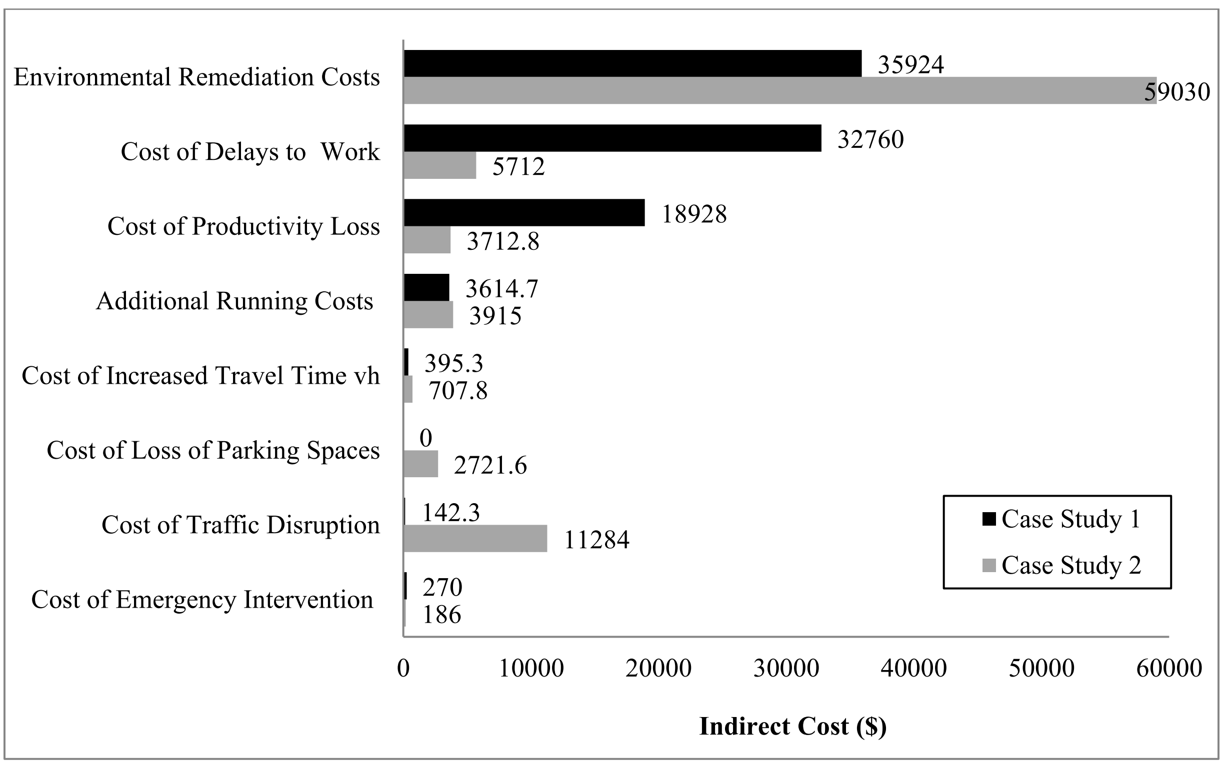


Figure 5.17: Indirect costs for the Case Studies

By applying the CBA equation with one-year study period for the two case studies, the benefit to cost ratio would be 0.5 and 0.34, respectively, which indicates that the benefits from avoiding failure in the first case study would be more than the benefits in the second case study. In other words, the 0.34 ratio indicates that failure of the sewer pipeline is more significant than the other pipe having a higher B/C equal to 0.5.

5.4. Risk of Failure Model Implementation

One of the challenges that face municipalities in making decisions regarding inspection is which sections should be included and their inspection order. Due to the lack of decision support tools, municipalities select sections randomly which would result in unnecessary inspections. The likelihood and consequences of failure for several pipeline sections are combined using Sugeno Fuzzy Inference Systems (S-FIS) using the same methodology presented in section 3.2.5.

5.4.1. Risk of Failure Case Study 1 – City of Doha, State of Qatar

To examine the applicability of the proposed risk assessment model, actual data for inspection reports of a sewage network in Doha, Qatar, was used to compare the output of the model with the pipe section's actual inspection dates and order. The data comprised 470 inspected sections with their names along the different defects in each section and the different pipeline characteristics (diameter, material, length, street category and depth). In addition, inspection dates for each section and the order of the inspection was also included in the data. Table 5.21 shows a comparison between the costs resulting from the current inspection practices in the municipality in Doha and the costs resulting in case the proposed model is deployed.

The significant difference in the two costs represents how this model is expected to reduce unnecessary costs. To compare between the actual and calculated costs, a planning horizon of 10 years in which inspection would take place was assumed. It was found that approximately 10 kilometers with an inspection cost of $34,470 did not require inspection because condition ratings for these pipelines was either excellent or very good and the risk of failure was extremely or very low. Additionally, the total costs of inspections were $154,940 for the 470 inspected sections. On the other hand, it was found that only 108 sections with a total length of 5570 meters required inspection (condition ratings for these sections were between critical and poor and the risk of failure was extremely or very high) with a total inspection cost of $34,625.

Table 5.21: Actual versus Calculated Inspection Costs for Risk Assessment Case Study 1

Diameter of Inspected Sections (mm)	Actual Inspection Cost (USD)	Calculated Inspection Cost (USD)
150 – 200	30,145	11985
> 200– 300	77,680	12860
> 300	47,115	3780
Total Inspection Costs	**154,940**	**34,625**

By calculating the differences between the actual and proposed inspection costs, it was found that almost 76% cost savings could be achieved. Table 5.22 shows a sample for a proposed inspection order calculated using the proposed tool. The table shows the likelihood, consequences, and risk of failure based on the defects and pipeline characteristics. It is obvious from the inspection order that several sections (sections having orders: 110, 172, 261, 302, 412, 422, etc.) were inspected in the years 2013, 2014 and 2015; however, they could have waited several years before they were inspected.

Table 5.22: Risk of Failure Indices with Corresponding Inspection Order for Case Study 1

Section	Inspection Order	Inspection Date	Length (m)	Diameter (mm)	Material	Inspection Cost ($)	Likelihood of Failure	Consequen ces of Failure	Risk of Failure (Overall	Proposed Inspection Order
A	1	Jan-2013	44.60	150	VC	133.81	0.78	1.36	0.751	3
B			49.40	150	VC	148.20	0.38	0.45	0.516	261
C			83.95	150	VC	251.87	0.35	0.13	0.677	81
D	2		22.91	150	VC	68.73	0.35	0.34	0.605	82
E			35.18	150	VC	105.56	0.28	0.44	0.522	8
F	3		53.54	150	VC	160.62	0.47	0.27	0.516	7
G			14.32	150	VC	42.96	0.36	0.32	0.314	422
--	--	---	---	--	--	--	---	---	---	--
AD	1	Feb-2013	54.69	150	VC	164.07	0.28	0.26	0.633	172
AE			81.96	450	VC	491.78	0.56	0.22	0.555	89
AF			66.13	500	VC	396.82	0.74	1.45	0.88	2
AG	2		40.41	300	VC	202.08	0.56	0.45	0.461	418
AH			43.65	300	VC	218.25	0.34	1.1	0.488	224
--	--	---	---	--	--	--	---	---	---	---
QU	1	Mar-2015	68.86	400	VC	413.17	0.56	0.67	0.613	110
QV			57.47	150	VC	172.42	0.23	1.40	0.478	90
QW			11.12	150	VC	33.36	0.16	0.98	0.246	302
QX			42.08	150	VC	126.25	0.35	0.56	0.503	174
QY	2		42.37	250	AC	211.89	0.22	0.67	0.364	262
QZ			79.05	450	VC	474.33	0.45	0.33	0.543	111
RA			48.10	150	VC	144.30	0.67	0.35	0.589	41
RB			70.88	150	VC	212.65	0.77	0.78	0.67	98

5.4.2. Risk of Failure Case Study 2 – City of Laval, Quebec, Canada

In the second case study, actual data for inspection reports of sewage pipelines in the city of Laval in Quebec, Canada, were used to compare the output of the model with the pipe section's actual inspection dates and order. The data comprised 33 inspected sections with the different defects in each section and the different pipeline characteristics (diameter, material, length, street category and depth). In addition, inspection dates for each section and the order of the inspection were also included in the data. The proposed risk assessment tool was used to assess the risk for the actual data and create a priority list for sewer sections to be inspected. The total inspection costs were calculated by multiplying the unit inspection cost and the lengths of inspected sections for the actual data, then they were compared with the inspection costs derived from the model as shown in Table 5.23.

Table 5.23: Actual versus Proposed Inspection Costs for Risk Failure Case Study 2

CCTV Sewer Inspection	Unit Cost ($ / Meters)	Inspected Section Length (m)	Actual Costs of Inspected Sections (USD)	Costs of Proposed Inspected Sections (USD)
300mm	3.00	780	2,340	1,200
> 300mm – 500mm	6.00	970	5,820	5,235
> 500mm	8.50	900	7,650	6,580
Mobilization (Lump Sum)	4,000			

It was found that 1 kilometer didn't require inspection (condition rating of the pipeline was either excellent or very good with a corresponding inspection cost of $4,468). It was also found that only 10 sections with a total length of 1.65 Km required inspection (Condition Rating was between Critical and Poor) with a total inspection cost of $13,015. Table 5.24 shows a sample for the different sections used in the tool implementation with their relevant information. To calculate the economic feasibility of using the proposed model, a planning horizon of 5 years was assumed in which inspection would take place (i.e. inspection costs calculated for pipelines to be inspected between the current year and the next 5 years). Using the proposed model, a cost reduction of more than $19,810 was achieved (i.e. Actual cost of inspected sections was $17,015, corresponding to 15% of the total inspection costs).

5.4.3. Sensitivity Analysis

To examine the robustness of the proposed risk assessment model, a sensitivity analysis was conducted on 4 cases representing the effect of variability in the confidence of decision makers about the level of failure and consequences. Different scenarios were set in each case to represent the confidence of the decision maker in deciding how likely the failure would be to take place, and its category. The details of these cases and the different scenarios are presented in Table 5.25. As shown in the table, scenario 1 indicates a high failure likelihood (confident decision-maker), whereas scenario 6 depicts a low likelihood of failure (a reluctant decision-maker). The results of the sensitivity analysis are presented in Figure 5.18.

Table 5.24: Risk of Failure Indices with Corresponding Proposed Inspection Dates for Case Study 2

Section	Inspection Date	Length	Diameter	Material	Actual cost of inspection	Proposed Inspection Date	Risk of Failure (Overall Condition ≥
1	2009	68.7	400	RC	274.8	2013	0.851
2		76.5	450	RC	306	2021	0.516
3		109.1	750	RC	436.4	2021	0.677
4		96.8	300	RC	387.2	2009	0.905
5		52.5	250	RC	210	2013	0.762
6		55.2	250	RC	220.8	2013	0.787
7		97.3	500	RC	389.2	2013	0.814
--	--	--	--	--	--	--	--
15	2009	69	900	AC	276	2019	0.563
16		60.2	300	AC	240.8	2016	0.545
17		69	300	RC	276	2016	0.567
18		70.1	700	RC	280.4	2008	0.890
19		53	300	RC	212	2013	0.870
--	--	--	--	--	--	--	---
33	2010	71.6	300	VC	286.4	2019	0.765

It is obvious that the scenarios related to the likelihood of failure show an exponential decay with respect to risk, whereas the consequences are linear. The fuzzified failure in risk calculations transformed the linear dependency to a non-linear relationship. This means that at a higher failure likelihood (confident decision-maker) it is likely that the risk is high; however, as the failure likelihood decreases (reluctant decision maker), the risk estimates would probably decrease, but at a comparatively slower rate.

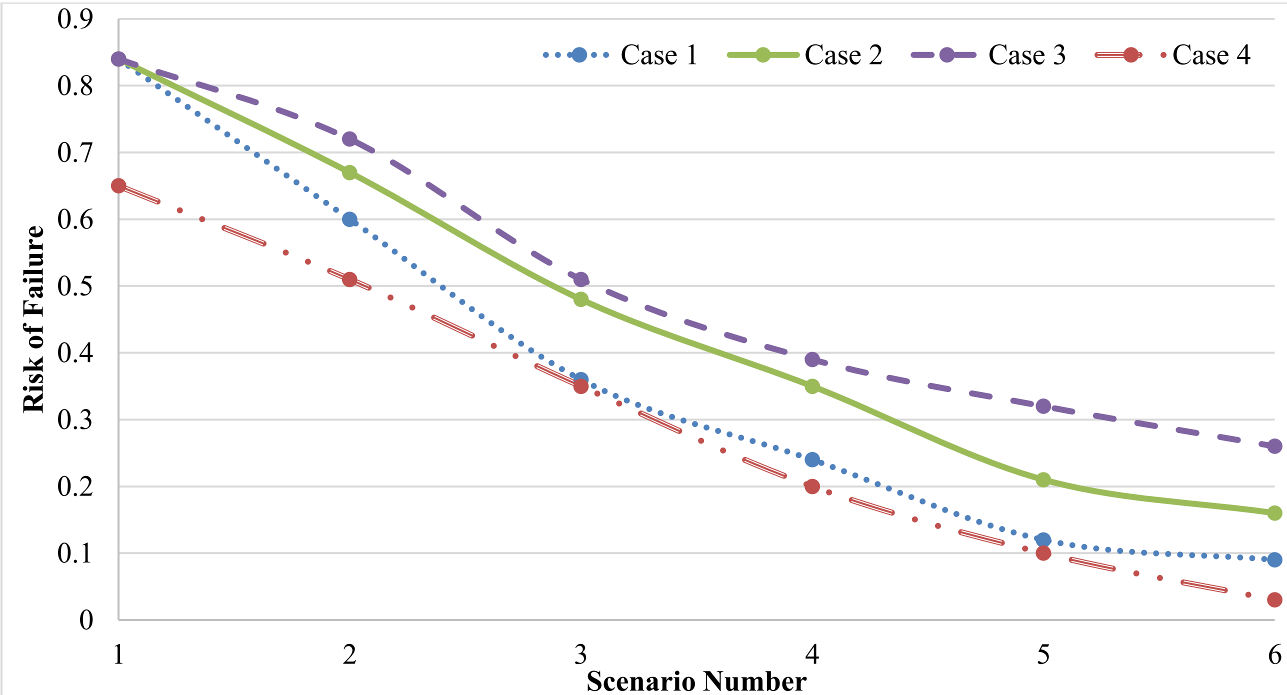


Figure 5.18: Sensitivity Analysis for Risk Values under Different Likelihood and Consequences of Failure Scenarios

5.5. Multi-Objective Optimization Model Implementation

To examine the efficiency and robustness of the proposed optimization algorithm, an actual case study was used to optimize the number of inspected pipelines based on resource availability. Three crews were available for inspection, using one inspection technology (CCTV). Table 5.26 shows a sample of the pipelines and corresponding time and cost of inspection based on the CCTV inspection technology. The data comprised 473 sections with a total length of 23.95 Kilometers from which certain pipelines were supposed to be selected for inspection. All sections were inspected in the year 2014 with a total inspection cost of $90,625. By comparing the number of pipeline sections to be inspected and the actual pipelines inspected, it was found that almost 12.80

Kilometers of pipelines did not require inspection and only 11.15 Kilometers required inspection. A planning horizon was set to 5 years starting the year of inspection (2014) and it was found that only 1.7 Kilometers required inspections within the upcoming 5 years with a cost savings of 67%.

Table 5.25: Different Cases and Scenarios for Sensitivity Analysis

Case	Scenarios	Scenario definition	Risk value
Case 1	1	Decision Maker is confident, failure likelihood is extremely high	0.84
	2	Decision Maker lacks confidence, failure likelihood is High	0.6
	3	Decision Maker is not confident, failure likelihood is Moderate	0.36
	4	Decision Maker is doubtful, failure likelihood is Low	0.24
	5	Decision Maker is doubtful, failure likelihood is very Low	0.12
	6	Decision Maker is doubtful about failure likelihood and consequences. Failure likelihood is very Low and Consequences is Moderate	0.09
Case 2	1	Decision Maker is confident, failure likelihood is extremely high	0.84
	2	Decision Maker lacks confidence failure likelihood is very high	0.67
	3	Decision Maker is not confident, failure likelihood is Moderate	0.48
	4	Decision Maker is doubtful, failure likelihood is low	0.35
	5	Decision Maker is doubtful, failure likelihood is very low	0.21
	6	Decision Maker is doubtful about failure likelihood and consequences. Failure likelihood is Low and Consequences is Moderate	0.16
Case 3	1	Decision Maker is confident, failure likelihood is extremely high	0.84
	2	Decision Maker lacks confidence failure likelihood is very high	0.72
	3	Decision Maker is not confident, failure likelihood is Moderate	0.51
	4	Decision Maker is doubtful, failure likelihood is low	0.39
	5	Decision Maker is doubtful, failure likelihood is very low	0.32
	6	Decision Maker is doubtful about failure likelihood and consequences. Failure likelihood is extremely Low and Consequences is Moderate	0.26
Case 4 (Only	1	Very high consequences	0.65
	2	High consequences	0.51
	3	Moderate consequences	0.35
	4	Very low consequences	0.2
	5	Extremely Low Consequences	0.1
	6	No consequences	0.03

The optimization algorithm was run on a 4GB RAM, 2.50 GHz i5 core CPU, and Windows 7 with 64 bit operating system, using GAMS IDE 23.5 by CPLEX solver. The running time ranged between 487 seconds (8.11 minutes) and 840 seconds (14 minutes). The performance of the optimization model could allow personnel working in municipalities to obtain real time optimal crew allocations required for performing inspections on sewer pipelines. Because the formulated optimization problems require the decision maker's input regarding the relative importance of each objective function; several weights were randomly generated to determine the optimal combination for the three objective functions.

Table 5.26: Sample for the Data Used in Evaluating the Optimization Model

Pipe ID	X	Y	Risk of Failure	Failure (Year)	Cost ($)	Diameter (mm)	Length (m)	Time (min)
0	205671.50	446715.438	0.24	2066	146.56	150	48.85	8
1	205430.57	446744.2995	0.25	2061	319.76	500	53.29	9
2	205671.49	446680.5135	0.26	2064	151.48	200	50.49	8
3	205786.75	446652.662	0.26	2064	137.42	150	45.80	8
4	205671.52	446643.193	0.27	2067	308.01	300	61.60	10
5	205801.45	446637.858	0.29	2077	150.57	200	50.19	8
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
230	232831.28	441877.666	0.88	2032	354.68	300	70.93	12
231	231949.66	441882.464	0.9	2020	151.27	200	50.42	8
232	231996.00	441879.512	0.9	2020	277.45	200	92.48	15
233	231747.91	441875.72	0.94	2022	405.68	300	81.13	14
234	233482.82	442136.226	0.59	2050	118.28	150	39.42	7
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
471	232959.98	442137.240	0.59	2050	282.54	400	47.09	8
472	232932.97	442146.541	0.59	2052	93.13	200	31.04	5
473	232266.22	442136.123	0.59	2063	137.62	150	45.87	8

Table 5.27 shows a sample for the different runs of the optimization problem using different weights. Figure 5.19 shows the different solution sets generated from 100 runs with

randomly generated weights. The optimal solution sets were chosen from the different combinations that would result in a maximum number of pipeline sections and minimum inspection time and cost. As shown in the figure, the highlighted solution sets are the ones that would maximize the number of pipeline sections to be inspected while minimizing time and costs.

Table 5.27: Different Optimal Solution Sets Resulting from Different Iterations

Iteration	W1	W2	W3	Cost	Time	No. of Sections	Weighted Objective Function
1	1	1	1	9.77	9.64	258	34.58
3	0.3	0.4	0.3	7.36	7.25	234	9.58
4	0.4	0.1	0.5	16.29	16.10	305	23.86
5	0.6	0.2	0.2	2.74	2.73	152	4.21
6	0.5	0.4	0.1	0.54	0.65	90	1.37
7	**0.8**	**0.1**	**0.1**	**0.26**	**0.31**	**62**	**1.06**
¦	¦	¦	¦	¦	¦	¦	¦
100	0.2	0.4	0.4	12.18	12	267	15.16

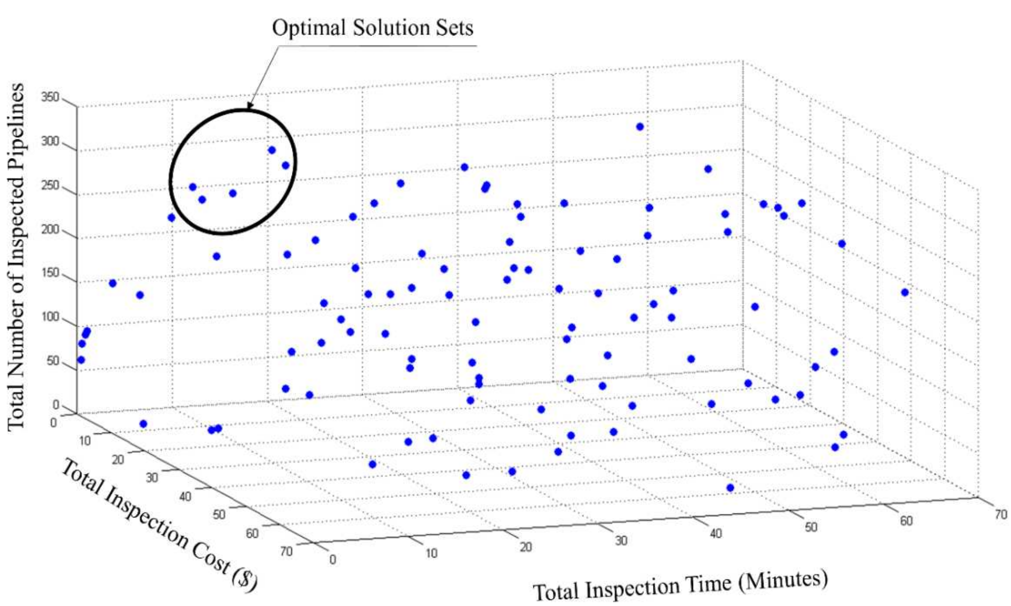


Figure 5.19: Optimal Solution Sets Generated from Running Optimization Algorithm

5.5.1. Optimization Model Evaluation

To evaluate the results of the model, the output was compared with the output of the optimization model using Genetic Algorithm (GA). GA was chosen because it is widely used in infrastructure problems. The inspection time, cost, and number of sections, were calculated for the case study discussed. The proposed optimization model showed improvement over the evolutionary algorithm model regarding the cost and time as shown in Table 5.28. Figure 5.20 shows the convergence of the two optimization models, in which the y axis represents the fitness function and the x axis represents the number of iterations after which the model would converge. It is evident from Table 5.28 that a cost saving could be achieved when using GAMS in solving the proposed optimization model. By determining the differences in inspection costs, it was found that a cost saving of 45%, equivalent to $8,600, for the 1.7 km inspected length could be achieved.

Table 5.28: Evaluation of Optimization Model Computational Efficiency

Parameter	Optimization Model	Evolutionary Algorithms	Enhancement (%)
Time (Minutes)	0.26	0.35	25.7
Cost ($)	0.31	0.56	44.5
Number of Pipelines	62	58	6.4

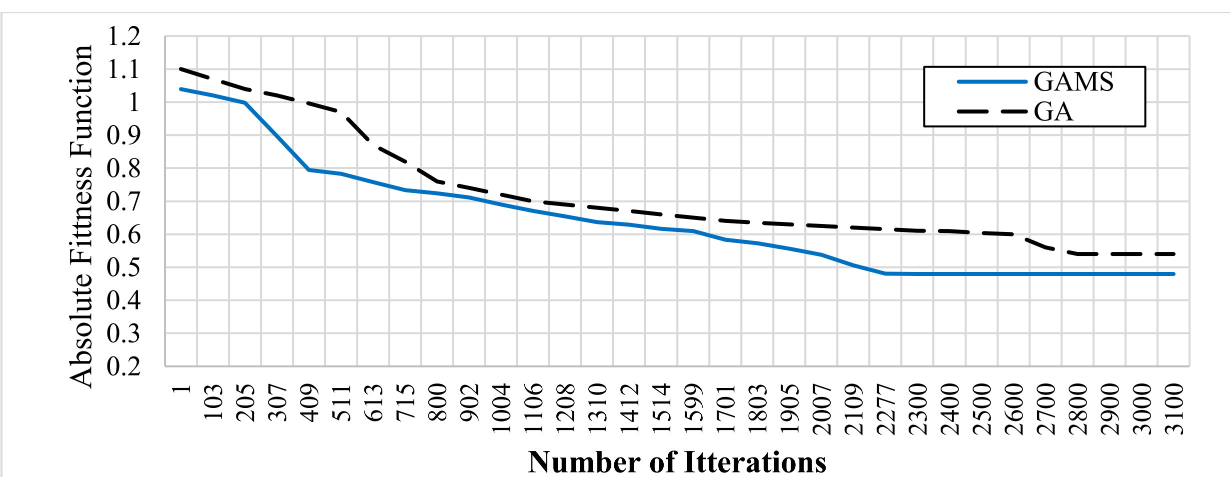


Figure 5.20: Comparison between Convergence Curves for Optimization Model Using Different Algorithms

5.5.2. Sensitivity Analysis

After determining the optimal relative weights, the optimization problem was solved separately three times (i.e. cost, time and number of pipeline sections were run separately and the other objectives were set to zero). When only cost was considered crew 2 was selected to do all the inspection because it had the lowest unit cost and the other crews were not used. This resulted in a greater total time required for inspection and minimum number of inspected sections. On the other hand, if the decision was only based on time and cost this would have made a significant impact on the number of sections to be inspected. For instance, if cost and time were the only considerations, the total number of sections would have been 21.

However, when only time was considered it resulted in a larger number of sections inspected (233 sections) but with costs exceeding the allocated budget by 35%. When the decision was based only on the number of sections, without considering the time and cost, this resulted in all sections being inspected, though the cost was twice the budget allocated. Figure 5.21 shows the effect of changing the relative weights of the different optimization model parameters. As shown in Figure 5.21a, the model is highly sensitive to the number of sections included, however it is equally sensitive to the time and cost. Figures 5.21b, 5.21c and 5.21d show the effect of changing two parameters while considering the other by setting it to zero. For instance, Figure 5.21b shows that the model is not as sensitive when considering the time and cost only without considering the number of sections.

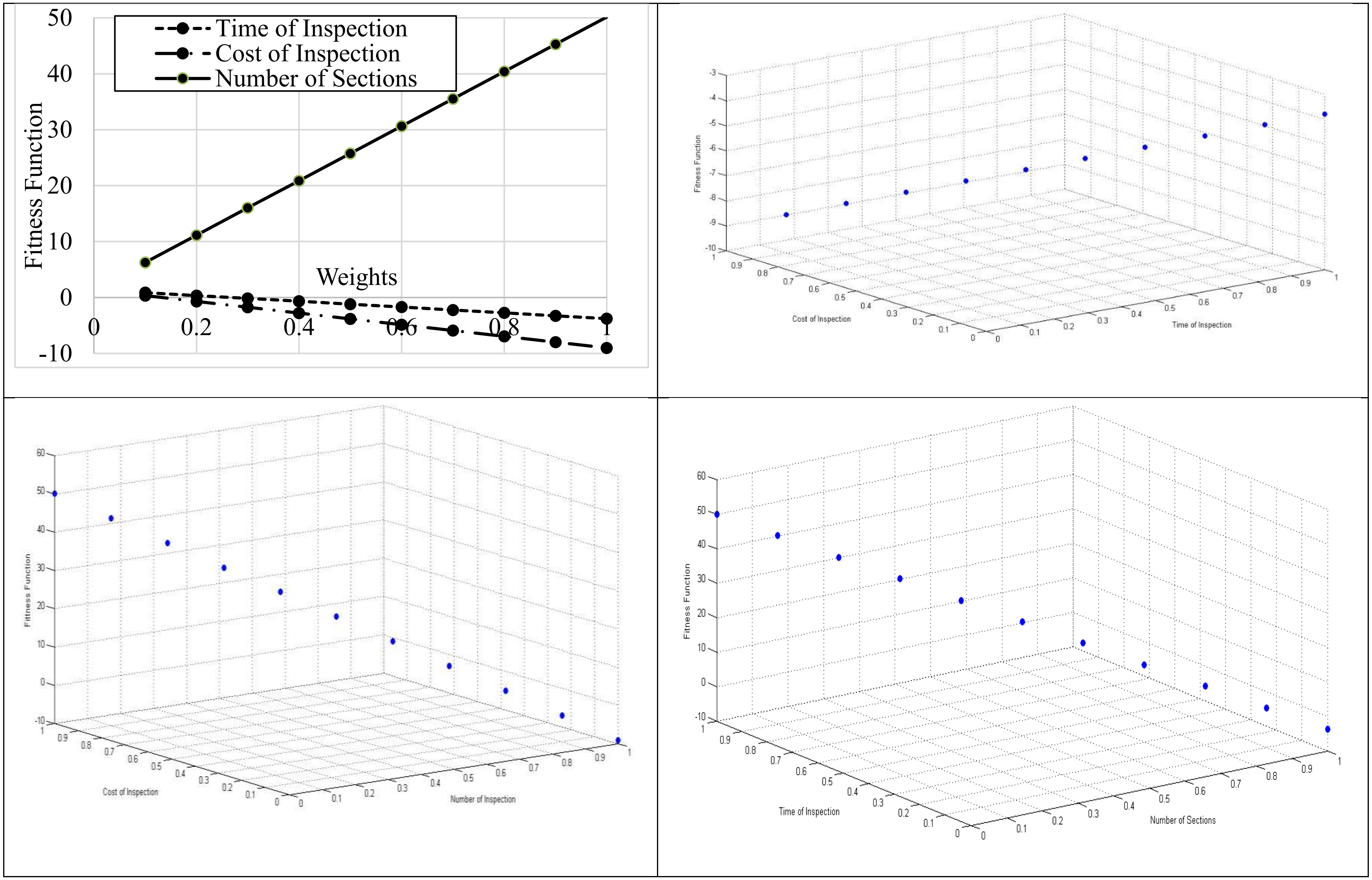


Figure 5.21: Sensitivity Analysis for Different Objectives of Optimization Model

5.5.3. Modeling Mathematical Optimization Model Using GAMS

To model the formulated problem in GAMS IDE there are several steps that must be carried out. For simplicity, GAMS has the option to import and export external data through "*GAMS Data Exchange (GDX) facilities and files*." The GDX files are binary files that are portable between different platforms.

5.5.3.1.Defining variables

GAMS uses notations of sets which makes them the most important set of elements in which defining the variables and constraints would greatly depend. Naming sets are similar to using indices in an ordinary problem. For example, assuming we have a set of pipelines, the following syntax would be used to define this set:

Sets

Pipes /p1, p2/;

In the above syntax the set of pipelines contains two elements namely p1 and p2. Variables and parameters have to be declared in a specific part of the model, initiated by "*Variables*" and "*Paramete*rs" keyword.

5.5.3.2.Defining constraints

Both the objective function and constraints are defined in the Equations section in the model.

Each constraint has its name and can be briefly described in the beginning of the section, to make the model easier to trace.

Constraint1 (t): t =l= t_p_f;

*Constraint2 (C_Ins):C_Ins *y=l= Budget;*

Where the symbol*" =l="* refers to *"≤"* operator and "t", "C_Insp" and "y" are different variables and parameters previously defined.

5.5.3.3.Exporting Solutions

When the model is executed, a log file and a solution file are created. The solution file contains model statistics, details about execution time, solver output and the final solution which is exported by using GDX files as well.

5.6. Recap

In this chapter the implementation of the proposed models was presented. Actual data from real case studies was used to examine the efficiency and accuracy of the proposed models. The deterioration model was validated by calculating the Mean Absolute and Root Mean Square Errors to determine the variation between the predicted and actual values for the pipeline's condition. The consequences of failure model was validated by comparing the deviation between the model's output and the actual case studies. Additionally, two cases were implemented to compare how this model could be used to evaluate the severity of failure in the pipelines at different locations. Risk indices were calculated by combining the output of the previously mentioned models, and the proposed inspection costs were compared with the actual inspection costs. The comparison showed that the proposed model would result in a cost saving if used instead of the current inspection practices. The optimization model was implemented and evaluated on actual data in which the performance of the model was evaluated. Also, GA was compared with the proposed optimization model and it was found that the performance of the proposed model is better than that of the GA model.

Chapter 6: Automated Tool- Optimal Crew Inspection Scheduler (OCIS)

6.1. Introduction

The previously mentioned models are integrated to provide the user with a schedule for pipelines that require inspection in a chronological order. These models could be converted into an add-in for ArcGIS or MS-Project to enable users to select the required pipelines, and identify the condition rating of that pipeline in terms of probability and the expected inspection date. Figure 6.1 shows the different inputs and outputs contributing to the process of visualizing the inspection schedule for sewer pipelines.

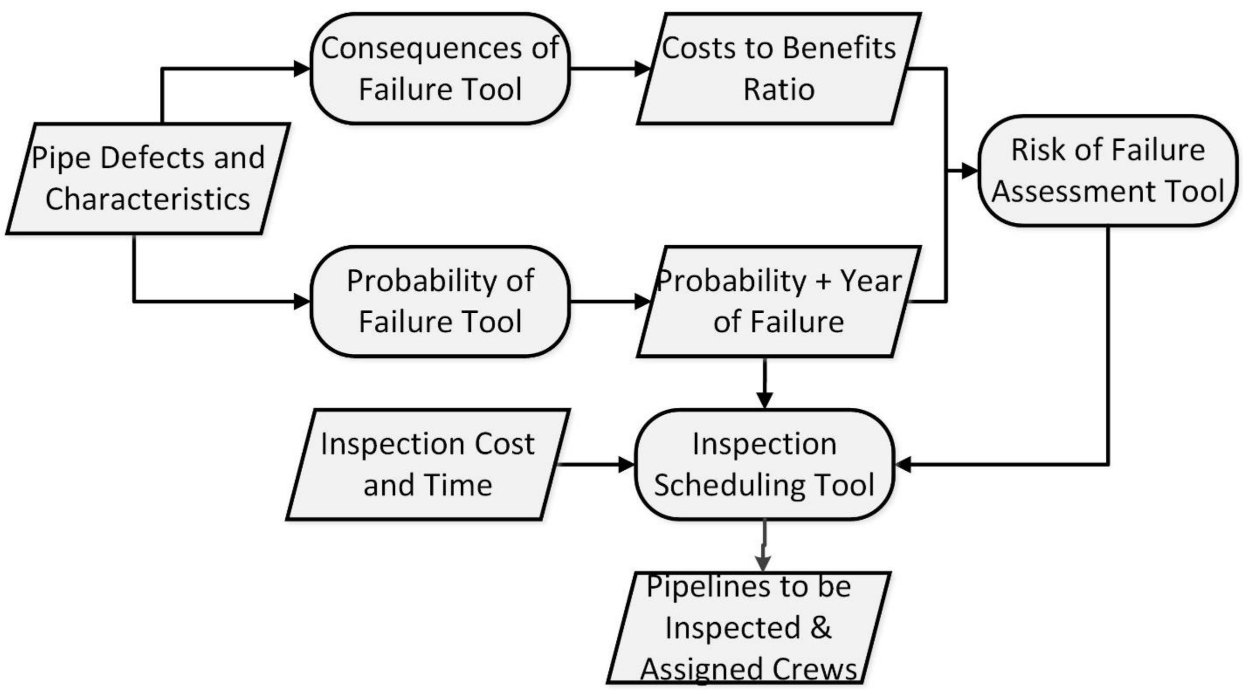


Figure 6.1: Different Inputs and Outputs for the Different Tools Used in the Inspection Scheduling Tool

The user imports the different pipelines with the relevant data such as pipe diameter, length, material, depth, etc., and different defects present in these pipelines. These inputs are used in the probability and consequences of failure modules from which the user can identify a priority list showing the different pipeline sections. Optimization module is then instantiated, in which the user can identify the different inspection intervals for the different pipelines based on the budget allocated for inspection. Figure 6.2 shows the home page for the risk assessment tool used to assess the failure of sewer pipelines. The user is given the option to select the required tool–whether probability, consequences, or risk of failure-from this feature window. In the following sections, the different interfaces are presented.

Figure 6.2: Home Page for Risk Assessment of Sewer Pipelines

6.2. Likelihood of Failure Module

The process of entering the defects to the developed likelihood of failure model could be time consuming and would require significant effort, especially if this is done more than once and for a large number of nodes. Thus, a tool has been developed using visual basic 6 to control the application. A flow chart for the multiple document interface development is shown in Figure 6.3.

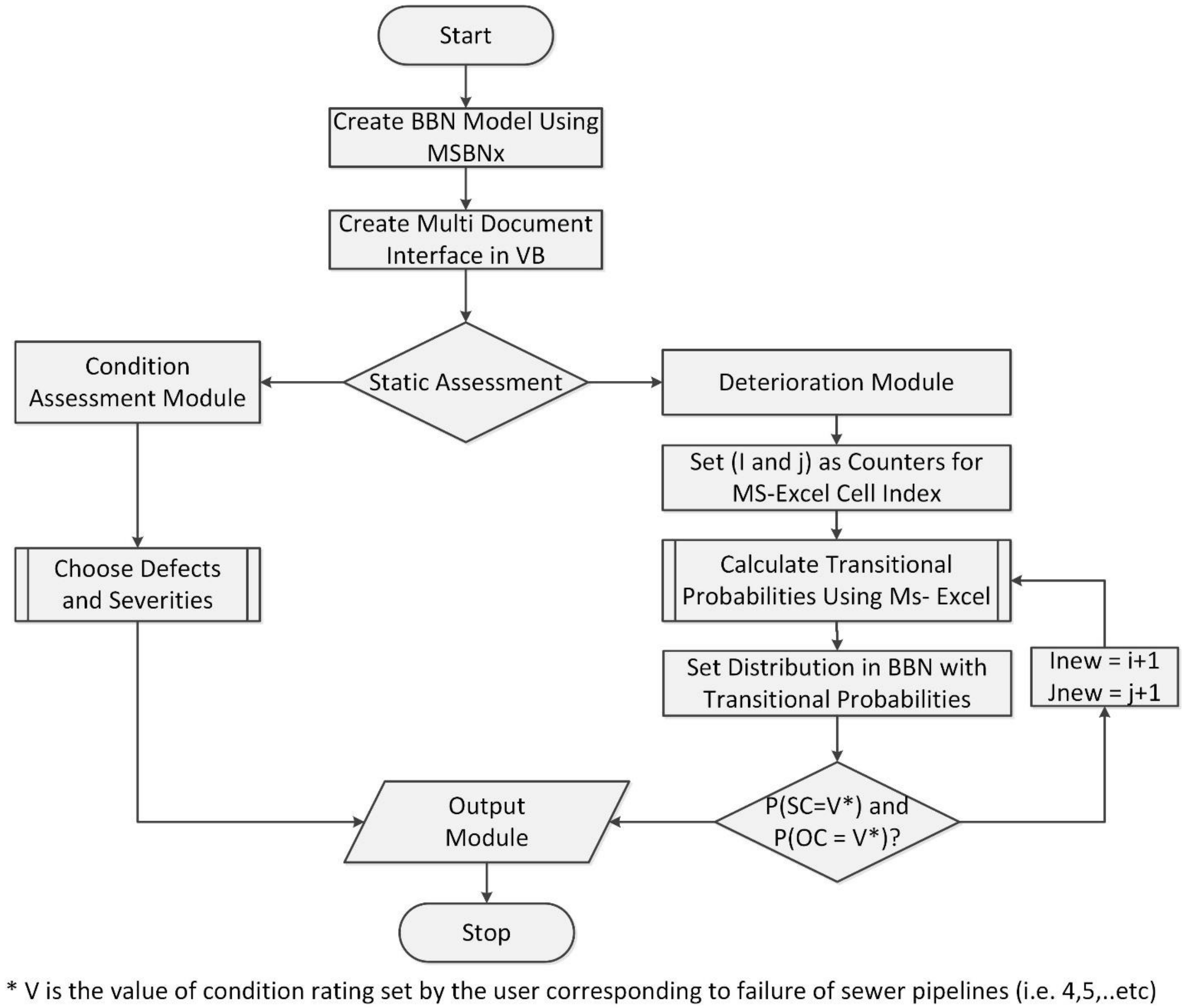


Figure 6.3: Flow Chart for the Developed Add-on Likelihood of Failure Tool

This add-on tool enables the user to check the different defects with the level of severity, and provides the user with the probability of the different condition ratings. In addition, the tool could be connected to MS excel (Microsoft Corporation, 2013) and MSBNx to determine the deterioration rates for pipelines based on their characteristics. In order to make it easier for the user to input the different values of the model parameters, a graphical user interface was developed using VBA from which the user can investigate the results and change the inputs. Figures 6.4 to 6.7 show a snapshot of the different feature windows for the developed graphical user interface. In the beginning the user is directed to choose the static condition assessment for which the different user forms appear. In these user forms, the user enters the different structural and operational defects in the pipelines.

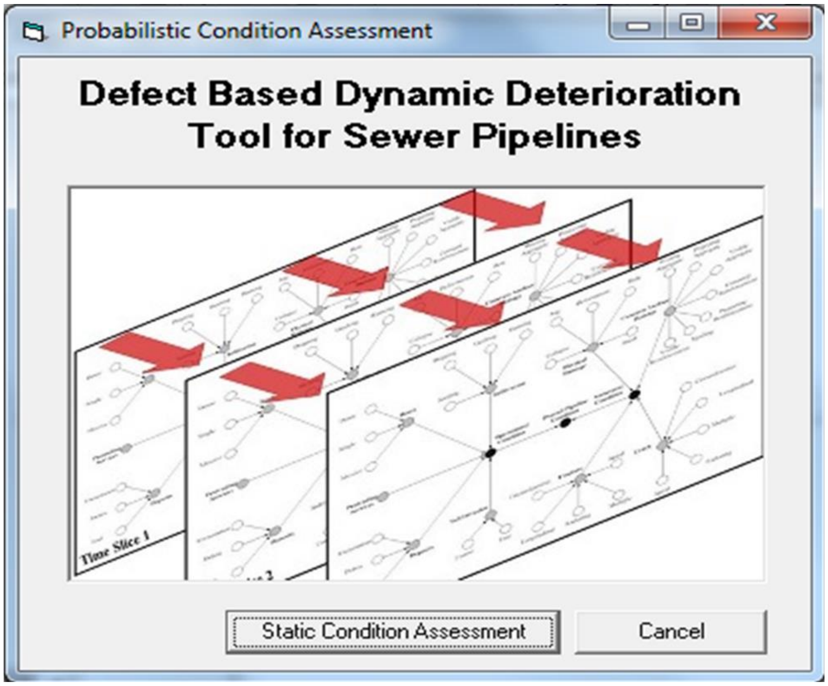


Figure 6.4: Home Page for the Defect Based Dynamic Deterioration Tool

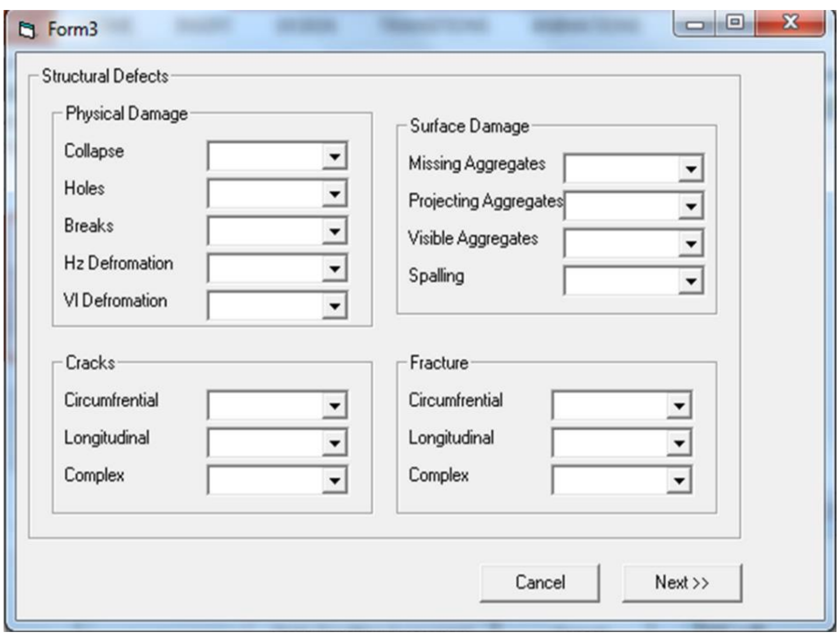


Figure 6.5: Structural Defects Input Window

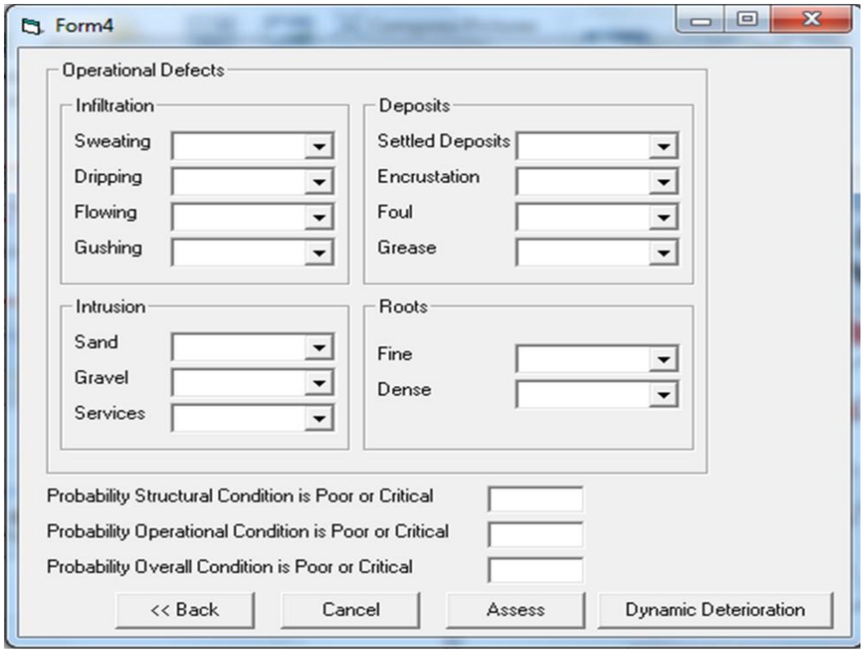


Figure 6.6: Operational Defects Input Window

By clicking the "Assess" button, the different probabilities of failures are the output. In the same window, the user is directed to choose dynamic deterioration from which he is redirected to the dynamic deterioration user form. By clicking the "Assess" button the user can determine the year at which the pipeline would fail.

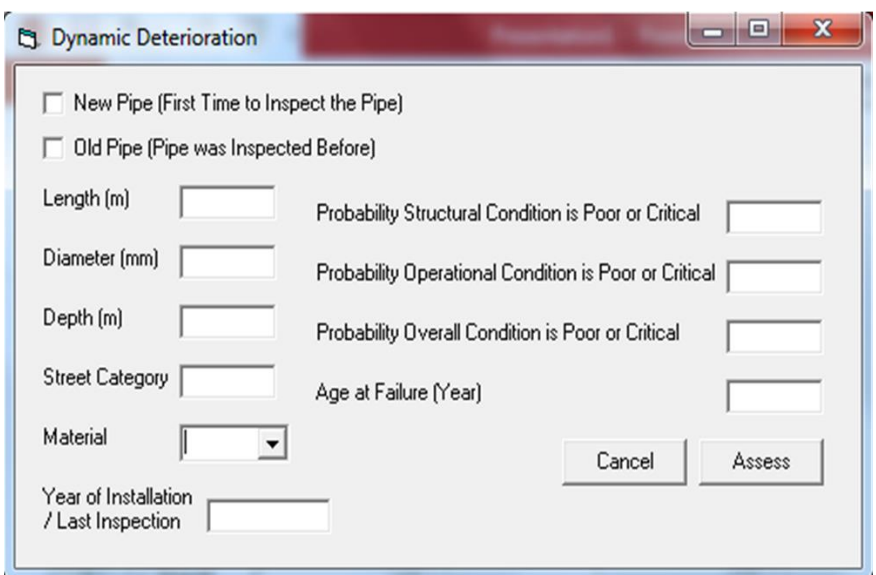


Figure 6.7: Dynamic Deterioration Input and Output Window

In the following section, the graphical user interface for the economic loss model is presented.

6.3. Consequences of Failure Module

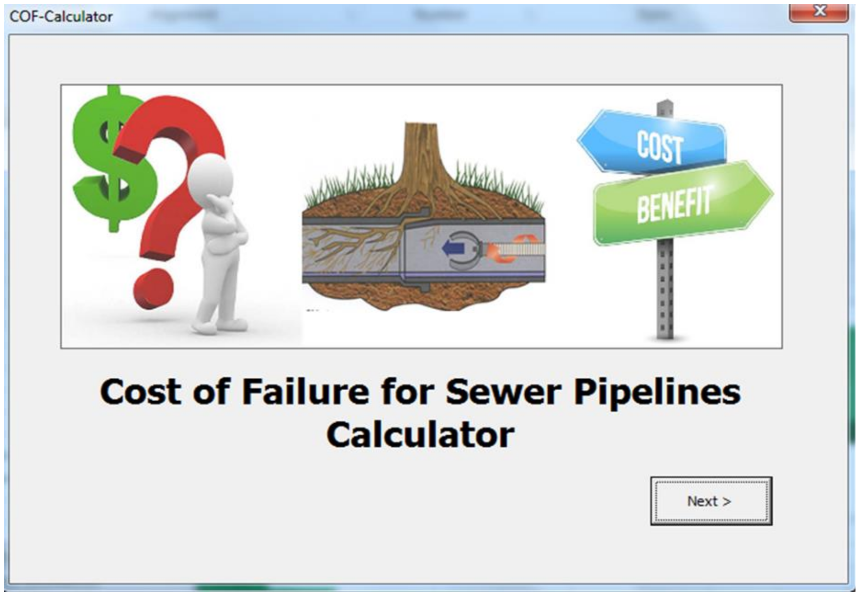


Figure 6.8: Home Page for Cost of Failure Calculator

Figure 6.8 shows the home page for the consequences of failure tool. In this home page the user is directed to the input window which is shown in Figure 6.9.

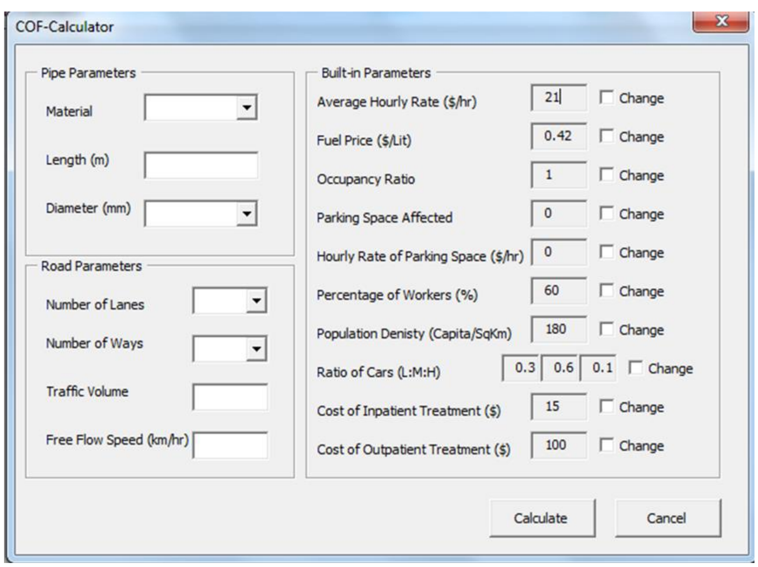


Figure 6.9: Input Window for Consequences of Failure Tool

After inputting the relevant required information and selecting “Calculate” button, the CBA feature window pops up with different outputs from the model as shown in Figure 6.10.

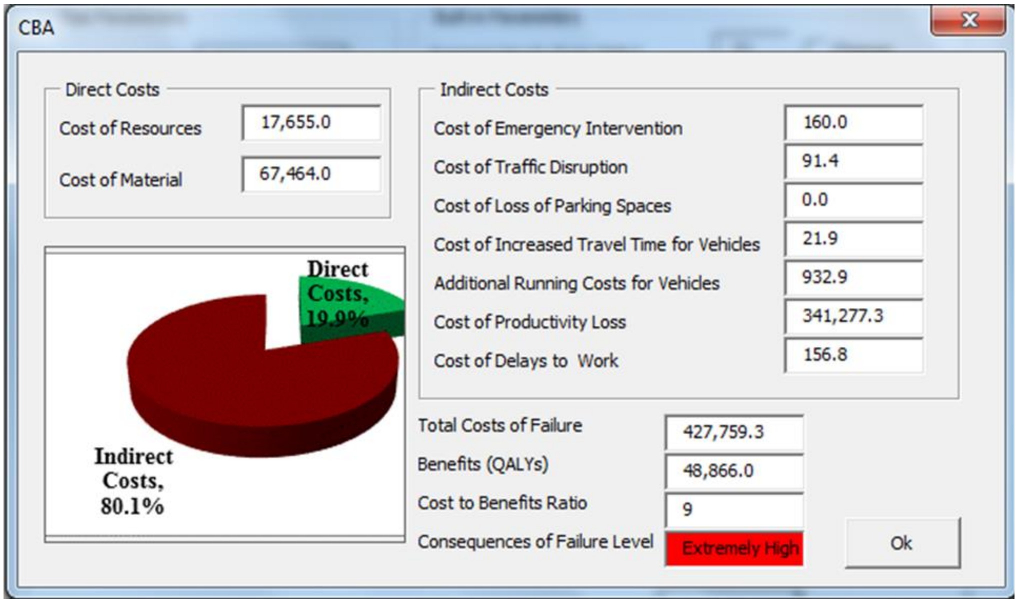


Figure 6.10: Output Window for Consequences of Failure Tool

6.4. Risk of Failure Assessment Module

To automate the proposed risk assessment model, an algorithm to calculate risk using S-FIS was implemented using python programming language with the aid of a special library for functions tailored especially for fuzzy logic called “scikit fuzzy” (Python Core Team, 2017) to be integrated in ArcGIS. Figure 6.11 shows the different tools forming the risk indexing automated tool. Python programming language was chosen because it could be easily integrated with ArcGIS in which there is a designated toolbox for that purpose. A python code was created to export the required attributes found in pipeline and roads geodatabases (layers) to perform the calculations for both the likelihood and consequences of failure and then importing the resulting risk and expected year of inspection back in the ArcGIS file.

The pipelines’ age, size, material, depth, year of installation, roads’ number of lanes and category were the attributes exported from attribute tables in ArcGIS. The different pipeline attributes were exported to MS-Excel from which likelihood of failure and time at which the pipeline would reach a certain condition state set by the user were identified using the deterioration model. Similarly, the road type and number of lanes were used to calculate the consequences of failure. Figure 6.12 shows a snapshot for the developed automation tool bar. The algorithm used in the Python code included syntax for fuzzy membership function generation, rules generation, fuzzification and de-fuzification and exporting the different data from ArcGIS.

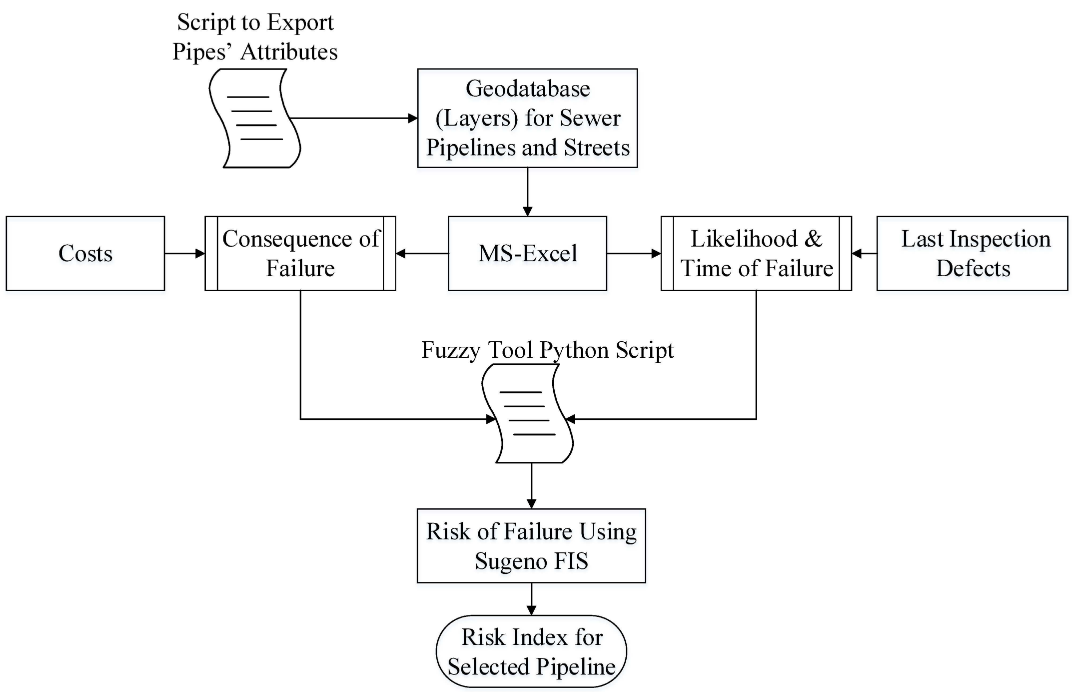


Figure 6.11: ArcMap Add-in Tool to Assess Risk of Failure for Sewer Pipelines' Inspection Prioritization

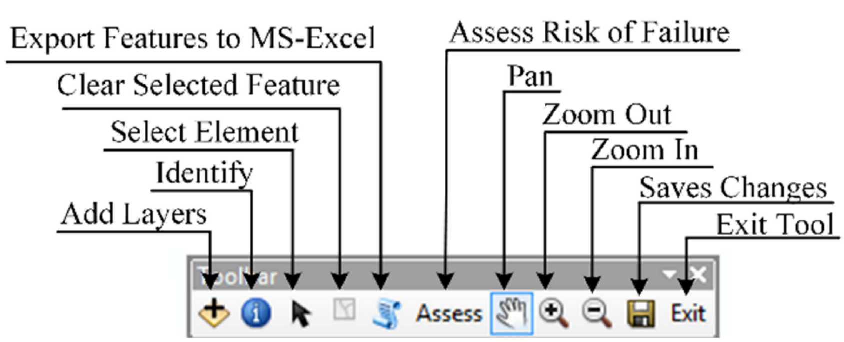


Figure 6.12: ArcMap Add-in for Risk Assessment Model

6.5. Inspection Scheduling Module

To integrate the previously developed models and tools, a VBA add-in tool was developed to export an inspection schedule for sewer pipelines. Figure 6.13 shows a scheme for the developed Graphical User Interface, in which the user inserts all the pipelines which he would like to choose to inspect with the corresponding years of failure, risk of failure, and the planning horizon year. Figures 6.14 to 6.16 shows the inspection scheduling GUI in which the user is instructed to select the pipelines that he would like to know when they would be inspected. The budget allocated for inspection and the inspection program planning horizon are also inputs required from the user. The user would have three options, which are either to schedule the inspections for the selected pipelines, or to optimize the inspections based on the selected pipelines and the available budget, and the last option is to visualize this information in the form of a schedule.

An automated tool was created to facilitate the use of the developed scheduling tool. The user is able to insert the inputs to GAMS IDE using MS-Excel and view the outputs from the GAMS IDE on MS-Project. A user form is created using Excel VBA from which the user can choose whether to schedule inspection or optimize the inspection activities based on the availability of inspection crews. If a user chooses to schedule inspection activities, pipes to be inspected are chosen based on the expected year of failure, compared to the planning horizon and arranged in a chronological order based on their risk indices. The output for this option can be visualized on MS-Project. If the user chooses to optimize inspection, GAMS is called and the relevant parameters and sets are entered from the VBA user form.

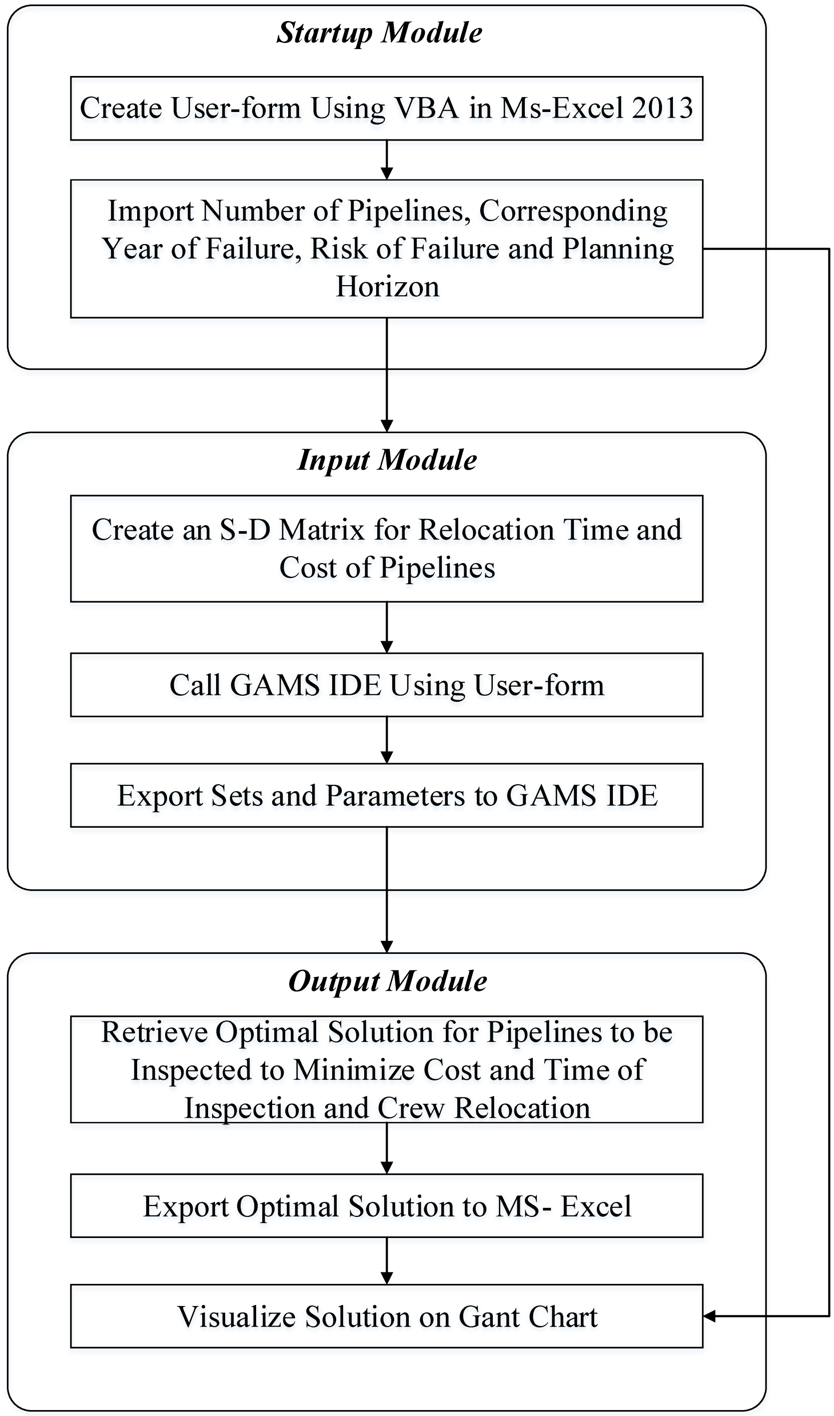


Figure 6.13: Modules of the Developed Inspection Scheduling Tool

Figure 6.14: Welcome Window for Optimization Tool

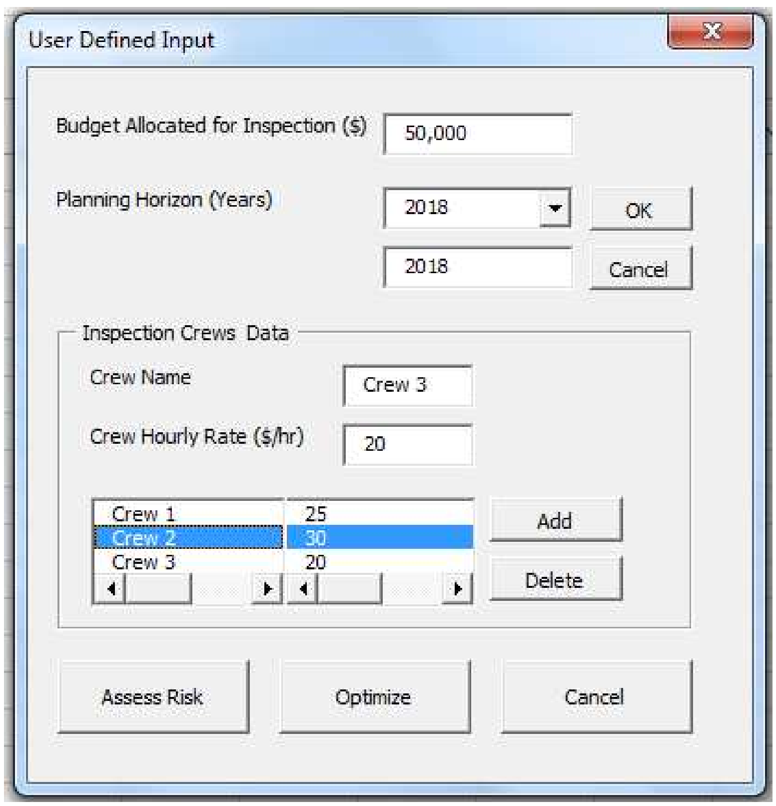


Figure 6.15: Input Window for Inspection Scheduling Tool

An Application Programming Interface (API) was created to extract the time and cost of relocation between the different pipelines using VBA integrated with Google Maps. The different servers and components of the API are shown in Figure 6.17, in which two functions were created to determine the distance and time from Google maps through the proxy server. The different pipelines selected by the user and source to destination matrix resulting from the API are then used as an input for the GAMS from which the user can determine the pipelines to inspected that would give the optimal cost and time.

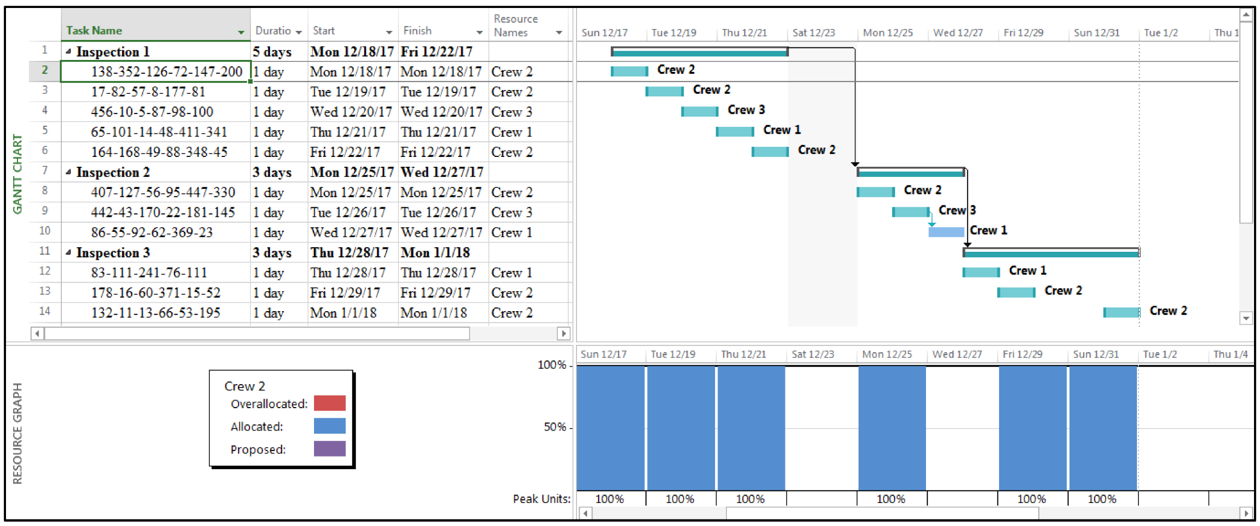


Figure 6.16: Output Window for Inspection Scheduling Tool

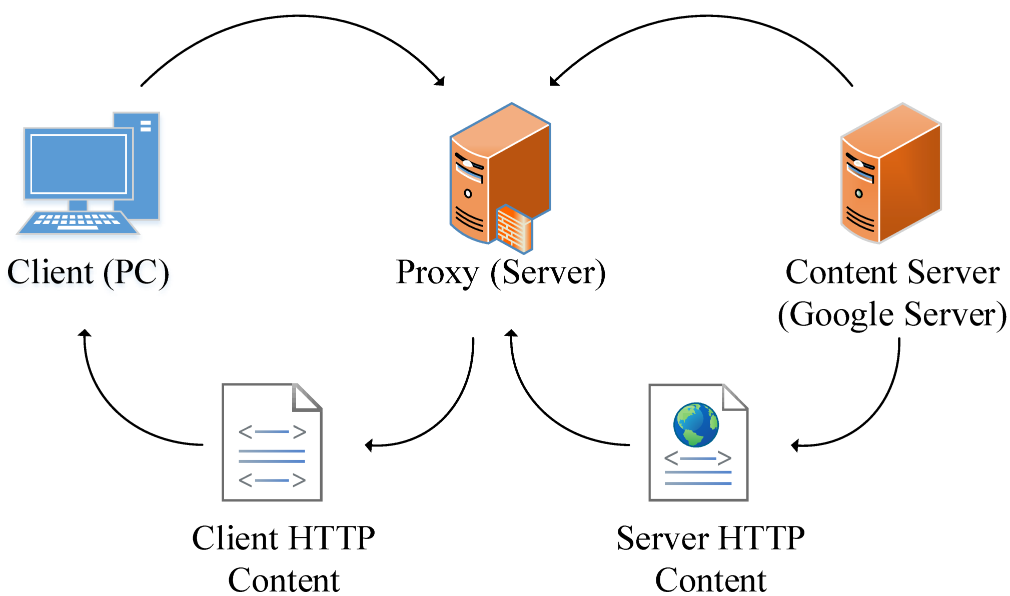


Figure 6.17: API Developed to Create Origin –Destination Matrix for Crew Relocation

6.6. OCIS as a Decision Support System

In this section, a demonstration for how to use the previously developed tool in assessing the risk of failure and making informed decisions regarding the appropriate course of action is presented. A numerical example for hypothetical data for a number of pipelines for which the user would be interested in determining the risk of failure and scheduling the inspection of them. The first window that appears to the user is the welcome page in which he is given the choice to assess the risk or schedule inspection as shown in Figure 6.18. If a user selects the first button "Risk of Failure Assessment", he is redirected to "Assessing the Risk of Failure" window where he has the option to examine the probability of failure, consequences of failure or risk of failure.

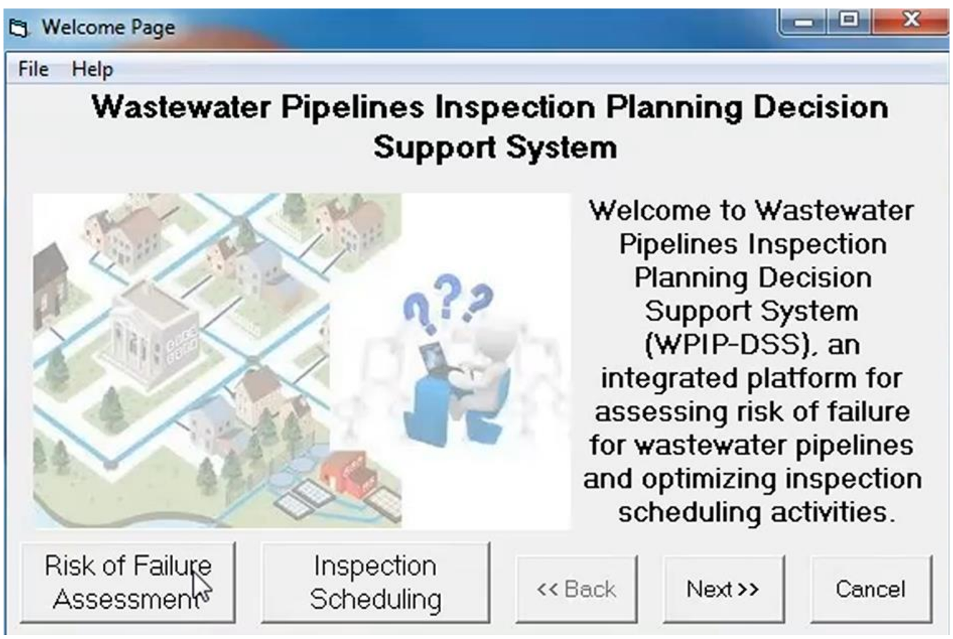


Figure 6.18: Welcome Page for the Developed OCIS Tool

In each option, the user has the liberty to determine any of these values for a single pipe or multiple pipe sections. If a user chooses to determine the values for several pipelines all at once, he is redirected to a "batch run" window where he can enter the relevant input in a predefined template MS- Excel file. Figure 6.19 shows a summary for how the different modules interact until the risk of failure indices are determined. In the likelihood of failure, the user is requested to input the different pipeline defects and characteristics. Whereas in the consequences of failure module, the population served along with the different pipeline characteristics are the inputs. The outputs from these two modules are considered the inputs for the risk of failure module which are then combined using the fuzzy inference system from which the risk index is then determined.

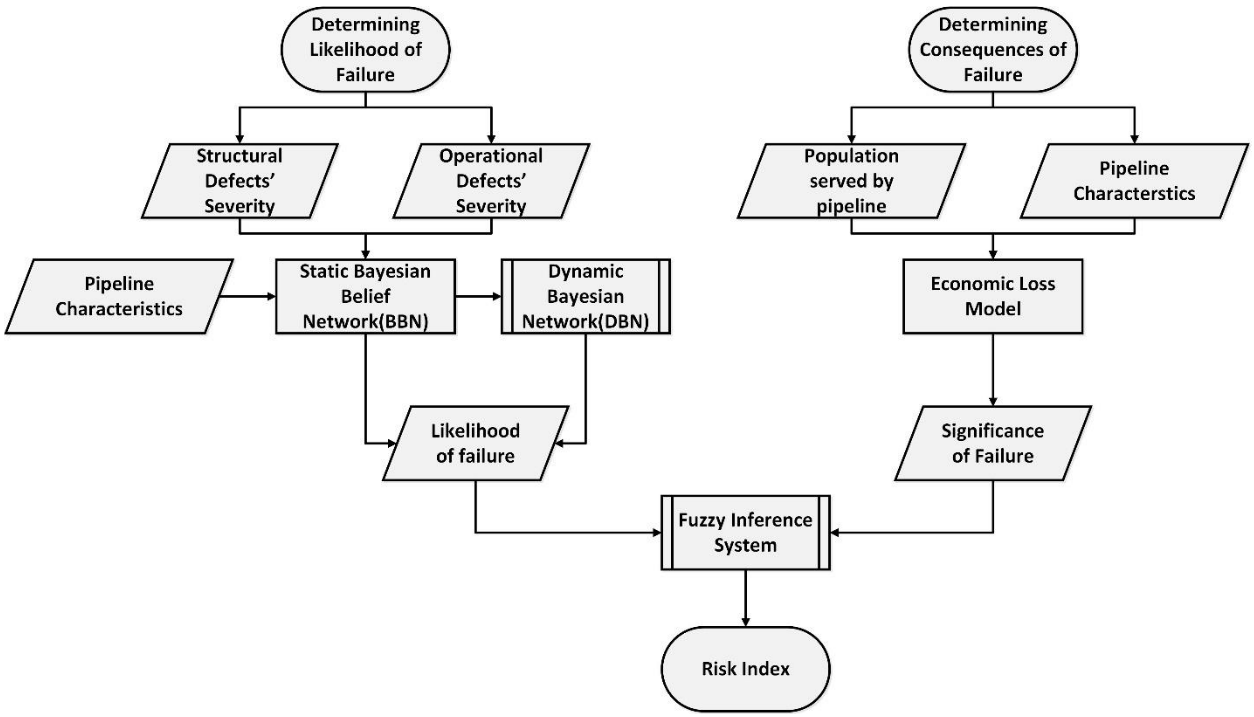


Figure 6.19: Summary for Inputs and Outputs of the Risk Assessment Module

6.6.1. Determining Likelihood of Failure for Single Pipe Sections

To demonstrate the usability of the first part of the tool; a single pipeline having a 2 mm collapse with more than three breaks, vertical deformation of 5 mm, and circumferential fracture of 3 mm as structural defects were converted into the structural input for the tool as shown in Figure 6.19. The same pipeline has sweating and flowing as infiltration defect, sand intrusion, and roots resulting in reduction of the pipeline cross sectional area of 23% and 25%, respectively.

Additionally, the pipe has foul deposits causing a reduction of the cross sectional area of 35%. The different defects were entered as inputs in the operational defects window as shown in Figure 6.20.

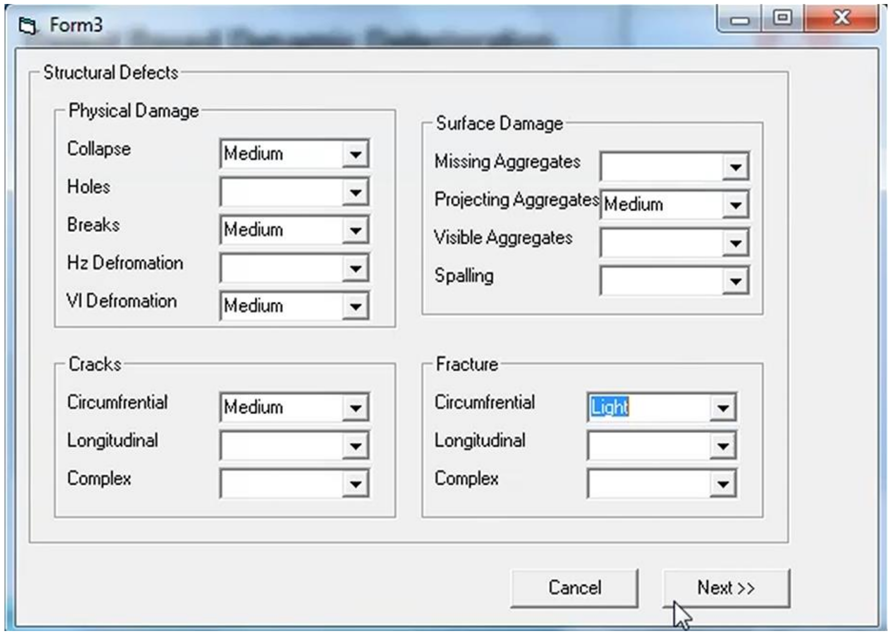


Figure 6.20: Structural input window in Case of Single Pipe Section Condition Assessment

The probability that the pipeline would reach a certain condition state based on the given defects was calculated using the developed BBN. Figure 6.21 shows the different condition ratings based on the highest probability of the output. The output is in the form of 5 scale grade in which a pipeline having any condition rating of 0 is in excellent condition, 1 is in a very good condition, 2 is in a good condition, 3 is in a poor condition and 4 is in a critical condition. The user is then directed to dynamic deterioration window in which he can identify the year at which the pipeline would fail or reach poor or critical condition. The pipe assessed above was 300 mm, vitrified clay with a total length of 45m buried 2 meters beneath a secondary road and was first laid in the year 1960.

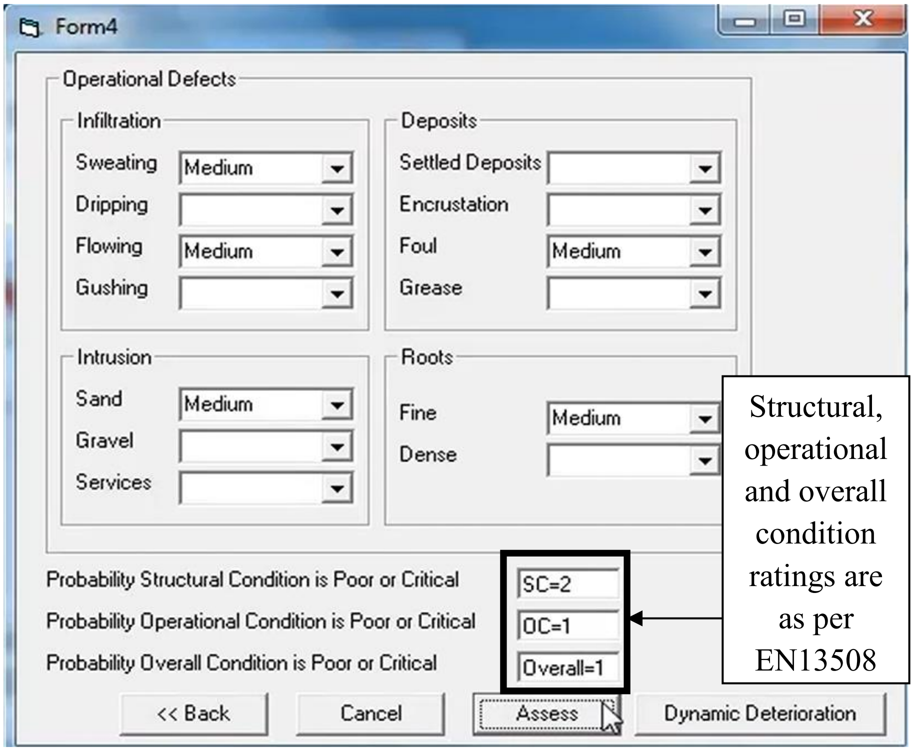


Figure 6.21: Operational input window in Case of Single Pipe Section Condition Assessment and Static Output as per EN13508

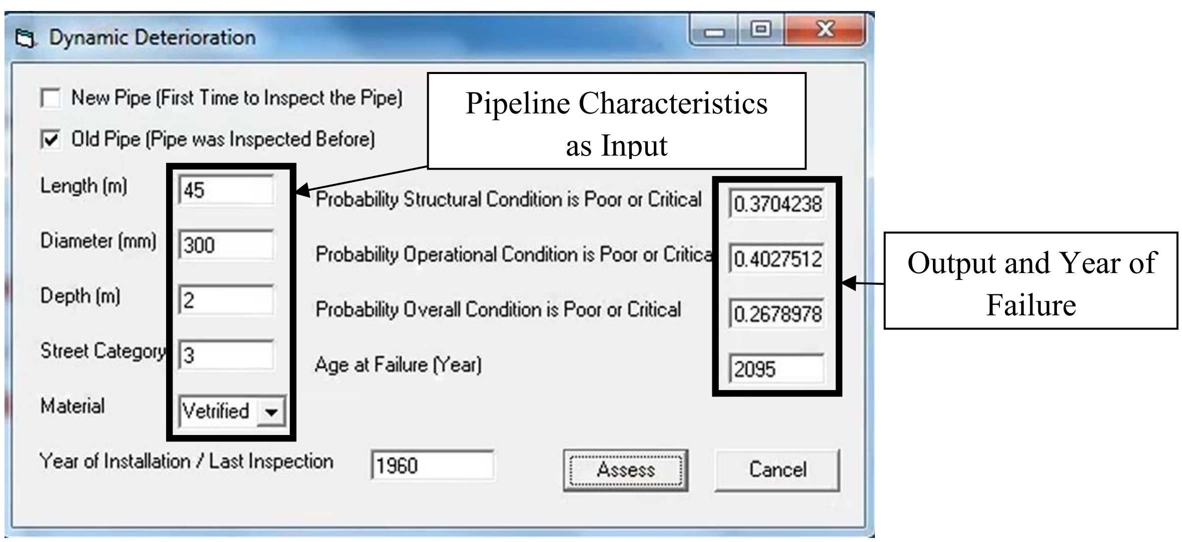


Figure 6.22: Dynamic Deterioration and Year of Failure Calculation Window

The different information was input in the relevant fields as shown in Figure 6.22 , and by pressing “Assess” button, the probability that this pipeline would reach a condition rating of 4 and the year in which it will reach this condition are displayed. As shown in the figure, the probabilities are 37%, 40% and 26% for the structural, operational and overall condition ratings and the year at which the pipeline would reach the condition rating of 4 (critical condition) is 2095.

6.6.2. Determining Consequences of Failure for Single Pipe Sections

In this section the user can determine the consequences of failure and determine the direct, indirect costs of failure along with the QALYs. In Figure 6.23, the user is directed to enter the relevant pipe section information such as material, length, and diameter, number of lanes, traffic volume and speed. Parameters such as the average hourly rate, fuel price, ratio of the different vehicle types, population density, costs of treatment for inpatient and outpatients are predefined.

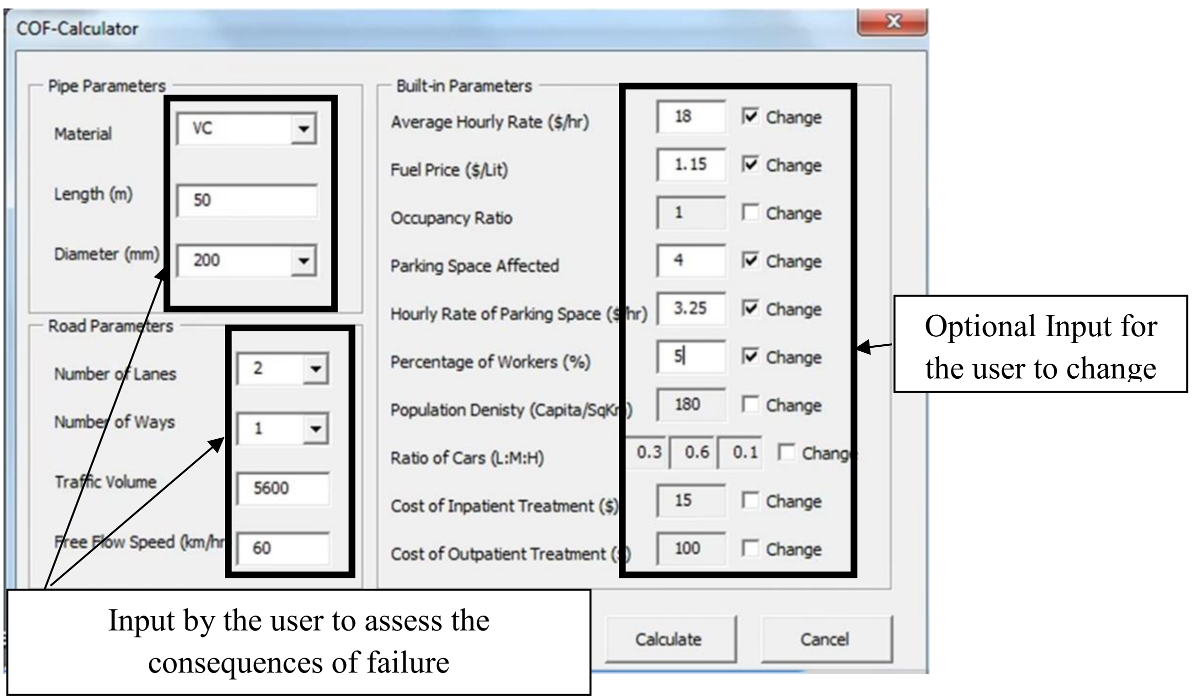


Figure 6.23: Input Window for Determining Direct, Indirect and QALYs in case of Single Pipe Section

A similar example for a 200 mm vitrified clay of 50-meter length is used to determine the consequences of failure. The volume of traffic above the pipeline was estimated to be 5600 in a one way – two lanes road with a free flow speed of 60 km/hr. The average hourly rate of commuters was 18 $/hr, fuel price was 1.15 $/liters, occupancy ratio was 1, number of parking spaces affected as a result of construction works were 4 with an hourly operating price of 3.25 $/hr and the percentage of workers in the premises of failure was 50% of the population served by the pipeline. By running the tool as shown in Figure 6.24, it was found that direct costs divided between resources and material were 3735$ and 11938$, respectively. As for the indirect costs they were 15188.5$. As for the QALYs, they were 9506$, which resulted in a ratio of 3 for the costs to benefits (>2) which indicates extremely high consequences of failure levels.

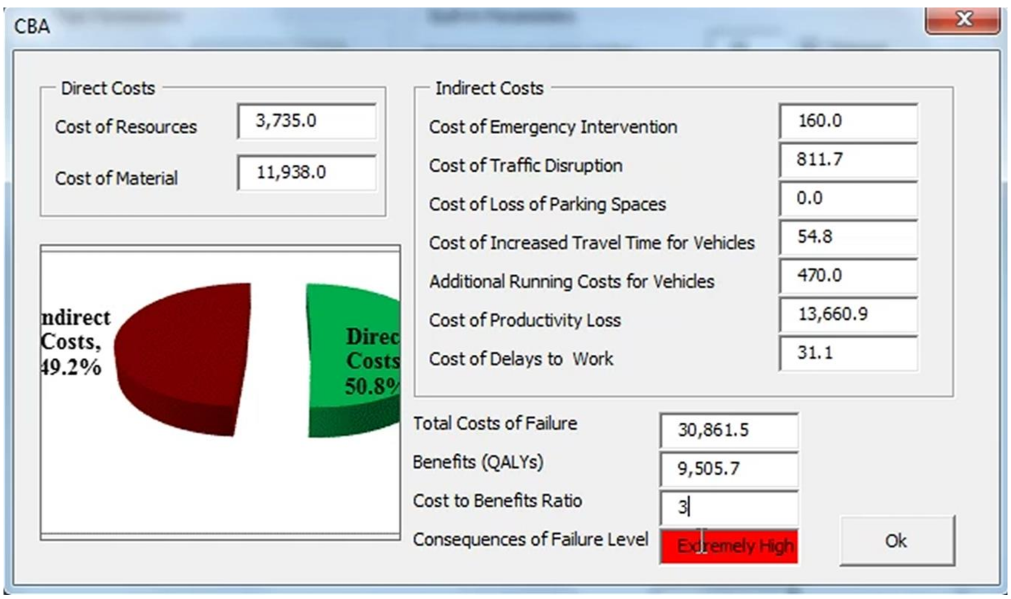


Figure 6.24: Output window for the Different Model Outputs

6.6.3. Determining Likelihood of Failure for Single Pipe Sections

After the user determines the likelihood and consequences of failure, he can input both values and then a message box is displayed as shown in Figure 6.25 from which he can assess the risk of failure. The user is asked to specify the values of likelihood and consequences of failure and input them in the input boxes then a message box pops up with the value of risk index.

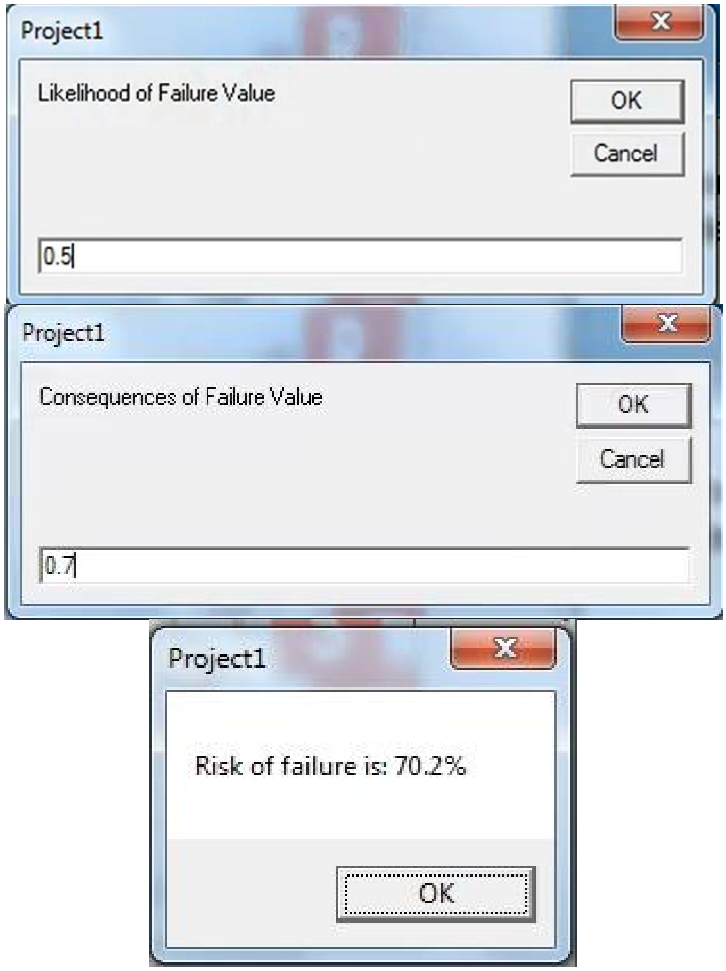
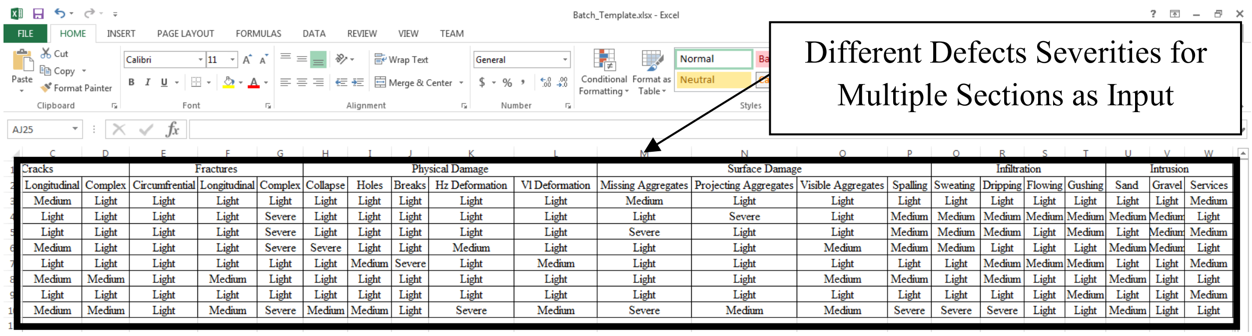


Figure 6.25: Risk of Failure Assessment in Case of Single Pipe Section

6.6.4. Creating a Defect Based Priority List for Several Pipeline Sections

There is an option in the developed tool from which the user can determine the likelihood, consequences and risk of failure for several pipeline sections all at once. The user is directed to a window, where he is requested to run the BBN and DBN, consequences of failure and risk of failure several times. Figure 6.26 shows the batch run window to calculate the likelihood of failure. Figure 6.27 shows the template in which the user is requested to fill with the different defects in different sections.

Figure 6.26: Batch Run Window for Determining Likelihood of Failure for Multiple Sections



Cracks		Fractures			Physical Damage				
Longitudinal	Complex	Circumfrential	Longitudinal	Complex	Collapse	Holes	Breaks	Hz Deformation	Vl Deformation
Medium	Light	Light	Light	Light	Light	Light	Light	Light	Light
Light	Light	Light	Light	Severe	Light	Light	Light	Light	Light
Light	Light	Light	Light	Severe	Light	Light	Light	Light	Light
Medium	Light	Light	Light	Severe	Severe	Light	Light	Medium	Light
Light	Light	Light	Light	Light	Light	Medium	Severe	Light	Medium
Medium	Medium	Light	Medium	Light	Light	Light	Light	Light	Light
Light	Light	Light	Light	Light	Light	Light	Light	Light	Light
Medium	Medium	Light	Medium	Severe	Medium	Medium	Light	Severe	Medium

Surface Damage				Infiltration				Intrusion		
Missing Aggregates	Projecting Aggregates	Visible Aggregates	Spalling	Sweating	Dripping	Flowing	Gushing	Sand	Gravel	Services
Medium	Light	Light	Light	Light	Light	Light	Light	Light	Light	Medium
Light	Severe	Light	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Light
Severe	Light	Light	Medium	Medium	Medium	Light	Medium	Light	Medium	Medium
Light	Light	Medium	Medium	Medium	Light	Light	Light	Medium	Medium	Light
Light	Light	Light	Light	Light	Medium	Medium	Medium	Light	Light	Medium
Light	Light	Medium	Medium	Light	Medium	Light	Light	Medium	Light	Light
Light	Light	Light	Light	Light	Light	Light	Medium	Light	Light	Medium
Severe	Medium	Medium	Severe	Severe	Severe	Light	Light	Medium	Light	Light

Figure 6.27: Input for Different Defects to Assess the Likelihood of Failure

After the user enters the different defects, the tool starts calculating the condition rating and the year at which the pipeline would reach failure. The likelihood of failure corresponding to the year at which a pipeline would fail, is stored with the pipeline ID in the batch template file as shown in Figure 6.28. The user is then directed to a similar window but this time a batch run window for the consequences of failure from which the user can determine the consequences of failure for multiple sections all at once as shown in Figure 6.29.

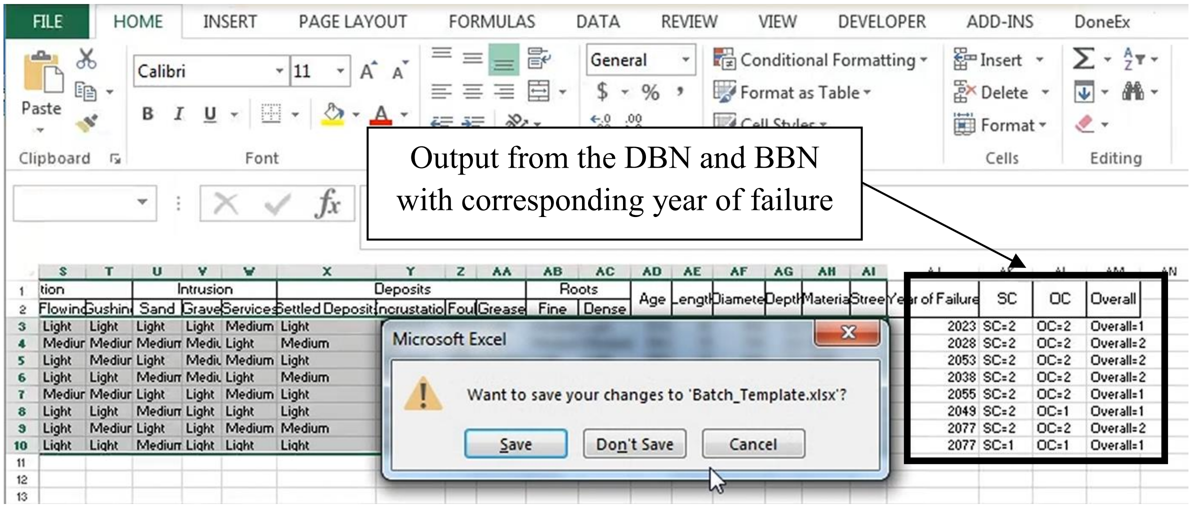


Figure 6.28: Output for the Different Condition Ratings Based on the Different Defects

Figure 6.29: Batch Run Window for Determining Consequences of Failure for Multiple Sections

The different relevant information is entered in the batch template file for the consequences of failure as shown in Figure 6.30. As shown in the same figure, the output including the direct, indirect and C:B are displayed to the user based on the different inputs. Similarly, the data are stored for each pipeline ID in the same file but in the consequences of failure sheet. Figure 6.31 shows the batch run window displayed after determining the consequences of failure in which the user can determine the value of the risk indices as shown in Figure 6.32. In this figure and based on the output the user can make an informed decision regarding the appropriate course of action from the resulting risk values.

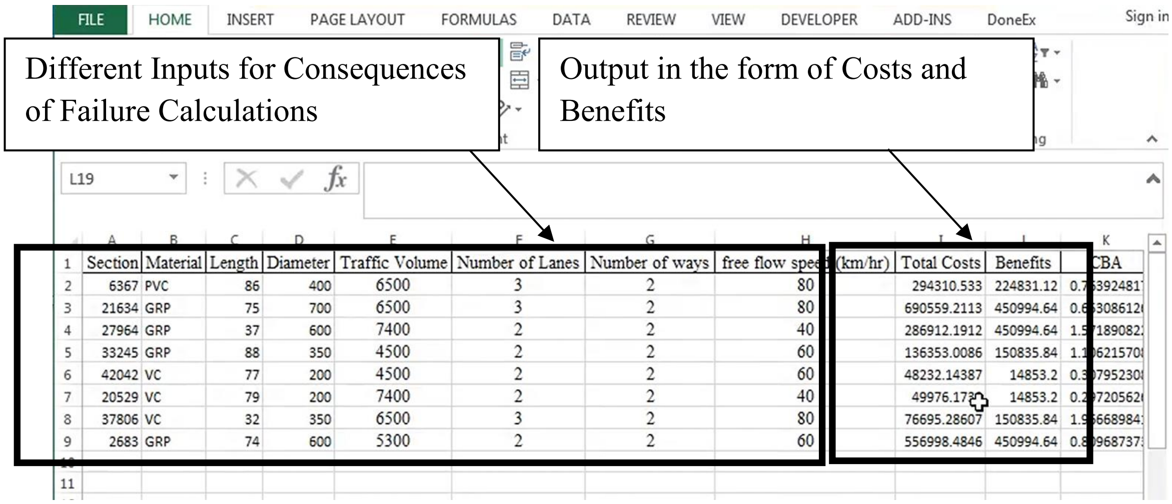


Figure 6.30: Output for the Different Costs and Benefits with the Corresponding Cost to Benefit Ratio

Figure 6.31: Batch Run Window for Determining Risk of Failure for Multiple Sections

Based on the output from the risk of failure module, pipeline having ID 27964 with a risk of failure value of 80.9% require immediate action, then comes pipelines with ID 2683, 20529, 37806, 21634, 42042 having risks of failure of 62.3%, 58.5%, 43.3%, 42.6%, 39.4% and lastly pipelines with ID 6367 and 33245 with risk values of 28.25% and 20.46%, respectively. Based on the resulting priority risk, decision makers can make informed decisions regarding the appropriate intervention.

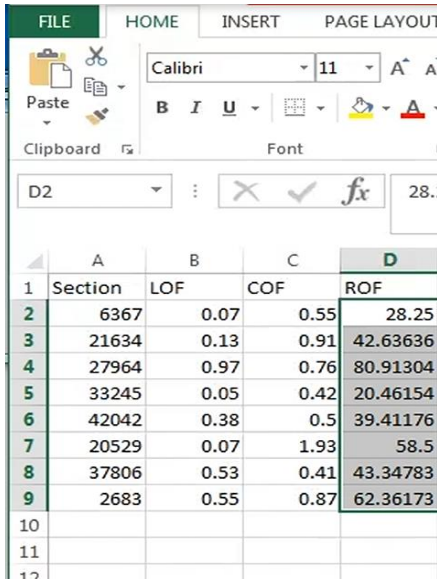


Figure 6.32: Output File for the Risk of Failure in Case of Multiple Pipe Sections

6.6.5. Inspection Schedule Visualization and Optimization

If a user chooses to schedule inspection, the user can obtain a list for the different pipeline sections in a chronological order based on the output of the risk assessment module (risk of failure and year at which a pipeline would fail). Figure 6.33 shows the different input fields required from the user to fill out and to visualize the schedule for pipelines to be inspected. The user is required to specify the available budget of inspection and the planning horizon. Based on these two values, the number of pipeline sections to be included in the inspection program can be identified. The planning horizon year represents the upper bound for which all pipelines having years of failure greater than this value won't be included in the inspection. As for the available budget, the different costs of inspections would be calculated for all the candidate sections until the budget is reached and all these pipelines would be included in the inspection set. Figure 6.34 shows the different pipelines to be inspected and the corresponding time of inspections and crews performing inspections.

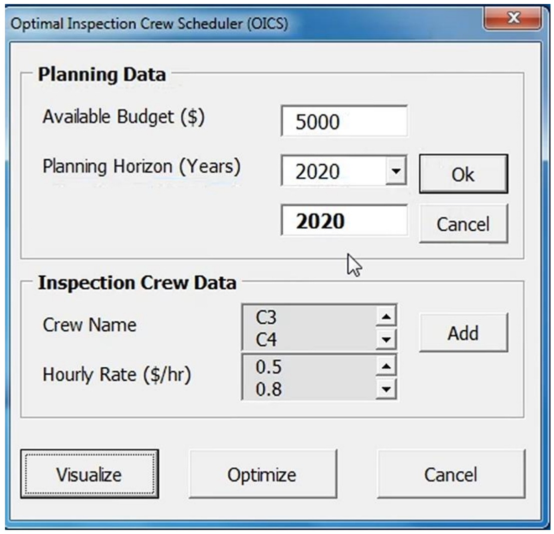


Figure 6.33: Pipeline Inspection Scheduling Module

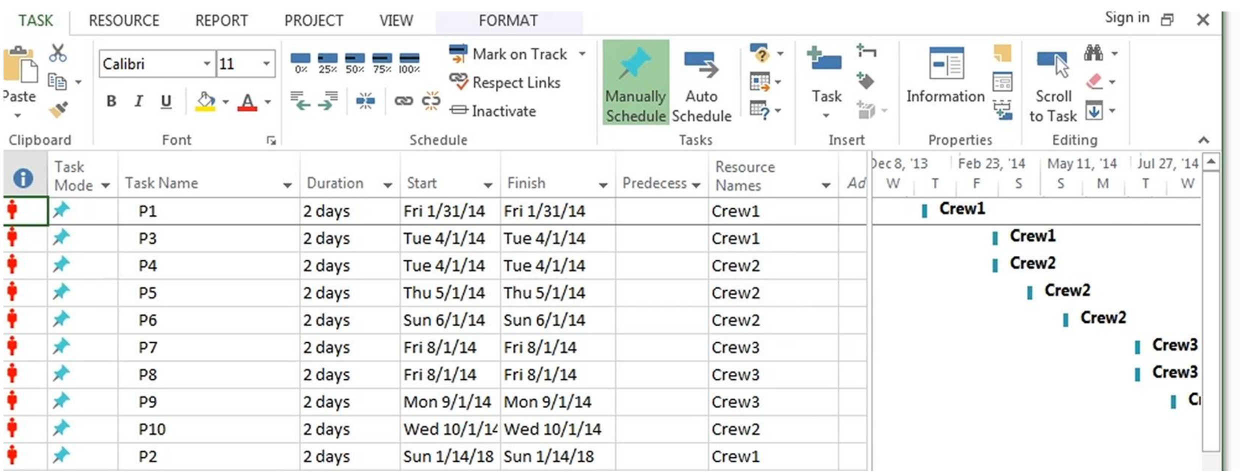


Figure 6.34: A Sample for the Schedule of Pipelines to be inspected

6.7. Recap

In this chapter the graphical user interface for the different developed models was introduced. Different feature windows for the inputs and outputs were shown. Additionally, the fields for the user defined variables in different modules were also presented. Also, a numeric example was presented to demonstrate how the developed tool can be used in the decision making process and the appropriate type of intervention.

Chapter 7: Conclusions and Recommendations

7.1. Introduction

In this chapter, the different contributions of this research are presented in addition to the conclusion and limitations of the proposed models. The areas of expected enhancements and the potential for expanding this research are also presented.

7.2. Summary

The objective of this research was to develop an inspection planning tool for sewer pipelines, which comprised two sub-models, namely: risk assessment and optimization models. The risk assessment model was used to prioritize inspection of sections on a risk of failure basis, whereas the optimization model was used to identify pipelines to be inspected and the crews to perform inspections. To assess the risk of failure, a defect based deterioration model was developed using BBN considering the effect of defects on the overall condition of a pipeline. BBN was deemed suitable because it helps in propagating uncertainties over the network. Because deterioration process is time dependent, time dimension was introduced to the BBN. A DBN was used to predict the likelihood of a pipeline to be in a certain condition state based on the defects from the static BBN and based on pipeline characteristics.

The transitional probabilities required for converting the BBN into DBN were derived from Multinomial Logistic Regression that takes into account pipeline age, material, diameter, cover depth, length, and street category. Due to the high uncertainties accompanied with estimating the costs of pipelines' failure and determining the consequences of failure, an economic loss model was used using Cost Benefit Analysis. The benefits versus the costs paid to restore the failed pipelines–in a "what-if" scenario-were analyzed using the ratio between these benefits and costs.

To integrate the likelihood and consequences of failures, fuzzy inference systems were used with different fuzzy inference rules. The Sugeno Fuzzy Inference System was envisaged suitable because it performs better in optimization problems and can be combined with different optimization techniques. An optimization problem was formulated in which pipelines to be inspected, inspection time, and costs for each pipeline, were optimized. Decision variables of the optimization problem were whether to inspect a pipeline or not using a certain crew, where the budget allocated for inspections and risk of failure were the constraints.

It is anticipated that decision makers working in the industry and governmental agencies would use the developed inspection planning tool to represent the optimum sequence of required inspection activities subject to fund availability. Additionally, the developed model would assist these agencies to serve the society and environment by directing their jobs efficiently and training their personnel on how to scientifically analyze their problems. It is anticipated that the developed tool would help advance the state of the art of inspection and management tools for waste water collection network.

7.3. Concluding Remarks

- A defect based deterioration model was developed using BBN taking into consideration the uncertainties in determining the probability of failure. The time dimension was introduced using MLR using different pipeline characteristics. The resulting deterioration model could combine both the cause and effect for sewer pipelines' deterioration.
- By examining the accuracy of prediction for the developed deterioration model using MAE and RMSE, it was found that the values were 0.67, 1.06, 0.56 and 1.05, 1.60, 0.95 for structural, operational and overall conditions, respectively. As for the DBN model, values achieved for

the year at which a pipeline would reach a certain condition state were close to the actual values from the validation dataset.

- To overcome the uncertainties that accompany estimating failure costs of infrastructures, an economic loss model was used to estimate these costs. Cost Benefit Analysis (CBA) was used in which costs resulting from failure and benefits from avoiding such failures were identified and analyzed.
- Costs paid to reinstate failed sewer pipelines in addition to the loss of productivity, traffic delays, and environmental degradation costs as a result of wastewater contamination, were considered in the economic loss model. Better sanitation and avoiding illness were considered the benefits of avoiding the failure of sewer pipelines.
- The economic loss model could estimate the direct and indirect costs with a deviation ranging between 10-12% and 22-30%, respectively. Additionally, it was found that indirect costs as a result of sewer pipelines' failure represent a significant portion of the total costs of failure. It was also found that costs related to environment, delays to work and traffic disruptions contribute with the highest share to the indirect costs.
- A mixed integer problem was formulated taking into consideration the sections to be inspected and crews to perform inspection. General Algebraic Modeling System (GAMS) was used to solve the optimization problem from which the different pipelines to be inspected were identified.
- The output from the optimization model was evaluated by comparing the results with the results using Genetic Algorithm (GA). It was found that the performance of the GAMS model was better than GA model in terms of convergence time.

- The optimization model could take into consideration the traffic disruption, environmental degradation and crews available for inspection. A cost saving of approximately 67% could be achieved if the proposed optimization model was deployed instead of the current inspection practices followed by the municipalities.

7.4. Research Contributions

This research provided a risk based inspection-scheduling model that can be used by practitioners and decision makers to decide the sequence of pipelines to be inspected based on resources availability. Additionally, the model could help in the decision making process regarding which sections to inspect based on the actual condition and available budget allocated for inspection. The following section presents the different areas of enhancements and limitations of this research study.

7.5. Research Limitations

- In the deterioration model, joints are included in the pipe length.
- The factors considered in transitional probabilities calculations as part of the deterioration model were limited to only 6 factors, namely: age, diameter, material, depth, length, and street type.
- Bayesian Belief Networks provided a powerful technique to handle uncertainties and missing information, however the fact that such technique results in cumbersome problems remains a challenge when using it.
- Structural defects in sewer pipelines that were included in the deterioration model were: cracks, fractures, surface and physical damages, whereas the operational defects were infiltration, roots, intruding services and deposits.

- Indirect costs included in the cost benefit analysis model included economic and environmental costs, however in these two aspects some costs such as productivity, air quality affected by failure weren't included.
- Although using economic loss models can help in reducing uncertainties when estimating indirect costs, the estimation process is accompanied with lots of uncertainties. Using fuzzy concepts or random sampling techniques can be used to reduce such uncertainties when estimating these costs.
- Risk assessment of failure included the likelihood and consequences of failure without considering the concept of reliability or criticality of pipelines.
- Only time and cost of inspection were included to determine the optimal inspection interval for sewer pipelines.

7.5.1. Recommendations for Future Research

- Different techniques such as hidden Markov chain can be used to determine the transitional probability required to construct the Dynamic Bayesian network.
- Other economic concepts to evaluate the cost of failure of sewer pipelines such as input-output or introducing fuzzy or simulation to cost benefit analysis can be used.
- Refinement of the deterioration model is advisable especially the deterioration trend of the defects, where other approaches can be used to determine the rate by which defects deteriorate instead of assuming that they deteriorate with the same rate of the pipe.
- Considering different distribution for the defects in the Bayesian Belief network other than considering them discrete random variables.
- Comparing different optimization techniques and the one used in this research. Additionally, solving the optimization problem using other evolutionary algorithms is also recommended.

7.5.2. Improving Current Research

- Studying the deterioration of pipe length, and joints separately based on their relevant defects.
- Additional indirect costs such as the environmental and economic costs as a result of construction works and failure of sewer pipelines can be included in the economic loss model.
- Optimizing the different membership functions of the fuzzy inference system to determine the best shape and distribution of them.
- Including the network's level of service and criticality in the developed optimization model.
- Considering the errors and inaccuracies in the inspection activities during the decision making process.
- Including other aspects such as breaks, overtime, absences of inspection crews' members to inspection scheduling model.

References

Adey, B.T. and Hajdin, R. (2011). "Methodology for determination of financial needs of gradually deteriorating bridges with only structure level data", Journal of Structure and Infrastructure Engineering.7 (8), 645-660.

Agresti, A. (2002). "Categorical data analysis", 2nd Ed., Wiley, Hoboken, New Jersey.

Allouche, E. N., and Freure, P. (2002). "Management and maintenance practices of storm and sanitary sewers in Canadian municipalities." Institute of Catastrophic Loss Reduction (ICLR), Dept. of Civil and Environmental Engineering, Univ. of Western Ontario-Geotechnical Research Centre, London, Ontario, Canada.

Allouche, E., Ariaratnam, S., and AbouRizk, S. (2000). "Multi-Dimensional Utility Model for Selection of a Trenchless Construction Method". Proceeding of Construction Congress VI: Building Together for a Better Tomorrow in an Increasingly Complex World. ASCE, VA.

American Water Work Association (2012). "Manual for water supply Practice MI Principal of rates Fees and Charges.", 6th Ed., American Water Works Association.

Ana, E., V., (2009). "Sewer asset management - sewer structural deterioration modeling and multicriteria decision making in sewer rehabilitation projects prioritization" Ph.D. dissertation, Univ.of Brussels, Belgium.

Ariaratnam, S., El-Assaly, A., and Yang, Y. (2001). "Assessment of infrastructure inspection needs using logistic models." J. Infrastruct. Syst., 7(4), 160 -165.

ASCE. (2013). "Report card for America's infrastructure" <http://www.infrastructurereportcard.org/> (May, 22, 2015).

Baik, H, Seok, H., and Abraham, D. M. (2006). "Estimating transition probabilities in markov chain-based deterioration models for management of wastewater systems." J. Water Resources Planning and Management., 132(1), 15 – 24.

Baur, R., and Herz, R. (2002). "Selective inspection planning with aging forecast for sewer types." Water Sci. Technol., 46(6-7), 389 – 396.

Berardi, L., Giustolisi, O., Savic, D. A., and Kapelan, Z. (2009). "An effective multi-objective approach to prioritization of sewer pipe inspection". Water science and technology, 60(4), 841.

Bibi S., Stamelos., I. (2004). "Software Process Modeling with Bayesian Belief Networks". Online proceedings IEEE Software Metrics 2004, NY.

Boyce, G., and Bried, E. (1994). “Benefit–cost analysis of micro-tunneling in an urban area.” Proceedings of North American No-Dig, 94,36-01.

British Standards Institution (BSI), (2012)."Investigation and assessment of drain and sewer systems outside buildings - General Requirements". BSI, London. ISBN: 978-0-580-70190-0.

CERIU. 1997. Manuel de standardisation des observations – inspections télévisées de conduitesd’égout. Centre d’expertiseet de rechercheen infrastructures urbaines. Montréal, Québec, Canada.

Chae, M-Y. and Abraham, D. M. (2001). “Neuro-Fuzzy Approaches for Sanitary Sewer Pipeline Condition Assessment”, ASCE Journal of Computing in Civil Engineering, 15 (1),4-14.

Cheung, S., Tong, T. K., and Tam, C. (2002). “Site pre-cast yard layout arrangement through genetic algorithms.” Automation in Construction, 11(1), 35-46.

Chi-Hui, C., Chun-Hung, C. and Yuh, J. C. (2009). “A strategy for the risk-based inspection of pressure safety valves.” Reliability Engineering and System Safety, 94, 810.

Chughtai, F., and Zayed, T. (2008). “Infrastructure condition prediction models for sustainable sewer pipelines.” Journ. Perf. Constr. Facilities, 22(5), 333 – 341.

Chung, H. Y., Manuel, L. and Frank, K. H. (2006). “Optimal inspection scheduling of steel bridges using nondestructive testing techniques.” Journal of Bridge Engineering, 11, 305-319.

Croarkin,C. and Tobias,P. (2006), NIST/SEMATECH e-Handbook of Statistical Methods. http://www.itl.nist.gov/div898/handbook/. Acessed July 2017

Cromwell, J. E., and Pearson, N. (2002). “Cost of infrastructure failure”. American Water Works Association Denver.

Csiszár, S. (2007). “Optimization algorithms (survey and analysis).” LINDI 2007 - International Symposium on Logistics and Industrial Informatics 2007, 185-188.

Daher, S., Zayed, T., Elmasry, M., and Hawari, A. (2017). Determining Relative Weights of Sewer Pipelines’ Components and Defects. Journal of Pipeline Systems Engineering and Practice, 9(1), 04017026.

Das, B., (2004). “Generating Conditional Probabilities for Bayesian Networks: Easing the Knowledge Acquisition Problem” Command and Control Division, DSTO, Edinburgh, SA 5111, Australia.

Davies, I. J. (2001). Empirical correction factor for the best estimate of Weibull modulus obtained using linear least squares analysis. Journal of materials science letters, 20(11), 997-999.

Dawid, A.P., Mortera, J., Pascali, V.L. and Van Boxel, D. (2002). “Probabilistic expert systems for forensic inference from genetic markers Scandinavian Journal of Statistics.” 29 (4), 577 – 595.

Deb, K. 2001. “Multi-objective optimization using evolutionary algorithms.” 2nd ed. Wiley, New York.

DeMonsabert, S., Ong, C., and Thornton, P. (1999). An integer program for optimizing sanitary sewer rehabilitation over a planning horizon. Water environment research, 71(7), 1292-1297.

Druzdzel, M.J. and van der Gaag, L.C. (1995). "Elicitation of probabilities for belief networks: Combining qualitative and quantitative information," Proceeding of 11th Conf. Uncertainty in Artificial Intelligence, Morgan Kaufmann Publishers: San Francisco, California, 1995, 141-148.

El-Assaly, A., Ariaratnam, S.T., Ruwanpura, J., and Ng, H., (2006). “Cost forecast model for sewer infrastructure.” Municipal Engineer, 159 (3), 155–160.

Elbeltagi, E., Hegazy, T., and Grierson, D. (2005). “Comparison among five evolutionary - based optimization algorithms.” Advanced Engineering Informatics, 19(1), 43 -53

Elhakeem,A. and Hegazy, T. (2010) “B uilding asset management with deficiency tracking .and integrated life cycle optimisation". Structure and Infrastructure Engineering First published on: 19 May 2010 (iFirst) Engineering, Taipei, Taiwan, April 3 - 5, 2002,1, pp. 701-706

Emergency Management Australia, (2003) “Critical Infrastructure Emergency Risk Management and Assurance Handbook”, Mount Macedon, Australia, 2003.

Erik, M.,Hakan,F.,and Kazunori,H., 1995. “Fire Safety Design Based on Calculations Uncertainty Analysis and Safety Verification”. Department of Fire Safety Engineering, Lund Institute of Technology, Lund University.

European Commission, (2006). “Proposal for a Directive of the Council on the Identification and Designation of European Critical Infrastructure and the Assessment of the Need to Improve Their Protection, COM(2006)787 Final”, Brussels, Belgium.

European Union, (2014) “Commission Implementing Decision of 26 June 2014 concerning formats for reporting on the national programmes for the implementation of Council Directive 91/271/EEC”.

Faber, H., Kroon, B., Kragh, E., Bayly, D., and Decosemaeker, P. (2002). “Risk assessment of decommissioning options using Bayesian networks.” Journal of Offshore Mechanics and Arctic Engineering, 124(4), 231–238.

Fares, H., and Zayed, T. (2010). “Hierarchical fuzzy expert system for risk of failure of water mains.” Journal of Pipeline Systems Engineering and Practice, 1(1), 53 – 62.

Fenner, R. A., Sweeting, L., and Marriott, M. (2000). “A new approach for directing pro-active sewer maintenance.” Proceedings of the institution of civil engineers, water and maritime Engineering Journal, 142(2), 67 – 78.

Fenton N., Krause,P., Lane, C. and Neil,M. (2001). “A Probabilistic Model for Software Defect Prediction”, IEEE Transactions on Software Engineering 44 (0), 1-35.

French AFNOR standard Maintenance - Terminologie de la maintenance NF-EN-13306

Friedman, N., Linial, M., Nachman, I., Pe’er, D. (2000). “Using Bayesian Networks to Analyse Expression Data Journal of Computational Biology 7 (3/4)”, 601- 620.

GAMSAUser’s.Guide. GAMS Development Corporation, Washington, DC, USA, 2010

German Association for Water, Wastewater and Waste (DWA), (2015)."State detection and assessment of drain and sewer systems outside buildings -Part 3: Assessment by optical inspection". DWA, Germany. ISBN: 978-3-88721-224-7.

Gharaibeh, N.G., Chiu, Yi, C. and Gurian, P.L. (2006), “Decision methodology for allocating funds across transportation infrastructure assets”, Journal of Infrastructure Systems, 12 (1), 1-9.

Gilchrist, A., Allouche, E., and Cowan, D. (2003). “Prediction and mitigation of construction noise in an urban environment”. Canadian journal of civil engineering, 30(4), 659-672.

Gilchrist, A., and Allouche, E. N. (2005). “Quantification of social costs associated with construction projects: state-of-the-art review.” Tunnelling and underground space technology, 201, 89-104.

Gourvil, L. and Joubert, F. (2004). “Évaluation de la congestion routièredans la région de Montréal: Québec: Transports Québec”.

Greenland, S., Pearl, J. and Robins, J.M. (1999) “Causal diagrams for epidemiologic research Epidemiology” 37 – 48.

Griffin, J. (Ed.). (2012). IPBA To Unveil New Pipe Bursting Guidelines At UCT. Underground Construction, 67(1), 52-53.

Grigg, N. S. (2003).” Water, wastewater, and stormwater infrastructure management”, Lewis Publishers, Boca Raton, Florida.

Gulliver, J., (2012). “Transport and Fate of Chemicals in the Environment: Selected Entries from the Encyclopedia of Sustainability Science and Technology” Springer-Verlag New York, USA, 10.1007/978-1-4614-5731-2.

Hahn, M. A., Palmer, R. N., Merrill, M. S., and Lukas, A. B. (2002). “Expert System for Prioritizing the Inspection of Sewers: Knowledge Base Formulation and Evaluation.” J. Water Resources Planning and Mngt., 128(2), 121 – 129.

Hajkowicz, S., Spencer, R., Higgins, A. and Marinoni, O. (2008), “Evaluating water quality investments using cost utility analysis”, Journal of Environmental Management, 88(4), 1601-1610.

Halfawy, M., Dridi, L., and Baker, S. (2008). “Integrated Decision Support System for Optimal Renewal Planning of Sewer Networks. Journal of Computing in Civil Engineering”, ASCE, 22 (6), 360-372.

Halfawy, M. and Hengmeechai, J. (2013). "Efficient Algorithm for Crack Detection in Sewer Images from Closed-Circuit Television Inspections." Journal of Infrastructure Systems, 10.1061/(ASCE)IS.1943-555X.0000161, 04013014.

Halfawy, M. and Hengmeechai, J. (2014a). "Automated defect detection in sewer closed circuit television images using histograms of oriented gradients and support vector machine." Automation in Construction, 10.1016/j.autcon.2013.10.012, 1-13.

Halfawy, M. and Hengmeechai, J. (2014b). "Integrated Vision-Based System for Automated Defect Detection in Sewer Closed Circuit Television Inspection Videos." Journal of Computing in Civil Engineering, 10.1061/(ASCE)CP.1943-5487.0000312, 04014024.

Hansen, B. E. (2000). Sample splitting and threshold estimation. Econometrica, 68(3), 575-603.

Hartford, D., and Baecher, G. (2004).”Risk and Uncertainty in Dam Safety”, Thomas Telford Ltd.

Hegazy, T., Elbeltagi, E., and El-Behairy, H. (2004). Bridge deck management system with integrated life-cycle cost optimization. Transportation Research Record: Journal of the Transportation Research Board, (1866), 44-50.

Hegazy, T. and Elhakeem, A. (2011). “Multiple optimization and segmentation technique (MOST) for largescalebilevel life cycle optimization”. Canadian Journal of Civil Engineering, 38(3), 263–71.

Hegazy, T. and Rashedi, R. (2013). “Large-Scale Asset Renewal Optimization Using Genetic Algorithms plus Segmentation”. Journal of Computing in Civil Engineering, 27(4), 419–426.

Hegazy, T., and Saad, D. (2014). “A microeconomic perspective on infrastructure rehabilitation, Construction Management and Economics”, 32(5), 433-455.

Hegazy, T., Elhakeem, A. Ahluwalia, S. S. and Attalla, M. (2012), “MOST-FIT: support techniques for inspection and life cycle optimization in building asset management”, Computer-Aided Civil and Infrastructure Engineering, 27(2), 130–42.

Higgins, A.M. and Harris, A.H. (2012), “Health economic methods: cost-minimization, cost-effectiveness, cost-utility, and cost-benefit evaluations”, Critical Care Clinics, 28(1), 11-24.

Hintz, A. M., Barnes, D., and Millar, D. C. (2007). “Establishing a collection system baseline condition assessment program one step at a time.” Proceeding Pipelines 2007: Advances and Experiences with Trenchless Pipeline Projects, ASCE, Reston, VA.

Hutton, G. and Haller, L. (2004). “Evaluation of the Costs and Benefits of Water and Sanitation Improvements at the Global Level” Water, Sanitation and Health Protection of the Human Environment, World Health Organization, Geneva, Switzerland.

IPCC (2012). “Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. Special Report of the Intergovernmental Panel on Climate Change”, Cambridge University Press.

Irfan, M., Khurshid, M., Labi, S. and Flora, W. (2009), “Evaluating the cost effectiveness of flexible rehabilitation treatments using different performance criteria”, Journal of Transportation Engineering, 135 (10), 753-763.

Kapelan, Z. (2002). “Calibration of water distribution system hydraulic models”, Doctoral dissertation, University of Exeter.

Karande, P., Gauri, S.K. and Chakraborty, S. (2013), “Applications of utility concept and desirability function for materials selection”, Journal of Materials and Design, 45, 349-358.

Karwowski, W., and Mital, A. (1986). Potential applications of fuzzy sets in industrial safety engineering. Fuzzy sets and systems, 19(2), 105-120.

Kaur,A.and Kaur, A., (2012)," Comparison of Mamdani-type and Sugeno-type fuzzy inference systems for air conditioning system International Journal of Soft Computing and Engineering", 2 (2), 323–325.

Kerzner, H. (2013). Project management: a systems approach to planning, scheduling, and controlling. John Wiley and Sons, England

Khan, F. I., Sadiq, R. and Haddara, M. M. (2004). “Risk-based inspection and maintenance (RBIM) Multi-attribute Decision-making with Aggregative Risk Analysis.” Process Safety and Environmental Protection, 82, 398–411.

Khogali, W. E., and Mohamed, E. H. (1999), “Managing utility cuts: Issues and considerations. Paper presented at the NCRR/CPWA Seminar Series: Innovations in Urban Infrastructure.” APWA International Public Works Congress NRCC/CPWA Seminar Series Innovations in Urban Infrastructure, 1-11.

Kim, S., Frangopol, D. M. and Soliman, M. (2013). “Generalized probabilistic framework for optimum inspection and maintenance planning. “Journal of Structural Engineering, 139, 435-447.

Kleiner. Y. (2001). “Scheduling inspection and renewal of large infrastructure assets.” Journal of Infrastructure System, 7(4), 136 – 143.

Kleiner, Y., Sadiq, R., and Rajani, B. (2004). “Modeling failure risk in buried pipes using fuzzy markov deterioration process.” Proc., Pipeline Engineering and Construction: What’s on the Horizon?, ASCE, Reston,VA., 1-12.

Kleiner, Y., Rajani, B., and Sadiq, R. (2005). “Risk management of large-diameter water transmission mains.” AWWA Research Foundation and American Water Works Association, Denver.

Kleiner, Y., Rajani, B., and Sadiq, R. (2007). “Sewerage infrastructure: Fuzzy techniques to manage failures.” Wastewater Reuse-Risk Assessment, Decision Making and Environmental Security, M.K. Zaidi, ed., Springer Netherlands, 241-252.

Klir, G. and Yuan, B. (1995). “Fuzzy sets and fuzzy logic theory and applications”, Prentice Hall, NewJersey.

Koriyama, T., Li, Y., Hamaguchi, Y., Yamashita, M. and Hirano, M. (2009). “Study on Risk-Informed In-Service Inspection for BWR Piping.” Journal of nuclear science and technology, 2009, 46, 846–873.

Labi, S. and Sinha, K. (2005), “Life-cycle evaluation of flexible pavement preventive maintenance”, Journal of Transportation Engineering, 131(10), 744-751.

Langseth, H. and Portinale, L. (2007). “Bayesian networks in reliability Engineering and System Safety”, 92, 92-108.

Le Gat, Y. (2008). “Modeling the deterioration process of drainage pipelines”. Urban Water Journal, 5(2), 97-106.

Lee, H. M. (1996). Applying fuzzy set theory to evaluate the rate of aggregative risk in software development. Fuzzy sets and Systems, 79(3), 323-336.

Li, H., and Love, P. E. D. (2000). “Genetic search for solving construction site-level unequal-area facility layout problems.” Automation in Construction, 9(2), 217-226.

Maji, A. and Jha, M. K. (2007). “Modeling highway infrastructure maintenance schedules with budget constraints.” Journal of the Transportation Research Board, 1991, 19-26.

Makar, J. M. (1999). “Diagnostic techniques for sewer systems.” Journal of Infrastructure Systems, ASCE, 5(2), 69 – 78.

Mamdani, E. H., and Assilian, S. (1975). “An experiment in linguistic synthesis with a fuzzy logic controller.” International Journal of Man-Machine Studies, 7, 1 – 13.

Manuilova, A., Dormuth, D., and Vanier, D. (2009). “MIIP Report: A Case Study of Use and External Components of Social Costs that are related to Municipal Infrastructure Rehabilitation.”

Marinoni, O., Adkins, P. and Hajkowicz, S. (2011), “Water planning in a changing climate: join application of cost utility analysis and modern portfolio theory”, Journal of Environmental Modelling and Software, 26 (1), 18-29.

Markowetz, F.; Spang, R. (2007). “Inferring Cellular Networks - A Review” BMC bioinformatics, 8(6), 1-S5.

Marlow, D. R., Beale, D. J. and Mashford, J. S. (2012). “Risk-based prioritization and its application to inspection of valves in the water sector.” Reliability Engineering and System Safety, 100, 67–74.

Martin, T., Johnson, D., and Anschell, S. (2007). “Using historical repair data to create customized predictive failure curves for sewer pipe risk modeling.” Proceeding, Leading Edge Conference on Strategic Asset Management, IWA, Lisbon, Portugal.

McCrone, D. (1998). “The sociology of nationalism: tomorrow's ancestors.”, Psychology Press, USA.

McCullagh, P. (1980). “Regression models for ordinal data.” Journal of the Royal Statistics Society, Series B (Methodological), 42(2), 109 – 142.

McDonald, S., and Zhao, J. (2001). “Condition Assessment and rehabilitation of large sewer sewers.” Int. Proc., Conf. on Underground Infrastructure Research, Centre for Advancement of Trenchless Technologies (CATT), National Research Council of Canada (NRC), 361 – 369.

Mendes, E. (2007), “Predicting Web Development Effort Using a Bayesian Network” Proceedings of (EASE'07), 11th International Conference on Evaluation and Assessment in Software Engineering, 83-93.

Micevski, T., Kuczera, G., and Coombes, P. (2002). “Markov model for storm water pipe deterioration.” J. Infrastruc. Syst., 8(2), 49 – 56.

Microsoft Corporation. (2001). "MSBNx: A Component-Centric Toolkit for Modeling and Inference with Bayesian Networks." Microsoft Research.

Microsoft Corporation. (2013). "Microsoft Office Professional Edition".

Ministry of the Interior and Kingdom Relations, (2008). “National Risk Assessment Method Guide”, The Hague, The Netherlands.

Moayyedi, P. and Mason, J. (2004), “Cost-utility and cost-benefit analyses: how did we get here and where are we going?”, European Journal of Gastroenterology and Hepatology, 16 (6), 527-534.

Moselhi, O. and Shehab-Eldeen, T. (2000). "Classification of Defects in Sewer Pipes Using Neural Networks." J. Infrastruct. Syst., 10.1061/(ASCE)1076-0342(2000)6:3(97), 97-104.

Najafi M., (2005).” Trenchless technology: pipeline and utility design, construction, and renewal”. McGraw-Hill, New York.

Najafi, M., and Kulandaivel, G. (2005). “Pipeline condition prediction using neural network models.” Proceedings of ASCE Pipeline 2005: Optimizing Pipeline Design, Operations and Maintenance in Today’s Economy, ASCE, Reston, VA., 767 – 781.

NASSCO. (2001). “Pipeline assessment and certification program manual, Pipeline Assessment and Certification Program (PACP)”.

Nielsen, J., and Sørensen, D. (2011).” Risk-based operation and maintenance of offshore wind turbines using Bayesian networks.” In Faber, Kohler, and Nishijima(Eds.), Applications of statistics and probability in civil engineering (311–317), The Netherlands: Belkema Publishers, A.A. / Taylor and Francis.

North American Electric Reliability Corporation, (2006) “Standard CIP-002-1, Cyber Security, Critical Asset Identification.” Washington, DC.

Nunoo, C. (2001). "Optimization of pavement maintenance and rehabilitation programming using shuffled complex evolution algorithm". doctoral dissertation, Florida International University, United States -Florida. (Publication No. AAT 3006861).

Olsen, J., Lee, Z.H. and Pong, W. (2007), “Optimal selection of concrete anchors for connection cost reduction”, Journal of Construction Management and Economics, 25 (4), 423-434.

Osman, H. M., Georgy, M. E., and Ibrahim, M. E. (2003). “A hybrid CAD-based construction site layout planning system using genetic algorithms.” Automation in Construction, 12(6), 749-764.

Osman, H., Atef, A., and Moselhi, O. (2012). Optimizing inspection policies for buried municipal pipe infrastructure. Journal of Performance of Constructed Facilities. 26(3), 345-352.

Pass, C. L., Bryan, L., and Leslie, D., (1993). “Unwin Hyman Dictionary of Economics”. Unwin Hyman, UK

Pearce, J. L., and Boyce, M. S. (2006). Modelling distribution and abundance with presence-only data. Journal of applied ecology, 43(3), 405-412.

Plevris, V., Karlaftis, M. G., Lagaros, N. D. (2010). “A swarm intelligence approach for emergency infrastructure inspection scheduling.” Sustainable and Resilient Critical Infrastructure Systems, 201-230.

Polinder, S., Toet, H., Panneman, M. and Beeck, E. (2011), “Methodological Approaches for Cost-effectiveness and Cost-utility Analysis of Injury Prevention Measures”, World Health Organization Regional Office for Europe, Denmark.

Pourret, O., Naïm, P., and Marcot, B. (Eds.). (2008). Bayesian networks: a practical guide to applications (Vol. 73). John Wiley and Sons.

Pucker, J., Allouche, E., and Sterling, R. (2006). “Social Costs Associated with Trenchless Projects: Case Histories in North American and Europe.” Proceeding of NASTT No-Dig Conference, C4-04.

Pucker, J., Allouche, E., and Sterling, R. (2006). “Social Costs Associated with Trenchless Projects: Case Histories in North American and Europe.”, Proceeding of NASTT No-Dig Conference, C4-04.

Python Core Team (2017). “Python: A dynamic, open source programming language. Python Software Foundation.” https://www.python.org/., 15-04-2017

Rafiq, I ,Chryssanthopoulos, M., and Sathananthan, S., (2015). “Bridge condition modelling and prediction using dynamic Bayesian belief networks, Structure and Infrastructure Engineering”, 2015, 11(1), 38–50.

Rahman, S. and Vanier, D. (2004)” An Evaluation of Condition Assessment Protocols for Sewer Management”, Municipal Infrastructure Investment Planning (MIIP) Report, National Research Council Canada, Canada

Rahman, S., Vanier, D.J., and Newton, L. A. (2005). “MIIP Report: Social Cost Considerations for Municipal Infrastructure Management.”, National Research Center, Canada

Rashedi R. and Hegazy T. (2014). “Capital renewal optimization for large-scale infrastructure networks: genetic algorithms versus advanced mathematical tools.” Structure and Infrastructure Engineering. 11(3), 253-262.

RedZone. 2010. “RedZone Robotics Inc.” http://www.redzone.com/ (August, 22,2016)

Richard, E. R. (2010). GAMS-a user’s guide. GAMS Development Corporation, Washington, DC, USA.

Ross, T. J. (2010). “Fuzzy logic with engineering applications”, 3rd Ed., Wiley, Chichester, U.K.

Ruwanpura, J., Ariaratnam, S., and El-Assaly, A. (2004). “Prediction models for sewer infrastructure utilizing rule-based simulation.” Civ. Eng. Environ. Syst., 21(3), 169 – 185.

Rylska, N. L., McCracken, M. C., Reza, A., Limited, I., Staff, I. L., Alliance, O., and Staff, O. R. (2006). “Societal Costs of Excavation Due to Excavation Damage to Underground Infrastructure in Ontario During 2000-2003” Informetrica Limited.

Saad, D.A. (2014). “A Microeconomic Perspective to Infrastructure Renewal Decisions.” PhD thesis, Civil and Environmental Engineering, University of Waterloo, Canada

Saaty, T. J, (1996), "Decision making in Complex Environments, The Analytical Hierarchy Process for decision Making with Dependence and Dependence and Feedback". USA: RWS Publications.

Salem, O., AbouRizk, S., and Ariaratnam, S. (2003). Risk-based life-cycle costing of infrastructure rehabilitation and construction alternatives. Journal of Infrastructure Systems, 9(1), 6-15.

Salman, B. and Salem, O. (2012) "Risk Assessment of Wastewater Collection Lines Using Failure Models and Criticality Ratings." Journal of pipeline systems engineering and practice, 3, 68-76.

Samrout, M., Châtelet, E., Kouta, R. and Chebbo, N. (2009). "Optimization of maintenance policy using the proportional hazard model." Reliability Engineering and System Safety, 94, 44-52

Sarma, K.C. and Adeli, H. (2000), "Cost optimization of steel structures", Journal of Engineering Optimization, 32 (6),777-802.

Shehab, T. and Moselhi, O. (2005). "Automated Detection and Classification of Infiltration in Sewer Pipes." Journal of Infrastructure Systems, 10.1061/(ASCE)1076-0342(2005)11:3(165), 165-171.

Shohet, I. and Perelstein, E. (2004), "Decision support model for the allocation of resources in rehabilitation projects", Journal of Construction Engineering and Management, 130 (2), 249-257.

Singh, P., Dhania, G., Sharma, A. and Jaiwal, P. (2007). "Biotechnological approach to improve phytoremediation efficiency for environmental contaminants". Environmental bioremediation technologies.223- 258.

Sinha, S., and McKim, R. A. (2007). "Probabilistic based integrated pipeline management system." Tunnelling and Underground Space Tech., 22(5-6), 543 – 552.

Stamelos, I. ,Dimou, P. , and Angelis, L. (2003). "On the Use of Bayesian Belief Networks for the Prediction of Software Development Productivity", Information and Software Technology, Elsevier, 45, 51-60.

Straub, D. (2009). "Stochastic modelling of deterioration processes through dynamic Bayesian networks". ASCE Journal of Engineering Mechanics, 135, 1089–1099.

Suarez, R. and Bradford, B.,(1993)." The economic impact of the cholera epidemic in Peru: an application of the cost-if-illness methodology, Water and Sanitation for Health Project; WASH Field Report No. 415".

Takagi, T. and Sugeno, M. (1985). "Fuzzy identification of systems and its applications to modeling and control." IEEE Transactions on Systems, Man, and Cybernetics, 15, 116 – 132.

The Canadian Infrastructure Report Card (2016) http://www.canadainfrastructure.ca/en/index.html

Tiena, S.,W., Hwanga, W.,T. and Tsaib, C.,H. (2007). "Study of a risk-based piping inspection guideline system." ISA Transactions, 46, 119–126.

Tong, T. K. L., Tam, C. M., and Chan, A. P. C. (2001). "Genetic algorithm optimization in building portfolio management." Construction Management and Economics, 19(6), 601-609.

Torterotot, J. P., Sousa e Silva, D., Barbier, R., Werey, C., Pereira A., Konig, A., Montginoul, M., and Waechter V. (2006). "Socio-economic consequences." CARE-S Computer Aided Rehabilitation of Sewer and Storm Water Networks. IWA Publishing,73-88.

Ugarelli, R. and Di Federico, V. (2009). "Optimal scheduling of replacement and rehabilitation in wastewater pipeline networks." Journal of Water Resources Planning and Management, 136, 348-356.

Vacheyroux, G. and Corotis, R. (2013), "Strategies of investment in the management of urban bridges: a life-cycle approach illustrated for Paris", Journal of Structure and Infrastructure Engineering, 9 (11), 1080-1093.

Van der Gaag, L.C. , Renooij, S. ,Witteman, L.M., Aleman, M.P., and Taal, B.G.(1999). "How to elicit many probabilities," Proceedings of the Fifteenth Annual Conference on Uncertainty in Artificial Intelligence, Morgan Kaufmann Publishers, San Francisco, CA, 647-654.

Vose, D. (2000) Risk Analysis, John Wiley and Sons, Chichester, England.

Washer, G., Connor, R., Ciolko, A., Fish, P., Kogler, R., Forsyth, D. and Nasrollahi, M. (2014) "Inspection Planning Based on Risk Analysis." Structures Congress 2014, 699-710

Water Environment Federation (WEF) and American Society of Civil Engineers (ASCE). (1992). "Design and Construction of Urban Stormwater Management Systems", ASCE, New York, NY; WEF, Alexandria, VA.

Water Research Center (WRC), (2001), "Manual of sewer condition classification. Water Research Centre", UK, 4th ed.

WEF (2009), World Economic Forum, Global Competitiveness Report 2009-2010 (www.weforum.org).

WEF/ASCE. (2009). "Existing sewer evaluation and rehabilitation." WEF Manual of Practice No.FD-6 and ASCE Manuals And Reports on Engineering Practice No.62, WEF, Alexandria, VA; ASCE, Reston, VA.

Weinstein, M. C., and Stason, W. B. (1977). "Foundations of cost-effectiveness analysis for health and medical practices." New England journal of medicine, 296(13), 716-721.

Winston, W., Venkataramanan, Mand (2003). “Introduction to mathematical programming”. Vol. 1. Thomson/Brooks/Cole.

Wirahadikusumah, R., Abraham, D., and Iseley T. (2001). “Challenging issues in modeling deterioration of combined sewers.” J. Infrastruc. Syst., 7(2), 77 – 84.

World Human Organization (WHO), (2001). “Project appraisal document on a proposed loan to the Socialist Republic of Vietnam for the Ho Chi Minh City environmental sanitation project.”, Urban Development Sector Unit, Vietnam Country, Department of the World Bank, Genève, Switzerland.

Younis, R., and Knight, M. A. (2010). A probability model for investigating the trend of structural deterioration of wastewater pipelines. Tunnelling and Underground Space Technology, 25(6), 670-680.

Zadeh, L.A. (1965), “Fuzzy sets. Information and Control”, 8(3), 338–353.

Zhang, A., Boardman, A. E., Gillen, D., and Waters, I. (2004).” Towards estimating the social and environmental costs of transportation in Canada. Report for Transport Canada”.

Zhang, S.; Song, S. (2011), ”A Novel Attack Graph Posterior Inference Model Based on Bayesian Networks Journal of Information Security”, 2, 8-27.

APPENDIX I

In this section, samples from the codes written for the development of the different modules are presented. The section starts with VB6 code for development of the likelihood module, then VBA code for the consequences of failure calculator module. The python code used to develop the fuzzy inference system and the Arc-GIS tool. Additionally, the GAMS code and the VBA code to export the results on the MS-Project are also presented.

1. Likelihood of Failure Module

```
Private Sub Command1_Click()
'Calling Excel Objects
Dim objExcel As Excel.Application
Dim excelWB As Excel.Workbook
Dim excelWS As Excel.Worksheet
Set objExcel = CreateObject("excel.application")
objExcel.Visible = True
Set excelWB = objExcel.Workbooks.Open("F:\POF Journal Paper\User Interface\Final
Software\Logistic Regression.xlsx")
Set excelWS = excelWB.Worksheets("Sheet1")
'Input to Excel sheet from userform
excelWS.Cells(13, 1).Value = Val(Text1.Text)
excelWS.Cells(13, 2).Value = Val(Text2.Text) / 1000
excelWS.Cells(13, 4).Value = Val(Text3.Text)
excelWS.Cells(13, 5).Value = Val(Text4.Text)
If Combo1.Text = "Vetrified Clay" Then
excelWS.Cells(13, 6).Value = "VC"
ElseIf Combo1.Text = "PVC" Then
excelWS.Cells(13, 6).Value = "PVC"
ElseIf Combo1.Text = "GRP" Then
excelWS.Cells(13, 6).Value = "GRP"
ElseIf Combo1.Text = "Reinforced Concrete" Then
excelWS.Cells(13, 6).Value = "RC"
ElseIf Combo1.Text = "Concrete" Then
excelWS.Cells(13, 6).Value = "C"
End If
'Structural Defects Nodes Definition
Dim aMSBN As New MSBN3Lib.MSBN
Dim BBNModel As MSBN3Lib.Model
Set BBNModel = aMSBN.Models.Add(FileName:="BBNModel.dsc",
ErrorFilename:="errorfile.log")
```

```
Dim Structural_Condition As MSBN3Lib.Node
Set Structural_Condition = BBNModel.ModelNodes("Structural_Condition")
Dim Spalling As MSBN3Lib.Node
Set Spalling = BBNModel.ModelNodes("Spalling")
Dim Cirumfrential_Crack As MSBN3Lib.Node
Set Cirumfrential_Crack = BBNModel.ModelNodes("Cirumfrential_Crack")
:
:
:
'Loop for entering transitional probabilities for structural defects
Dim j As Double
j = 13
Dim excelWS2 As Excel.Worksheet
Set excelWS2 = excelWB.Worksheets("Sheet3")
Dim inferAuto As MSBN3Lib.Engine
Set inferAuto = BBNModel.Engine
While inferAuto.Belief("Structural_Condition", "2") > 0.15
Spalling.Dist(0, "L") = excelWS.Cells(j, 11).Value
Spalling.Dist(0, "M") = excelWS.Cells(j, 12).Value
Spalling.Dist(0, "S") = excelWS.Cells(j, 13).Value
Cirumfrential_Crack.Dist(0, "L") = excelWS.Cells(j, 11).Value
Cirumfrential_Crack.Dist(0, "M") = excelWS.Cells(j, 12).Value
Cirumfrential_Crack.Dist(0, "S") = excelWS.Cells(j, 13).Value
:
:
:
j = j + 1
Debug.Print inferAuto.Belief("Structural_Condition", "4")
excelWS2.Cells(j, 2).Value = inferAuto.Belief("Structural_Condition", "0")
excelWS2.Cells(j, 3).Value = inferAuto.Belief("Structural_Condition", "1")
excelWS2.Cells(j, 4).Value = inferAuto.Belief("Structural_Condition", "2")
excelWS2.Cells(j, 5).Value = inferAuto.Belief("Structural_Condition", "3")
excelWS2.Cells(j, 6).Value = inferAuto.Belief("Structural_Condition", "4")
Wend
'Operational Defects Nodes Definition
Dim Operational_Condition As MSBN3Lib.Node
Set Operational_Condition = BBNModel.ModelNodes("Operational_Condition")
Dim Sweating As MSBN3Lib.Node
Set Sweating = BBNModel.ModelNodes("Sweating")
Dim Dripping As MSBN3Lib.Node
Set Dripping = BBNModel.ModelNodes("Dripping")
:
:
:
Dim k As Double
k = 13
```

```
While inferAuto.Belief("Operational_Condition", "2") > 0.15
Sweating.Dist(0, "L") = excelWS.Cells(k, 14).Value
Sweating.Dist(0, "M") = excelWS.Cells(k, 15).Value
Sweating.Dist(0, "S") = excelWS.Cells(k, 16).Value
Dripping.Dist(0, "L") = excelWS.Cells(k, 14).Value
Dripping.Dist(0, "M") = excelWS.Cells(k, 15).Value
Dripping.Dist(0, "S") = excelWS.Cells(k, 16).Value
:
:
:
k = k + 1
Debug.Print inferAuto.Belief("Operational_Condition", "4")
excelWS2.Cells(k, 7).Value = inferAuto.Belief("Operational_Condition", "0")
excelWS2.Cells(k, 8).Value = inferAuto.Belief("Operational_Condition", "1")
excelWS2.Cells(k, 9).Value = inferAuto.Belief("Operational_Condition", "2")
excelWS2.Cells(k, 10).Value = inferAuto.Belief("Operational_Condition", "3")
excelWS2.Cells(k, 11).Value = inferAuto.Belief("Operational_Condition", "4")
excelWS2.Cells(k, 12).Value = inferAuto.Belief("Overall_Condition", "0")
excelWS2.Cells(k, 13).Value = inferAuto.Belief("Overall_Condition", "1")
excelWS2.Cells(k, 14).Value = inferAuto.Belief("Overall_Condition", "2")
excelWS2.Cells(k, 15).Value = inferAuto.Belief("Overall_Condition", "3")
excelWS2.Cells(k, 16).Value = inferAuto.Belief("Overall_Condition", "4")
Wend
BBNModel.Save FileName:="F:\POF Journal Paper\User Interface\Final Software\Auto0.xbn",
FileFormat:=fileformat_Xml
Text5.Text = inferAuto.Belief("Structural_Condition", "4")
Text7.Text = inferAuto.Belief("Operational_Condition", "4")
If excelWS.Cells(j, 3).Value > excelWS.Cells(k, 3).Value Then
Text6.Text = excelWS.Cells(j, 3).Value
ElseIf excelWS.Cells(j, 3).Value < excelWS.Cells(k, 3).Value Then
Text6.Text = excelWS.Cells(k, 3).Value
End If
Text8.Text = inferAuto.Belief("Overall_Condition", "4")
End Sub
```

2. Consequences of Failure Module

```
Private Sub CheckBox1_Click()
If CheckBox1.Value = True Then
TextBox8.BackColor = RGB(255, 255, 255)
TextBox8.Text = ""
Worksheets("CBA").Range("B22").Value = TextBox8.Text
End If
End Sub
Private Sub CheckBox10_Click()
If CheckBox10.Value = True Then
```

```
TextBox16.BackColor = RGB(255, 255, 255)
TextBox16.Text = ""
Worksheets("CBA").Range("C34").Value = TextBox16.Text
End If
End Sub
Private Sub CheckBox11_Click()
If CheckBox11.Value = True Then
TextBox17.BackColor = RGB(255, 255, 255)
TextBox17.Text = ""
Worksheets("CBA").Range("C35").Value = TextBox17.Text
End If
End Sub
Private Sub CheckBox2_Click()
If CheckBox2.Value = True Then
TextBox9.BackColor = RGB(255, 255, 255)
TextBox9.Text = ""
Worksheets("CBA").Range("B13").Value = TextBox9.Text
End If
End Sub
Private Sub CheckBox4_Click()
If CheckBox4.Value = True Then
TextBox10.BackColor = RGB(255, 255, 255)
TextBox10.Text = ""
Worksheets("CBA").Range("B20").Value = TextBox10.Text
End If
End Sub
Private Sub CheckBox5_Click()
If CheckBox5.Value = True Then
TextBox11.BackColor = RGB(255, 255, 255)
TextBox11.Text = ""
Worksheets("CBA").Range("B18").Value = TextBox11.Text
End If
End Sub
Private Sub CheckBox6_Click()
If CheckBox6.Value = True Then
TextBox12.BackColor = RGB(255, 255, 255)
TextBox12.Text = ""
Worksheets("CBA").Range("B19").Value = TextBox12.Text
End If
End Sub
Private Sub CheckBox7_Click()
If CheckBox7.Value = True Then
TextBox13.BackColor = RGB(255, 255, 255)
TextBox13.Text = ""
Worksheets("CBA").Range("B27").Value = Val(TextBox13.Text) / 100
End If
```

```
End Sub
Private Sub CheckBox8_Click()
If CheckBox8.Value = True Then
TextBox14.BackColor = RGB(255, 255, 255)
TextBox14.Text = ""
End If
End Sub
Private Sub CheckBox9_Click()
If CheckBox9.Value = True Then
TextBox18.BackColor = RGB(255, 255, 255)
TextBox19.BackColor = RGB(255, 255, 255)
TextBox15.BackColor = RGB(255, 255, 255)
TextBox18.Text = ""
TextBox19.Text = ""
TextBox15.Text = ""
Worksheets("CBA").Range("B12").Value = TextBox18.Text
Worksheets("CBA").Range("C12").Value = TextBox19.Text
Worksheets("CBA").Range("D12").Value = TextBox15.Text
End If
End Sub
Private Sub ComboBox1_Change()
ComboBox1.AddItem "VC"
ComboBox1.AddItem "PVC"
ComboBox1.AddItem "GRE"
If ComboBox1.Value = "VC" Then
Worksheets("CBA").Range("B2").Value = ComboBox1.Value
ElseIf ComboBox1.Value = "PVC" Then
Worksheets("CBA").Range("B2").Value = ComboBox1.Value
ElseIf ComboBox1.Value = "GRE" Then
Worksheets("CBA").Range("B2").Value = ComboBox1.Value
End If
End Sub
Private Sub ComboBox2_Change()
If ComboBox2.Value Then
Worksheets("CBA").Range("B4").Value = ComboBox2.Value
End If
End Sub
Private Sub ComboBox3_Change()
If ComboBox3.Value Then
Worksheets("CBA").Range("B10").Value = ComboBox3.Value
End If
End Sub
Private Sub ComboBox4_Change()
If ComboBox4.Value Then
Worksheets("CBA").Range("B11").Value = ComboBox4.Value
End If
```

```
End Sub
Private Sub CommandButton1_Click()
UserForm3.Show
UserForm3.TextBox1.Text = Format(Worksheets("CBA").Range("G42").Value, "#,##0")
If Worksheets("CBA").Range("G42").Value >= 0 And
Worksheets("CBA").Range("G42").Value < 0.3 Then
UserForm3.TextBox2.BackColor = RGB(0, 255, 0)
UserForm3.TextBox2.Text = "Extremely Low"
ElseIf Worksheets("CBA").Range("G42").Value >= 0.3 And
Worksheets("CBA").Range("G42").Value < 0.7 Then
UserForm3.TextBox2.BackColor = RGB(0, 255, 255)
UserForm3.TextBox2.Text = "Very Low"
ElseIf Worksheets("CBA").Range("G42").Value >= 0.7 And
Worksheets("CBA").Range("G42").Value < 1 Then
UserForm3.TextBox2.BackColor = RGB(255, 255, 0)
UserForm3.TextBox2.Text = "Low"
ElseIf Worksheets("CBA").Range("G42").Value >= 1 And
Worksheets("CBA").Range("G42").Value < 1.6 Then
UserForm3.TextBox2.BackColor = RGB(255, 128, 0)
UserForm3.TextBox2.Text = "Medium"
ElseIf Worksheets("CBA").Range("G42").Value >= 1.6 And
Worksheets("CBA").Range("G42").Value < 1.8 Then
UserForm3.TextBox2.BackColor = RGB(255, 128, 0)
UserForm3.TextBox2.Text = "High"
ElseIf Worksheets("CBA").Range("G42").Value >= 1.8 And
Worksheets("CBA").Range("G42").Value < 2 Then
UserForm3.TextBox2.BackColor = RGB(255, 128, 0)
UserForm3.TextBox2.Text = "Very High"
ElseIf Worksheets("CBA").Range("G42").Value >= 2 Then
UserForm3.TextBox2.BackColor = RGB(255, 0, 0)
UserForm3.TextBox2.Text = "Extremely High"
End If
UserForm3.TextBox3.Text = Format(Worksheets("CBA").Range("G28").Value, "#,##0.0")
UserForm3.TextBox4.Text = Format(Worksheets("CBA").Range("G29").Value, "#,##0.0")
UserForm3.TextBox5.Text = Format(Worksheets("CBA").Range("G30").Value, "#,##0.0")
UserForm3.TextBox6.Text = Format(Worksheets("CBA").Range("G31").Value, "#,##0.0")
UserForm3.TextBox7.Text = Format(Worksheets("CBA").Range("G32").Value, "#,##0.0")
UserForm3.TextBox8.Text = Format(Worksheets("CBA").Range("G33").Value, "#,##0.0")
UserForm3.TextBox9.Text = Format(Worksheets("CBA").Range("G34").Value, "#,##0.0")
UserForm3.TextBox10.Text = Format(Worksheets("CBA").Range("G35").Value, "#,##0.0")
UserForm3.TextBox11.Text = Format(Worksheets("CBA").Range("G36").Value, "#,##0.0")
UserForm3.TextBox12.Text = Format(Worksheets("CBA").Range("G37").Value, "#,##0.0")
UserForm3.TextBox13.Text = Format(Worksheets("CBA").Range("B39").Value, "#,##0.0")
Set currentchart = Sheets("CBA").ChartObjects(1).Chart
Fname = ThisWorkbook.Path & "\temp.gif"
currentchart.Export Filename:=Fname, FilterName:="GIF"
```

```
UserForm3.Image1.Picture = LoadPicture(Fname)
End Sub
Private Sub CommandButton2_Click()
Unload Me
End Sub
Private Sub TextBox2_Change()
Worksheets("CBA").Range("B3").Value = TextBox2.Text
End Sub
Private Sub TextBox6_Change()
Worksheets("CBA").Range("B9").Value = TextBox6.Text
End Sub
Private Sub TextBox7_Change()
Worksheets("CBA").Range("B23").Value = TextBox7.Text
End Sub
```

3. Risk Assessment of Failure Module

```
import numpy as np
import skfuzzy as fuzz
import matplotlib.pyplot as plt
Likelihood = np.arange(0, 2, 1)
Consequence = np.arange(0, 2, 1)
Risk = np.arange(0, 2, 1)
Likelihood_EL_mf = fuzz.trimf(Likelihood , [0, 0, .17])
Likelihood_VL_mf = fuzz.trimf(Likelihood , [0, .17, .33])
Likelihood_L_mf = fuzz.trimf(Likelihood , [.17, .33, .50])
Likelihood_M_mf = fuzz.trimf(Likelihood , [.33, .50, .67])
Likelihood_H_mf = fuzz.trimf(Likelihood , [.50, .67, .80])
Likelihood_VH_mf = fuzz.trimf(Likelihood , [.67, .80, 1.00])
Likelihood_EH_mf = fuzz.trimf(Likelihood , [.80, 1.00, 1.00])
Consequence_EL_mf = fuzz.trimf(Consequence , [0, 0, .17])
Consequence_VL_mf = fuzz.trimf(Consequence , [0, .17, .33])
Consequence_L_mf = fuzz.trimf(Consequence , [.17, .33, .50])
Consequence_M_mf = fuzz.trimf(Consequence , [.33, .50, .67])
Consequence_H_mf = fuzz.trimf(Consequence , [.50, .67, .80])
Consequence_VH_mf = fuzz.trimf(Consequence , [.67, .80, 1.00])
Consequence_EH_mf = fuzz.trimf(Consequence , [.80, 1.00, 1.00])
Risk_EL_mf = fuzz.trimf(Risk , [0, 0, .17])
Risk_VL_mf = fuzz.trimf(Risk , [0, .17, .33])
Risk_L_mf = fuzz.trimf(Risk , [.17, .33, .50])
Risk_M_mf = fuzz.trimf(Risk , [.33, .50, .67])
Risk_H_mf = fuzz.trimf(Risk , [.50, .67, .80])
Risk_VH_mf = fuzz.trimf(Risk , [.67, .80, 1.00])
Risk_EH_mf = fuzz.trimf(Risk , [.80, 1.00, 1.00])
x= 1
y = 0.9
```

```
fig, (ax0, ax1) = plt.subplots(nrows=2, figsize=(8, 9))
ax0.plot(Likelihood, Likelihood_EL_mf, 'b', linewidth=1.5, label='Most Unlikely')
ax0.plot(Likelihood, Likelihood_VL_mf, 'g', linewidth=1.5, label='Less Unlikely')
ax0.plot(Likelihood, Likelihood_L_mf, 'r', linewidth=1.5, label='Unlikely')
ax0.plot(Likelihood, Likelihood_M_mf, 'k', linewidth=1.5, label='Equally Probable')
ax0.plot(Likelihood, Likelihood_H_mf, 'y', linewidth=1.5, label='Probably')
ax0.plot(Likelihood, Likelihood_VH_mf, 'm', linewidth=1.5, label='More Probably')
ax0.plot(Likelihood, Likelihood_EH_mf, 'c', linewidth=1.5, label='Most Probably')
ax0.set_title('Likelihood of Failure')
ax0.legend()
ax1.plot(Consequence, Consequence_EL_mf, 'b', linewidth=1.5, label='Insignificant')
ax1.plot(Consequence, Consequence_VL_mf, 'g', linewidth=1.5, label='Very Low')
ax1.plot(Consequence, Consequence_L_mf, 'r', linewidth=1.5, label='Low')
ax1.plot(Consequence, Consequence_M_mf, 'k', linewidth=1.5, label='Moderate')
ax1.plot(Consequence, Consequence_H_mf, 'y', linewidth=1.5, label='Very High')
ax1.plot(Consequence, Consequence_VH_mf, 'm', linewidth=1.5, label='High')
ax1.plot(Consequence, Consequence_EH_mf, 'c', linewidth=1.5, label='Catastrophic')
ax1.set_title('Consequences of Failure')
ax1.legend()
for ax in (ax0, ax1):
   ax.spines['top'].set_visible(False)
   ax.spines['right'].set_visible(False)
   ax.get_xaxis().tick_bottom()
   ax.get_yaxis().tick_left()
plt.tight_layout()
Likelihood_EL = fuzz.interp_membership(Likelihood , Likelihood_EL_mf , x)
Likelihood_VL = fuzz.interp_membership(Likelihood , Likelihood_VL_mf , x)
Likelihood_L = fuzz.interp_membership(Likelihood , Likelihood_L_mf , x)
Likelihood_M  = fuzz.interp_membership(Likelihood , Likelihood_M_mf , x)
Likelihood_H = fuzz.interp_membership(Likelihood , Likelihood_H_mf , x)
Likelihood_VH = fuzz.interp_membership(Likelihood , Likelihood_VH_mf , x)
Likelihood_EH = fuzz.interp_membership(Likelihood , Likelihood_EH_mf , x)
Consequence_EL = fuzz.interp_membership(Consequence , Consequence_EL_mf , y)
Consequence_VL = fuzz.interp_membership(Consequence , Consequence_VL_mf , y)
Consequence_L = fuzz.interp_membership(Consequence , Consequence_L_mf , y)
Consequence_M = fuzz.interp_membership(Consequence , Consequence_M_mf , y)
Consequence_H = fuzz.interp_membership(Consequence , Consequence_H_mf , y)
Consequence_VH = fuzz.interp_membership(Consequence , Consequence_VH_mf , y)
Consequence_EH = fuzz.interp_membership(Consequence , Consequence_EH_mf , y)
rule1 = np.fmin(Likelihood_EL, Consequence_EL)
rule2 = np.fmin(Likelihood_EL, Consequence_VL)
rule3 = np.fmin(Likelihood_EL, Consequence_L)
rule4 = np.fmin(Likelihood_EL, Consequence_M)
rule5 = np.fmin(Likelihood_EL, Consequence_H)
rule6 = np.fmin(Likelihood_EL, Consequence_VH)
rule7 = np.fmin(Likelihood_EL, Consequence_EH)
```

```
rule8 = np.fmin(Likelihood_VL, Consequence_EL)
rule9 = np.fmin(Likelihood_VL, Consequence_VL)
rule10 = np.fmin(Likelihood_VL, Consequence_L)
rule11 = np.fmin(Likelihood_VL, Consequence_M)
rule12 = np.fmin(Likelihood_VL, Consequence_H)
rule13 = np.fmin(Likelihood_VL, Consequence_VH)
rule14 = np.fmin(Likelihood_VL, Consequence_EH)
rule15 = np.fmin(Likelihood_L, Consequence_EL)
rule16 = np.fmin(Likelihood_L, Consequence_VL)
rule17 = np.fmin(Likelihood_L, Consequence_L)
rule18 = np.fmin(Likelihood_L, Consequence_M)
rule19 = np.fmin(Likelihood_L, Consequence_H)
rule20 = np.fmin(Likelihood_L, Consequence_VH)
rule21 = np.fmin(Likelihood_L, Consequence_EH)
rule22 = np.fmin(Likelihood_M, Consequence_EL)
rule23 = np.fmin(Likelihood_M, Consequence_VL)
rule24 = np.fmin(Likelihood_M, Consequence_L)
rule25 = np.fmin(Likelihood_M, Consequence_M)
rule26 = np.fmin(Likelihood_M, Consequence_H)
rule27 = np.fmin(Likelihood_M, Consequence_VH)
rule28 = np.fmin(Likelihood_M, Consequence_EH)
rule29 = np.fmin(Likelihood_H, Consequence_EL)
rule30 = np.fmin(Likelihood_H, Consequence_VL)
rule31 = np.fmin(Likelihood_H, Consequence_L)
rule32 = np.fmin(Likelihood_H, Consequence_M)
rule33 = np.fmin(Likelihood_H, Consequence_H)
rule34 = np.fmin(Likelihood_H, Consequence_VH)
rule35 = np.fmin(Likelihood_H, Consequence_EH)
rule36 = np.fmin(Likelihood_VH, Consequence_EL)
rule37 = np.fmin(Likelihood_VH, Consequence_VL)
rule38 = np.fmin(Likelihood_VH, Consequence_L)
rule39 = np.fmin(Likelihood_VH, Consequence_M)
rule40 = np.fmin(Likelihood_VH, Consequence_H)
rule41 = np.fmin(Likelihood_VH, Consequence_VH)
rule42 = np.fmin(Likelihood_VH, Consequence_EH)
rule43 = np.fmin(Likelihood_EH, Consequence_EL)
rule44 = np.fmin(Likelihood_EH, Consequence_VL)
rule45 = np.fmin(Likelihood_EH, Consequence_L)
rule46 = np.fmin(Likelihood_EH, Consequence_M)
rule47 = np.fmin(Likelihood_EH, Consequence_H)
rule48 = np.fmin(Likelihood_EH, Consequence_VH)
rule49 = np.fmin(Likelihood_EH, Consequence_EH)
for ax in (ax0, ax1, ax2):
    ax.spines['top'].set_visible(False)
    ax.spines['right'].set_visible(False)
    ax.get_xaxis().tick_bottom()
```

```
    ax.get_yaxis().tick_left()
plt.tight_layout()
r_EL = np.fmin(rule1,Risk_EL_mf)
r_VL = np.fmin(rule2,np.fmin(rule3,np.fmin(rule8, np.fmin(rule9,
np.fmin(rule15,Risk_VL_mf)))))
r_L = np.fmin(rule4, np.fmin(rule5, np.fmin(rule10, np.fmin(rule11, np.fmin(rule16,
np.fmin(rule17, np.fmin(rule22, np.fmin(rule23, np.fmin(rule29, Risk_L_mf)))))))))
r_M = np.fmin(rule6, np.fmin(rule7,np.fmin(rule12,np.fmin(rule13,np.fmin(rule18,
np.fmin(rule19, np.fmin(rule24,np.fmin(rule25, np.fmin(rule26, np.fmin(rule30,
np.fmin(rule31,np.fmin(rule36,np.fmin(rule37,np.fmin(rule43, Risk_M_mf))))))))))))))
r_H = np.fmin(rule14, np.fmin(rule20, np.fmin(rule21,np.fmin(rule27, np.fmin(rule32,
np.fmin(rule33, np.fmin(rule35, np.fmin(rule38, np.fmin(rule39,np.fmin(rule44, np.fmin(rule45,
Risk_H_mf)))))))))))
r_VH = np.fmin(rule28,np.fmin(rule34,np.fmin(rule40,np.fmin(rule41,np.fmin(rule46,
np.fmin(rule47,np.fmin(rule48, Risk_VH_mf)))))))
r_EH = np.fmin(rule42,np.fmin(rule49, Risk_EH_mf))
r_agg = np.fmax(r_EL,np.fmax(r_VL,np.fmax(r_L,np.fmax(r_M,np.fmax(r_H, np.fmax(r_VH,
r_EH))))))
r_index = fuzz.centroid(Risk, r_agg)
risk_index = 0.25+0.458*(x)+0.427*(y)
if risk_index >1:
    risk_index =1
print "Risk Index for Pipeline is=" ,risk_index
```

4. ArcGIS Tool

```
import arcpy, pythonaddins, xlwt, xlrd
from xlwt import Workbook
class ButtonClass1(object):
    def __init__(self):
        self.enabled = True
        self.checked = False
    def onClick(self):
        wbw = Workbook()
        wsw = wbw.add_sheet("sheet1")
        wbr = xlrd.open_workbook('swl.xls')
        wsr = wbr.sheet_by_index(0)
        for i in range(0,10):
            wsw.write(i,2, wsr.cell(i,1).value)
        wbw.save('data.xls')
        pythonaddins.MessageBox('Please Join the table in excel file called data', 'Risk Tool', 0)
        pass
```

5. GAMS Module

```
Sets
      i  'index for pipelines' /p1*p99/
      l(i)  'index for pipelines' /p1*p99/
      j  'index for crews' /c1, c2, c3/
      k  'index for inspection technology' /k1/;

Parameter c_ins(i,k)  'cost of inspection for each pipe';
$call GDXXRW input.xlsx par = c_ins rng=sheet1!a1:b100 rdim = 1 cdim = 1
$GDXIN input.gdx
$LOAD c_ins
Parameter t_ins(i,k)  'time of inspection for each pipe';
$call GDXXRW input.xlsx par = t_ins rng=sheet1!a101:b200 rdim = 1 cdim = 1
$GDXIN input.gdx
$LOAD t_ins
Parameter hc_ins(j,k) 'cost of inspection for each pipe';
$call GDXXRW input.xlsx par = hc_ins rng=sheet1!a201:b204 rdim = 1 cdim = 1
$GDXIN input.gdx
$LOAD hc_ins
Parameter c_rel(i,i) 'cost of crew relocation';
$call GDXXRW input.xlsx par = c_rel rng=sheet1!a205:cv304 rdim = 1 cdim = 1
$GDXIN input.gdx
$LOAD c_rel
Parameter t_rel(i,i) 'time of crew relocation';
$call GDXXRW input.xlsx par = t_rel rng=sheet1!a305:cv404 rdim = 1 cdim = 1
$GDXIN input.gdx
$LOAD t_rel

binary variable
      x(i)  'decision variable for inspecting pipes'
      z(i,i)  'decision variable for inspecting remaining pipes'

Variables
      tc       'total cost of inspection'
      tt       'total time of inspection'
      tn       'total number of inspected pipes'
      f        'weighted function';

Equations
      cost        'first objective function'
      time        'second objective function'
      number      'thrid objective function'
      global      'multiobjective function'
      cons_1      'constraint 1'
      cons_2      'constraint 2'
      cons_3      'constraint 3';
```

```
cost ..        tc  =e= sum((i,k), c_ins(i,k)*x(i))
               +sum((i,l)$(not sameas(i,l)),c_rel(i,l)*z(i,l));
time ..        tt  =e= sum((i,k), t_ins(i,k)*x(i))
               +sum((i,l)$(not sameas(i,l)), t_rel(i,l)*z(i,l));
number ..      tn  =e= sum((i),x(i));

cons_1(i,l)$(not sameas(i,l))..  z(i,l) =l= x(i);
cons_2(i,l)$(not sameas(i,l))..  z(i,l) =l= x(l);
cons_3(i,l)$(not sameas(i,l))..  z(i,l) =g= x(i) + x(l) - 1;

Model inspection /all/;
global..      f =e= 0.9*tc+0.05*tt-0.05*tn;
Solve inspection using mip minimizing f;
Display  x.l, x.m, f.l, tc.l, tt.l, tn.l;

execute_unload "results.gdx" x.L x.M
execute 'gdxxrw.exe results.gdx o=results.xls var=x.L'
execute 'gdxxrw.exe  results.gdx o=results.xls var=f.l rng=NewSheet!f1:i4'
```

6. MS Project Module

```
Private Sub CommandButton1_Click()
Dim wb As Workbook
Dim ws As Worksheet
Dim Crw, Tsk, Strt, Dur, Fnsh As Variant
Dim Start, Counter As Long
Set wb = ThisWorkbook
Set ws = wb.Worksheets(1)

With ws
Start = .Range("D65536").End(xlUp).Row
Tsk = .Range("A2:A" & Start).Value
Dur = .Range("B2:B" & Start).Value
Strt = .Range("C2:C" & Start).Value
Fnsh = .Range("D2:D" & Start).Value
Crw = .Range("E2:E" & Start).Value
End With

Dim prApp As MSProject.Application
Dim prProject As MSProject.Project
Set prApp = New MSProject.Application
prApp.FileOpen "C:\Users\Lenovo\Desktop\V.mpp"
Set prProject = prApp.ActiveProject
```

```
With prProject
For Counter = 1 To UBound(Tsk)
.Tasks.Add Tsk(Counter, 1)
With .Tasks(Tsk(Counter, 1))
.Duration = Dur(Counter, 1) & " days"
.Start = Strt(Counter, 1)
.Finish = Fnsh(Counter, 1)
.ResourceNames = "Crew" & Crw(Counter, 1)
End With
Next Counter
End With
With prApp
.FileSave
.Quit
End With
MsgBox "Inspection Schedule has been updated and saved!", vbInformation
End Sub
```

APPENDIX II

To examine the usability of the developed scheduling tool, a survey was constructed and distributed on professionals working in the field of infrastructure's design and construction management. Table II.1 summarizes the affiliation and years of experience of the addressed professionals.

Table II.1: Summary for Experts Affiliation and Experience

Expert	Affiliation	Years of Experience
E1	Cost Control Specialist, City of New York, USA	15
E2	Head of Design Unit, Cairo, Egypt	30
E3	Senior Environmental Engineer, Doha, Qatar.	20
E4	Project Coordinator, Cairo, Egypt	8
E5	Assistant Professor, Colorado, USA	15

Table II.2: Criteria Description for Scheduling Tool Survey

Criteria	Description	Excellent (5)	Very Good (4)	Good (3)	Fair (2)	Poor (1)
CP	Purpose is well defined in the welcome page					
CR	Program achieves its purpose					
CL	Language in the program is clear and correct					
CM	User materials are easy to use and appealing to users					
CI	Individuals has the choice of going directly to desired information					
CE	Individuals can operate the program easily					
CC	Commands are handled correctly					
CS	Individuals can easily start and exit the program					
CA	Program is attractive and intuitive					
CF	Program is effective with the intended audience					
CG	Program can be used by various cultural groups					
CO	Organization is clear and logical					

Table II.2 shows the different criteria that the experts were asked to assess. The experts were asked to assess the usability and ease of the developed tool on a 5 grade scale starting with excellent and ending with poor. The criteria for the survey covered the user's interaction with the tool as well as the objectives and features of the tool. Table II.3 shows the scores given by the experts for the different criteria in the survey.

Table II.3: Scores Given by Experts for Different Criteria

Criteria / Experts	E1	E2	E3	E4	E5	Overall Grade
CP	4	5	5	4	4	4
CR	5	5	4	5	2	4
CL	4	4	5	5	3	4
CM	3	4	3	5	4	4
CI	4	4	3	4	2	3
CE	5	5	4	4	3	4
CC	5	4	4	5	5	5
CS	4	5	5	3	4	4
CA	3	3	3	4	2	3
CF	4	3	4	5	4	4
CG	4	4	5	5	3	4
CO	4	5	5	5	5	5