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A METHODOLOGICAL FRAMEWORK FOR DIGITAL SHADOW-BASED STORMWATER INFRASTRUCTURE MANAGEMENT

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A METHODOLOGICAL FRAMEWORK FOR DIGITAL SHADOW-BASED STORMWATER INFRASTRUCTURE MANAGEMENT

By

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A METHODOLOGICAL FRAMEWORK FOR DIGITAL SHADOW-BASED STORMWATER INFRASTRUCTURE MANAGEMENT

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DECLARATION OF CO-AUTHORSHIP/PREVIOUS PUBLICATION

I. Co-Authorship:

I hereby declare that this thesis incorporates material that is the result of joint research, as follows:

This thesis was completed under the supervision of my advisor, Dr. Rajeev Ruparathna, and co-advisor, Dr. Tirupati Bolisetti. In all cases, the key ideas, primary contributions, data analysis, interpretation, and writing were carried out by the author. The contribution of the co-authors (co-advisors) was primarily in the form of feedback on the refinement of ideas and editing of the manuscript.

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Thesis Chapter	Publication Title	Publication Status
Chapter 5	A methodological framework for digital shadow-based stormwater infrastructure management	Under preparation

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ABSTRACT

Recently, there has been an increasing trend in using state-of-the-art technology for infrastructure management solutions. Yet, some civil infrastructure systems, such as stormwater, are currently managed manually. However, this current approach results in data losses and inconsistencies, which subsequently contribute to inaccurate stormwater infrastructure management. Building Information Modeling (BIM) offers a promising platform capable of creating a digital shadow (DS) of infrastructure assets, that can address these complexities in infrastructure management. An extensive literature review has revealed that the infrastructure asset management sector is lacking a DS-based model that facilitates proactive stormwater infrastructure management.

The objective of this study is to develop a DS-based proactive stormwater infrastructure management system. This study developed a DS-based methodological framework for proactive maintenance planning of stormwater infrastructure systems. The proposed framework used Markov Chain approach for simulating the stormwater infrastructure condition, and Genetic Algorithm (GA) was used for multi-objective optimization. The optimization was conducted to minimize the lifecycle cost and risk level while maximizing the physical condition. The proposed framework was developed as a tool in the BIM platform and was applied as a case study. Then, the proposed framework was compared to the conventional model of stormwater infrastructure management. The outcome revealed that the Lifecycle Cost (LCC) of the DS-based model is about 63% less than the conventional stormwater infrastructure management approach in long-term planning. The proposed framework enables maintaining an acceptable physical condition while minimizing the risk of failure and LCC. Unlike the conventional approach, the DS-based model can store data for easy reference. This will aid asset managers to eliminate data fragmentation in infrastructure management. Also, it will facilitate collaboration among stakeholders by effectively serving as a data warehouse for the proactive management of stormwater infrastructure systems.

DEDICATION

This thesis is dedicated to my family and Victoria Ocran for their immense support and patience during my graduate studies.

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LIST OF ABBREVIATIONS

AC - Asbestos Cement

AEC - Architecture, Engineering, and Construction

BMP - Best Management Practise

BIM - Building Information Modelling

CCTV - Closed-Circuit Television

CoF - Consequence of Failure

CONC - Concrete

DM - Decision-Making

DS - Digital Shadow

DT- Digital Twin

FM - Facility Management

GA - Genetic Algorithm

GIS - Geographic Information Systems

ID - Identification

KPI - Key Performance Indicators

MDP - Markov Decision Process

MOO - Multi-Objective Optimisation

MR&R - Maintenance, Repair & Replace

O&M - Operation & Maintenance

PoF - Probability of Failure

LCCA - Life Cycle Cost Analysis

LCC - Life Cycle Costing

LOS - Level of Service

TPM -Transition Probability Matrix

WRC - Water Research Center

1 INTRODUCTION

1.1 Background

Wastewater and stormwater collection and transportation systems are critical components of the urban water infrastructure. Yet, Stormwater infrastructure systems including storm sewer pipelines and treatment facilities present a great challenge to municipal asset managers. This is due to their varied components that have different repair and rehabilitation requirements (Hahn et al., 2002; Elbeltagi, Elbeltage, and Dawood, 2013; Marzouk and Osama, 2017). According to the Canadian Infrastructure Report Card (CIRC) (2019), about 30% of the municipal stormwater infrastructure is rated from fair to poor in condition (CIRC, 2019). A study conducted by Infrastructure Canada (2016) has indicated that the anticipated repair and rehabilitation costs of these stormwater infrastructure systems in "fair" and "poor or very poor" conditions are estimated to be $21 billion and $10 billion, respectively. However, the funding gap makes it difficult for the proper management of the stormwater infrastructure systems.

Again, due to urbanization, the permeable surfaces are replaced with impermeable surfaces which disrupt natural drainage patterns. This change increases the risk of flash flooding and influences the quantity and quality of stormwater (Barbosa et al., 2012; De Paola et al., 2018). Aside from urbanization, climate change also poses an adverse impact on stormwater infrastructure systems (Cook et al., 2020). Various studies involving climate change predictions have shown that heavy precipitation events are expected to intensify the quantity of surface runoff (Karl et al., 2008; Davies et al., 2008; Wu et al., 2008). The rise in urbanization and climate change coupled with declining funds for maintenance results in the deterioration of stormwater infrastructure systems. As a result, municipal stormwater infrastructure managers are faced with a challenge of keeping the operation, maintenance, and rehabilitation of these deteriorating systems under limited funds (Kabir et al., 2018; Abu-Samra et al., 2020).

The deterioration of stormwater infrastructure systems is caused by several factors including age, urbanization, lack of maintenance, climate change, physical and chemical properties of the surrounding soil, and surrounding environment (Ariaratnam et al., 2001). Previously, challenges caused by aging and deteriorating stormwater infrastructure systems were dealt reactively, with repair or rehabilitation being attended to only after a pipe had failed (Baah et al., 2015). These emergency repairs are of extremely high cost (Fenner, 2000). Moreover, the above failures hinder the service provided to the public. Hence, it is important to implement predictive asset management practices to ensure cost-effective and reliable service to the public (Lee et al., 2021).

The ISO 55000 series serves as the basis for asset management standards. The ISO 55001:2014 standard specifies the requirements for an integrated and efficient asset management system, while the ISO 55002:2014 standard directs the implementation of such a management system (Standardization, 2014). The aforementioned asset management standards comprise leadership, planning, support, operation and management, performance assessment, and continuous improvement. The planning, operation and management, and continuous improvement related to this research. The implementation of this standard enhances decision-making, manages risk, and improves asset performance. Therefore, the adoption of this ISO standard will enable municipalities and organizations to achieve their aim of managing their assets effectively. Given that stormwater infrastructure systems lack tools that aid planning, operation and management, and continuous improvement, it is necessary to develop a digital tool that integrates this standard to aid plan stormwater infrastructure assets more effectively.

According to Baik et al. (2006), proactive stormwater infrastructure management should take into account the current and future physical conditions, risk, and performance level of all system components. A proactive management approach relies strongly on data which is used for predicting future performance (Harvey and McBen 2014; Van et al. 2013). Proactive stormwater infrastructure management has many advantages, including asset failure prevention, risk management associated with asset failure, accurate forecasting of future expenditure requirements, and improvement of maintenance and rehabilitation strategies (InfraGuide, 2004). Moreover, there are no comprehensive data management tools or cutting-edge solutions that aid proactive stormwater infrastructure management (Eggimann et al., 2017).

A Digital Shadow (DS) can be adopted to resolve these challenges faced by municipal stormwater infrastructure managers (Callcut et al., 2021; Bello et al., 2021). Bello et al. (2021) define DS as a combination of an automatic one-way data flow between the condition of an existing physical asset and a digital asset. A change in the physical object's state causes a change in the digital object's state but not the other way around. In other words, DS is the mirror representation of the physical object, mimicking the operation stage in real-time.

BIM provides the platform for implementing a DS. BIM facilitates handling the operation and maintenance information of an infrastructure (Cheng et al., 2016). A BIM model contains a database of all infrastructure components and can be used to coordinate construction and operational activities in a virtual 3D space (Liao et al., 2012). This research, therefore, seeks to develop a DS-based approach for predictive maintenance planning of Stormwater Infrastructure systems.

1.2 Knowledge Gap

The following knowledge gaps were identified based on a comprehensive literature review:

Limited research on stormwater infrastructure management: Recent studies on stormwater infrastructure management include predictive maintenance of stormwater infrastructure using Internet-of-Things (IoT) technology (Strauss and Wadzuk, 2022) and Bayesian network-based methodology for selecting a cost-effective sewer asset management model (Guzmán-Fierro et al., 2020). Mohammadi et al. (2020) conducted a study on predicting the condition of sanitary sewer pipes with gradient boosting trees. Lee et al. (2021) and Baah et al. (2015) performed a risk-based prioritization of sewer pipe inspection and asset management. The above literature has focused on sewer infrastructure management rather than stormwater infrastructure. Also, most research in stormwater infrastructure management focuses on either predicting the condition, Life Cycle Cost (LCC), level of service, or risk level of the stormwater infrastructure without considering effective data management. State-of-the-art data management strategies have the potential to increase the efficiency, accuracy, and effectiveness of decision-making.

No standard methodology for predicting the physical condition of stormwater infrastructure:

Predicting the physical condition of stormwater infrastructure systems is necessary for proactive asset management (Daher et al., 2021). Elbeltagi et. al. (2013) stated that there are no standard methodologies for assessing the condition of stormwater infrastructure systems. Hawari et al. (2020) highlighted various methodologies that can be used in assessing the physical condition of stormwater infrastructure including, artificial intelligence-based models, and statistical models. However, the accuracy of the above models and their impact on making effective decisions remain questionable.

DS adaptation in municipal infrastructure management is in a prenatal stage

Heaton et al. (2019) argued that the operation and maintenance of stormwater infrastructure systems account for more than half of the total lifecycle cost. Shou et al. (2015) indicated that BIM adoption and use in infrastructure management is still in its early stages. The role of BIM technology in stormwater infrastructure operation and maintenance is yet to be determined (Wang et al., 2021; Kelly et al. 2013). The capabilities of BIM can be effectively used for the management of stormwater infrastructure.

1.3 Motivation for this Research

The main motivation for this research has stemmed from the above-identified research gaps. This research tries to address the following questions.

i. How and when can we intervene to maximize physical conditions and minimize the risk of failure at the lowest life cycle cost?
ii. How can we budget for the above interventions?
iii. How do we eliminate the data fragmentations in infrastructure management?

Current stormwater infrastructure management practices have led to data fragmentation, which has resulted to significant inefficiencies (Halfawy, 2008). Therefore, resources should be developed for municipalities to aid in proactive decision-making.

1.4 Research Objectives

The main objective of this research is to develop a DS-based stormwater infrastructure management framework to predict long-term performance and aid maintenance decision-making by optimizing the physical condition of infrastructure, life cycle cost, and risk. The proposed framework was used to develop a user-friendly tool in the BIM platform that supports asset management decision-making. The above objective was achieved via the following sub-objectives.

i. Develop the physical deterioration rate model for municipal stormwater infrastructure.
ii. Determine the impact of the physical deterioration rate on future asset condition, risk, and lifecycle cost of stormwater infrastructure systems.
iii. Develop a multi-objective optimization algorithm to optimize maintenance activities.
iv. Integrate the optimization algorithm in the BIM platform to create a digital shadow of a stormwater infrastructure system.

v. Develop Best Management Practices (BMP) and implementation guidelines for proactive stormwater infrastructure management.

1.5 Research Methodology

To achieve this objective, the research methodology is divided into four interrelated phases. Figure 1-1 illustrates the four phases of this study.

Phase 1: This phase of the study involved data collection from GIS maps and municipal reports to determine the physical, spatial, social, and environmental characteristics of the stormwater infrastructure systems. Furthermore, data on the physical condition of stormwater infrastructure and different maintenance procedures were collected.

Phase 2: This phase of the study developed the physical deterioration model to determine the impact of the physical deterioration on future conditions, risk level, and lifecycle cost by using a Markov Chain (MC) model.

Phase 3: In the third phase, GA was used to develop an optimization model to identify the optimal maintenance, repair, and replacement option. The algorithm was linked with the deterioration model to develop a methodological framework.

Phase 4: During the final phase a tool was developed in the Autodesk InfraWorks platform to optimize infrastructure maintenance planning. A case study was conducted to demonstrate the capabilities of the proposed tool. Furthermore, best management practices and implementation guidelines were developed for proactive stormwater infrastructure management.

1.6 Thesis Organization

This thesis is made up of six chapters. Chapter One highlights the background and objectives of stormwater infrastructure management. Chapter Two reviews relevant published literature on stormwater infrastructure management. Chapter Three describes the methodological framework for stormwater infrastructure management. Chapter Four details the DS-based decision support tool for stormwater infrastructure management. Chapter Five presents a case study that demonstrates the above decision support tool and comparative evaluation of the proposed method versus the traditional stormwater asset management approach. Chapter Six presents the conclusions of this research, limitations, and recommendations for future research.

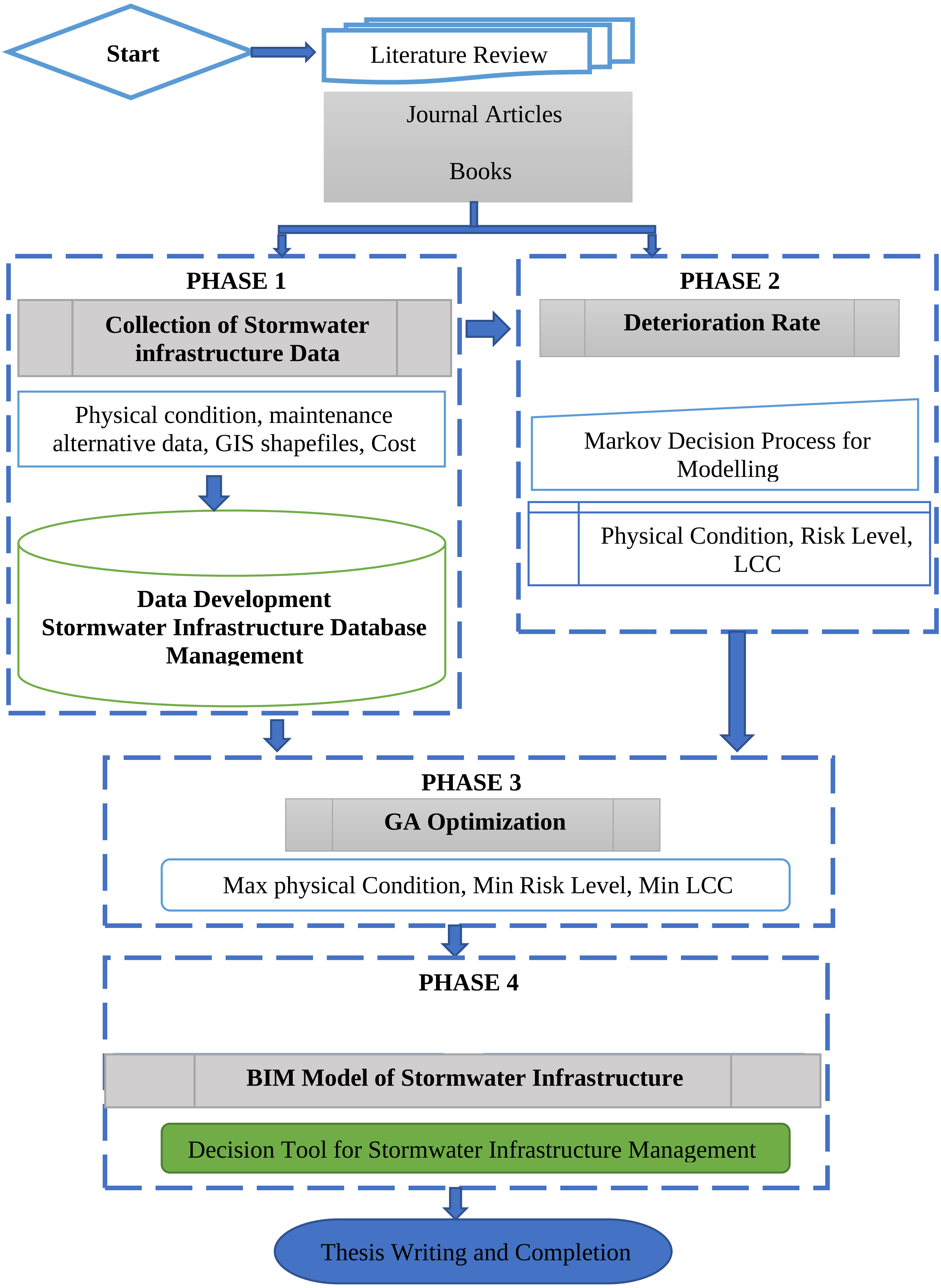


Figure 1-1: Research Methodology

2 LITERATURE REVIEW

2.1 Overview of Civil Infrastructure

Infrastructure refers to the collection of physical systems that enable the delivery of public services (Grigg, 2012). Civil infrastructure is the bedrock of economic growth (Elbeltagi et al., 2013). However, Miyamoto et al. (2006) indicated that maintenance, repair, and rehabilitation (MR&R) of civil infrastructures have been addressed in a reactive manner which has led to a high maintenance cost. As a result, government agencies, municipalities, and public sector organizations are increasingly under pressure to develop new strategies for managing deteriorating civil infrastructures to ensure their long-term sustainability (Šelih et al., 2008). Over the years, government agencies, municipalities have allocated substantial budgets for the MR&R of civil infrastructure to ensure a performance level that meets user requirements (Schraven et al., 2011). Given the above investment, it is imperative to develop a proactive management approach with the available funds.

2.1.1 Asset Management

ISO 55000:2014 defined asset management as a method that "involves the balancing of costs, opportunities, and risks against the desired performance of assets, to achieve the organizational objectives" (International Organization for Standardization 2014). Asset management has emerged as a strategy for achieving greater value with fewer resources in the civil infrastructure sector (Moon et al., 2009). The asset management procedure should answer the following questions;

- What assets do you have?
- Where are these assets located?
- What condition(s) are these assets in?
- How will these assets affect your ability to meet performance goals?

This information is utilized to make decisions about investing in new assets and maintaining the existing ones (Fane et al., 2004). According to Yazdandoost and Izadi (2018), the idea of asset management was first conceived in New Zealand in the 1980s. Petchrompo and Parlikad (2019) have stated that asset management evolved from simply managing and maintaining structures to improving the efficiency and performance of the whole infrastructure system.

2.1.2 The Increasing Significance of Asset Management

The increased interest in infrastructure management has risen due to new governance and institutional challenges (Lee et al., 2021). Organizations, government agencies, and municipalities have paid extra attention towards infrastructure maintenance due to budgetary constraints (Arif et al., 2016). Additionally, infrastructure managers are being challenged to respond to aging infrastructure by implementing more efficient business practices (TRB, 2006).

The growing awareness of the need for infrastructure asset management is to improve asset productivity and overall asset performance (Zang and Hudson, 1998). This growing awareness cannot be underestimated because it will ensure full accountability for the asset's condition and performance. As a result, infrastructure asset management firms are motivated to use a formal and comprehensive approach to infrastructure asset management to deliver services as cost-effectively as possible (Too, 2012). Moreover, managing the infrastructure asset will ensure the needs of the stakeholders and clients are met

The primary goal of the increasing significance of infrastructure asset management is to achieve the required performance level in the most cost-effective way possible by managing assets for current and future customers (IPWEA, 2006; Gollier 2018).

2.1.3 Need for Stormwater Infrastructure Management

Most municipalities and government agencies have effective management systems for their visible infrastructure such as roads, bridges, and pavement. Stormwater infrastructure, on the other hand, is frequently overlooked due to the "out of sight, out of mind" philosophy (Perrin Jr and Dwivedi, 2006). Stormwater infrastructure system is a system for managing precipitation-related stormwater runoff and snowmelt (CIRC, 2019). A stormwater infrastructure system comprises pipes and culverts, open drains, catchment basins, retention ponds, filters, vegetated swales and roofs, pollution and drainage control devices, tree boxes, stormwater reuse tanks, and natural watercourses (Wood, 2020). These systems are available in a variety of sizes, shapes, and configurations. Catch basins and manholes are typically the first point of contact in a stormwater infrastructure system. A catch basin is a storm grate that can be found along the side of the road or in people's backyards. Stormwater runoff enters these grates or manholes and flows into the storm sewer system, where it is discharged through an outlet. Stormwater runoff frequently finds its way to bodies of water (Demello, 2017).

Stormwater infrastructure systems are designed to prevent flooding and transport rainwater to storm drains in communities. Figure 2-1 illustrates a graphical representation of stormwater infrastructure.

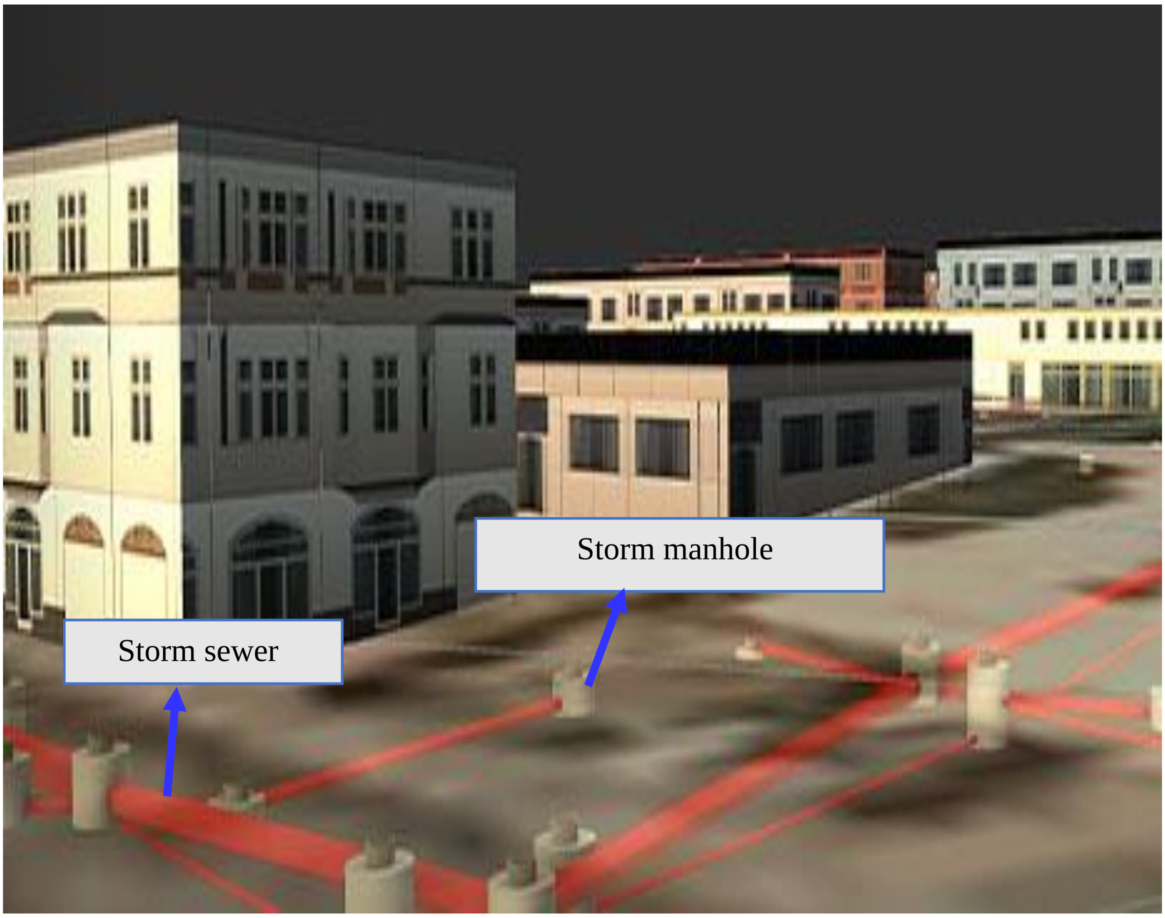


Figure 2-1: Depicts a graphical representation of stormwater infrastructure

Table 2-1 presents a literature review for infrastructure asset management, and this indicates the lack of literature on stormwater infrastructure systems. Based on the significance of the infrastructure asset management framework, it is important to adopt an asset management framework for stormwater infrastructure.

Table 2-1**:** A literature review of various infrastructure asset management

Infrastructure Class(es)	**References**
Building,	Alavi et al. (2022); Elhakeem (2006)
Sewer	Lee et al. (2021)
Road, Water, and Sewer	Abu-samra et al. (2020)
Transportation	Chen et al. (2019)
Road and Water	Abu Samra et al. (2018)

Road, Water, and Sewer	Marzouk and Osama (2017a)
Road, Water, and Wastewater	Shahata and Zayed (2016)
Sanitary Sewer	Baah et al. (2015)
Railway	Rama and Andrews (2013)
Urban Water Systems	Alegre and Coelho (2012)
Water, Wastewater, and Stormwater	Grigg (2012)
Rail, Road, and Water	Haider (2012)
Naval Ship	Frangopol et al. (2012)
Water and Transportation	Schraven et al. (2011)
Urban Wastewater Pipe	Ugarelli et al. (2010)
Highway Infrastructure	Šelih et al. (2008)
Culvert	Perrin Jr and Dwivedi (2006)
Bridge Deck	Morcous (2006)
Sanitary and Stormwater, Sewer	Halfawy et al. (2002)
Water and Sewer	Kleiner (2001)

2.1.4 Components of Stormwater Asset Management

Analyzing the current condition of an infrastructure asset, establishing the desired performance of an infrastructure asset, determining the risk level of the infrastructure asset, analyzing the life-cycle cost, and developing a long-term funding plan are the five core components of infrastructure asset management (Harvey and McBean, 2014; Grigg, 2012; InfraGuide, 2006; IPWEA, 2006). This has been illustrated in Figure 2-2. The study adopted this framework for managing stormwater infrastructure.

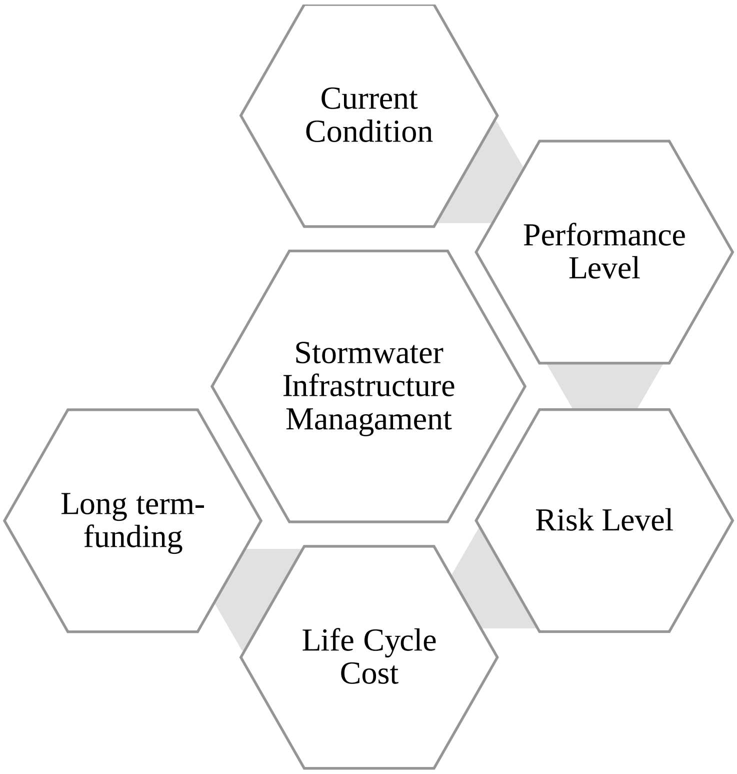


Figure 2-2: Asset management framework

2.2 Current Stormwater Infrastructure Management Practices

Before an infrastructure asset manager can start managing a portfolio of assets, the manager must first understand what assets are currently available (InfraGuide, 2004). This includes an itemized and accurate inventory of a portfolio's infrastructure, and key information such as the condition, location, expected service life, and replacement cost (Grussing, 2015). A detailed stormwater infrastructure management practice is presented below:

2.2.1 Stormwater Infrastructure Inventory

An asset inventory, also known as an asset register or catalog, is a list of assets that require separate identification (Mathew et al., 2011; Jafari et al., 2014). Environmental Finance (2016) states that the asset inventory entails all information on the current condition of the asset, including the estimated remaining useful life of the asset, the date the asset was installed, manufacturer, the manufacturer's suggested maintenance approach, the replacement and historic value of the asset, and any other important information (Anderson, 2016). In order to prepare asset inventories, identification numbers must be assigned to the stormwater infrastructure components (Zhang et al. 1994). As per Grussing (2015), the stormwater infrastructure inventory should be reviewed and updated on a regular basis to reflect any changes to the stormwater assets, such as maintenance and corrective repairs, or renovation.

Moreover, Grussing (2015) indicated that stormwater infrastructure managers must understand and be familiar with the assets they are responsible for. This will facilitate the creation of an accurate asset inventory to keep track of all pertinent information.

2.2.2 Establishing Condition Assessment

Several studies have shown that the most vital part of the asset management process is condition assessment. The outcome of the condition assessment serves as a starting point for other functions like deterioration rate and repair selection (McDonald and Zhao 2001; IPWEA, 2006; Ahluwalia, 2008). Condition assessment can be established through internal and external inspections. The internal inspections emphasize the evaluation of the internal condition of pipes and the expected remedial measures prior to any collapse. Similarly, the external inspections emphasize the soil surrounding the pipes, that is, the structure of the soil and its ability to support the pipe (Tran, 2007).

The core strategy of condition assessment focuses on data collection for managing critical assets and tracking key performance indicators (KPIs) (IPWEA, 2006). A stormwater infrastructure system condition rating is mainly used to estimate the remaining service life, assess the probability of failure, or guide inspection planning (Baur and Herz, 2002).
A study conducted by IPWEA (2006) has shown that knowing an asset's current condition and performance level provides the following advantages:

- Capability to plan for and manage the delivery of the essential level of service.
- Avoid premature asset failure while allowing for cost-effective renovation.
- Risk management is associated with asset failures, as well as the mitigation of failure consequences.
- Enhancement of maintenance and rehabilitation strategies.
- Precise prediction of future expenditure requirements by understanding remaining asset life and capital investment needs.

2.2.3 Monitoring the Infrastructure Performance Level

Infrastructure performance defines the services that the community expects of the asset (IPWEA, 2006). It is measured in terms of effectiveness, reliability, and cost (Wu et al., 2014).

According to IPWEA (2006), asset performance and condition assessment are intrinsically linked. The terms 'cause' and 'effect' can be used interchangeably to describe condition and performance failure. That is, deterioration of the condition is a cause of failure, and poor performance is the result of failure (i.e., failure to meet required levels of service).

Ugarelli et al. (2010) suggested that the specific parameters recommended for monitoring the performance level of stormwater infrastructure systems include the condition of the pipe, the material of the pipe, age of the pipe, the diameter of the pipe, number of blockages, and stoppages experienced in a year and per pipe length, the collapses per year per pipe length, etc. The performance assessment provides a clear framework for decision support in the diagnosis and rehabilitation of stormwater infrastructure systems (Fenner, 2000).

2.2.4 Establishing the Risk Level of Stormwater Infrastructure

Prioritizing stormwater infrastructure for renewal requires determining the risk of failure. The risk level is typically estimated by multiplying the consequences of failure (CoF) by the probability of failure (PoF) (Halfawy et al., 2008). Stormwater collection pipes are closely connected to buildings and other infrastructure facilities. As a result, a failure of these pipes can cause massive damage to the city and pose a serious threat to public health and safety. Therefore, when prioritizing pipe rehabilitation, the severity of failure should be taken into account along with the stormwater pipe condition (BSI, 2008; Montoya, 2019).

The first step to evaluate an asset's risk is to determine the PoF. The following are the main questions addressed in this step (Auken et al., 2016);

i. How likely is the asset to fail?
ii. What is the asset's current physical state?
iii. What is the asset's performance capability?

These questions provide answers for records of repairs and replacements, as well as data from condition assessments. Syachrani et al. (2013) stated that a high PoF asset is old and in bad shape, or on the verge of failing. Therefore, when estimating the PoF of an asset, the calendar age should be frequently considered (Syachrani et al., 2013).

The second step to assess an asset's risk is to determine the CoF. This step targets the response to the question, "What happens if something goes wrong?". Moreover, the word "Consequence" connotes a loss (Fares and Zayed, 2010). Losses are estimatable in terms of direct and indirect costs. Notable examples of direct costs are property damage, human health damages, environmental damage, loss of production, repair costs, clean-up, and renovation costs. On the other hand, litigation and contract violations, customer dissatisfaction, political reactions, market share loss, and government fines and penalties are all examples of indirect costs (Bhave and Gupta, 2006: Muhlbauer, 2004).

The CoF score quantifies the likelihood of service disruption and the severity of the impact (Auken et al., 2016). In terms of quality, determining the CoF of an asset considers the asset's environmental, financial, and social consequences. In addition, the quantification of the CoF score is complex because it indicates where failure will have a significant impact if it occurs (EPA, 2017).

2.2.5 Establishing Life Cycle Costing (LCC)

LCC is defined as the total cost of an asset over its service life, either in present value or annual value, that consists of the initial costs, maintenance, repair, and renewal (MR&R) costs (Rahman & Vanier, 2004b). LCC is based on the idea that the value of money fluctuates over time, so expenditures made at different times are not equal. The time value of money, as it is known, is the foundation for life cycle cost analysis (LCCA) (Rahman & Vanier, 2004b).

The Royal Institute of Chartered Surveyors identified three goals of LCC analysis (Flanagan & Norman 1983):

i. To make it easier to evaluate investment options;
ii. To consider all costs rather than just initial capital costs and;
iii. To make it easier to choose between competing options.

The following parameters must be determined in order to achieve these goals: initial capital costs, operating and maintenance costs, disposal costs, asset service life, and discount rate (Ammar et al., 2013). Figure 2-3 presents the life cycle cost stages for an infrastructure asset. However, LCC can be difficult to establish because it requires the creation of a cost structure that includes all relevant cost factors (Rahman and Vanier, 2004). Data on these factors are sometimes difficult to come by (Langston, 2013).

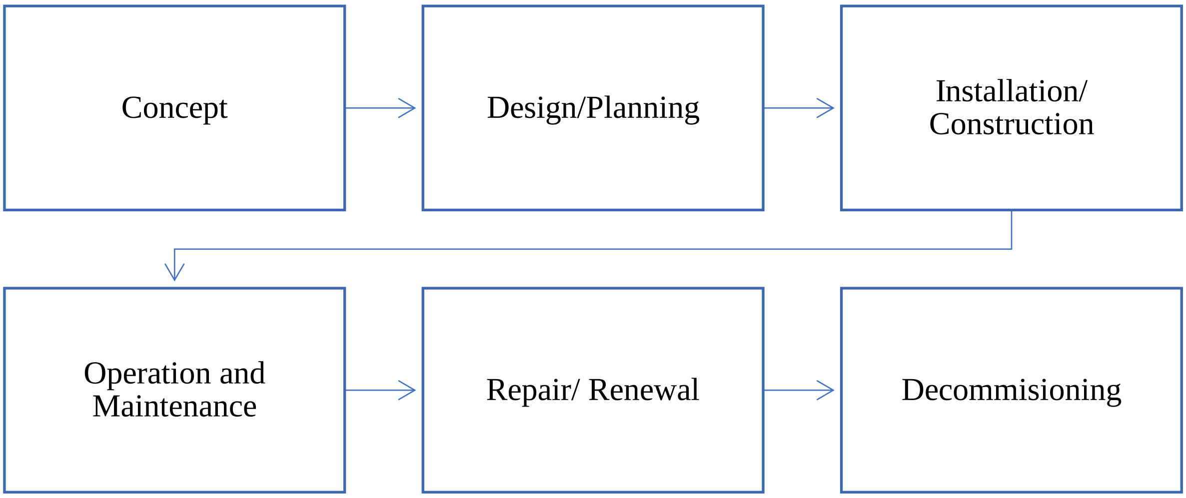


Figure 2-3: Life Cycle Phases for Municipal Infrastructure

2.3 Current Infrastructure Management Practices

In order to maintain acceptable performance and service levels of municipal infrastructure assets, municipalities must implement effective renewal strategies that improve network conditions while reducing the risk of stormwater pipe failure based on the available budget. Several studies have shown that many tools have been developed to help choose the optimal stormwater network renewal strategy (Franco-Duran and Mejia, 2016; Halfawy et al., 2008). Notable examples of these tools are the advancement in geographic information systems (GIS), dynamic modeling, and high-resolution closed-circuit television (CCTV) which have made it possible for wastewater utilities to accurately predict when a stormwater pipe will fail (Boulos, 2010). Although several technologies for stormwater condition assessment and internal inspection are available, they are costly, time-consuming, and have numerous drawbacks (Wirahadikusumah et al., 1998). Again, some studies have developed condition assessment models that use statistical approaches to predict the deterioration of various infrastructures as a replacement for traditional methods of condition assessment (Baik et al., 2006; Kleiner, 2001; Madanat and Ben-Akiva, 1994; Madanat et al., 1997; Micevski et al., 2002; Salman and Salem, 2012; Wirahadikusumah et al., 2012). These approaches have proven to be of great significance but lack the ability to store the asset inventory.

Table 2-2 portrays a literature review of current stormwater infrastructure management models utilized by agencies and municipalities. Most infrastructure management approaches proposed in the literature are focused on GIS, stochastic, and individual infrastructures asset components such as risk level, levels of service, condition assessment, and lifecycle cost. These approaches do not focus on the integration of infrastructure asset components as a complete system.

Although GIS has proven to be of great significance by providing geographical location data, there is still a big gap between the spatial information technologies that apply at the micro spatial scale and the macro scale (Castro-Lacouture et al., 2014). To address these shortcomings, a Building Information Modelling (BIM)-Based approach has been adopted. BIM has the capability to create, store, manage, share and analyze the lifecycle data of the stormwater infrastructure (Eastman et al., 2011). Therefore, the implementation of BIM will help to eliminate the data gap between multiple collaborative enterprises through the use of a virtual model that is loaded with useful information.

Table 2-2: Current stormwater management practices

Reference(s)	BIM	GIS	Stochastic	Risk	Condition	Levels of service	Lifecycle Cost	Description
Strauss and Wadzuk (2022)		✓		✓				Developed an approach for assessing the stormwater system's vulnerability using real-time sensors
Appiah (2021)		✓		✓		✓		Centered on developing a methodological framework for assessing the level of service of stormwater infrastructure systems
Lee et al. (2021)		✓	✓	✓	✓			Built on a risk-based prioritization of sewer pipe inspection from an infrastructure asset management perspective
Le et al. (2020)	✓						✓	Based on a BIM-Integrated Relational Database Management System (RDMS) for evaluating building lifecycle costs
Vladeanu and Matthews (2019)			✓	✓	✓			Built to improve the consequence of the failure of stormwater infrastructure via the use of a weighted-sum- multicriteria decision-making approach.
Wang et al. (2019)	✓	✓						Built to enhance the efficiency of underground utility administration from the standpoint of utility components and urban utility networks, as well as to make utility maintenance decision-making easier.

(Kabir et al., 2018)		✓	✓		✓			Centered on sewer structural condition prediction integrating Bayesian Model averaging with Logistic Regression
(Baah et al., 2015)		✓	✓	✓	✓	✓		Built on a risk-based approach to sanitary sewer pipe asset management
(Elbeltagi et al., 2013)			✓		✓		✓	Centered on a framework for condition assessment of Sewer Pipelines
(Atef et al., 2012)			✓	✓	✓		✓	Based on a multi-objective genetic algorithm to allocate budgetary resources for condition assessment of water and sewer networks
(De Gueldre et al., 2007)			✓				✓	Based on an integrated approach for sewer asset management
(Baik et al., 2006)			✓		✓			Built on estimating transition probabilities in Markov Chain-based deterioration models for the management of wastewater systems
(Bengassem and Bennis, 2000)			✓	✓	✓			Centered on fuzzy expert system for sewer networks diagnosis

2.4 Building Information Modelling (BIM)

Sacks et al. (2018) stated that BIM is a shared digital representation of any built object's physical and functional characteristics that can be used to simplify design, construction, and operation processes to develop a solid decision base. BIM includes a unified information base, which consists of a Big Data database, providing a building owners' manual, useful support for analysis, support for emergency response, security management, and scenario planning in infrastructure management (Rodrigues et al., 2019; Teicholz, 2012). Shahrour et al. (2017), emphasized that a BIM model is a knowledge-sharing tool in which building data and information are shared in a single collaborative model throughout the facility's life cycle.

Several studies have emphasized that BIM has a great tendency to influence people, processes, technology, and information in the construction sector through its primary principles which are Interoperability, Parametric Objects, and 3D Modeling. These principles are accompanied by an incredibly technological Information Management System that allows multi-disciplinary collaboration (Annex and Rules, 2015; Sacks et al., 2018; Pathirage and Underwood, 2015; Wei et al., 2017).

2.4.1 BIM for Facility Management (FM)

The operational phase of a building accounts for the majority of the cost of a building's lifecycle (Won et al., 2013). The lifecycle cost of a facility is estimated to be five to seven times the initial investment cost and three times the construction cost (BIM Task Group, 2012; Lee et al. 2012). The need for efficient management of both new and existing facilities has been immense in terms of both economics and the environment (Kelly et al., 2013). With the introduction of BIM and the notion that BIM data captured during the project lifecycle could improve the efficiencies of FM functions, the industry has now shifted its attention to its adoption (Patacas et al., 2015). FM is a broad term that encompasses a variety of property and user-related functions that are brought together for the benefit of the company and its employees as a whole (Spedding, 1994).

The current information handover to the FM phase process is largely manual. As a result, the information given out is frequently incomplete and incorrect (Patacas et al. 2015). The industry is investing millions of dollars and tens of thousands of man-hours in re-creating such data and working with inefficient workflows (Keady, 2009). Due to the capabilities of BIM and its implementation in FM, handover data has significantly improved thereby leading to cost reduction and reworks (Sunil and Pathirage, 2015). Again, BIM Task Group (2012) indicated that BIM will provide a fully populated asset data set into FM systems, reducing the time spent obtaining and populating asset information and allowing us to achieve optimum performance, minimize operating costs, and refine target outcomes faster.

Several BIM software tools are available for infrastructure management and FM. Table 2-3 displays some BIM software used for infrastructure management and FM (Chong et al., 2016).

Table 2-3: Illustrates BIM software for infrastructure management and FM

Organization	Software
Autodesk Incorporated series	AutoCAD Map 3D; Storm and Sanitary Analysis; ReCap; InfraWorks; AutoCAD Civil 3D; Bridge Module; Rail Layout Module; River and Flood Analysis Module; AutoCAD Utility Design; Robot Structural Analysis Professional
Bentley System Incorporated series:	Power Rail Track; Power Rail Overhead Line; Power InRoads; Power GEOPAK; MXROAD; PowerCivil; RM Bridge; LEAP Bridge Enterprise; Bentley PowerRebar; LEAP Bridge Steel; gINT software; InspectTech; ProjectWise; AssetWise
Tekla and Trimble Incorporated series:	TEKLA Structures; TEKLA BIMSight; TEKLA Field3D; TRIMBLE Feedback; TRIMBLE Locus; TRIMBLE DMS; TRIMBLE Eservices; TRIMBLE Webmap; TRIMBLE Communication Networks.

Although there are several BIM software available for infrastructure management, its implementation is only at an average level (Shou et al. 2015). Moreover, Shou et al. (2015) indicated that BIM adoption and use in infrastructure management is still in its early stages.

2.5 Digitalizing Infrastructure System

According to Callcut et al. (2021), digitalization is a broad term describing the process of acquiring data from physical assets and transforming it into a digital representation that can be handled automatically. Further, smart infrastructure is propelled by the digitalization of infrastructure systems. The development of a digital counter of a physical infrastructure is highly dependent on accurate data. Kritzinger et al. (2018) stated that the techniques in which data is produced and handled have evolved considerably. In recent times, new approaches have streamlined the data creation process by integrating sensors into infrastructure systems, lowering the cost of digitizing pre-existing data, and providing infrastructure managers with a plethora of fresh data (Alavi et al., 2018; Callcut et al., 2021). Furthermore, Rosen et al. (2015), indicated that virtual product and process planning was possible because of the application of digitalization. Based on these facts by previous researchers, it can be said that digitization has the potential to promote infrastructure network convergence by enabling cross-sector platforms that integrate previously uncoordinated activities, hence enhancing infrastructure management effectiveness. This effectiveness extends beyond day-to-day operations to include infrastructure maintenance, planning, and development.

2.5.1 Incorporating Digitalization into Stormwater Infrastructure Management

Following the definition of digitalization, a common understanding of Digital Twin as a digital counterpart to physical items may be identified (Kritzinger et al., 2018). Digital Model (DM), Digital Shadow (DS), and Digital Twin (DT) are used consistently within these descriptions. According to Kritzinger et al. (2018), the extent of data integration between the physical and digital counterparts, however, differs between the aforementioned definitions. Some digital representations are created manually and have no physical connection, whereas others are fully integrated with real-time data transmission.

Although much has been said about the level of integration in digitalization, this research focuses on utilizing digital shadow in managing stormwater infrastructure systems. Bello et al. (2021), define DS as a combination of an automatic one-way data flow between the condition of an existing physical asset and a digital asset. A change in the state of the physical object causes a change in the digital object's state, but not the other way around. In other words, DS is the mirror representation of the physical object, mimicking the operation stage in real-time. Moreover, the digital shadow revolution has revealed new opportunities when it comes to smart operation of stormwater infrastructure systems and enhances the understanding of the performance of the infrastructure systems (Kritzinger et al., 2018). Therefore, incorporating digital shadow into infrastructure management will aid improve infrastructure performance.

2.6 Deterioration of Infrastructure Assets

Asset management systems were established to help asset managers maximize the safety and serviceability of infrastructure facilities (Hudson & Hudson, 1994). The quality of asset management systems is heavily influenced by the accuracy and efficiency of the deterioration models used to forecast time-dependent performance and the remaining service life of infrastructure facilities (Madanat et al., 1997). Over the previous decades, infrastructure deterioration has been extensively researched by various researchers (Madanat et al., 1997; Rajani and Kleiner, 2001; Edirisinghe et al., 2015). The deterioration models proposed in these various researches are aimed at predicting the deterioration patterns of the infrastructure asset. The advances in research on materials, structures, and management strategies have resulted in the development of effective tools for estimating deterioration as a function of design and construction parameters, usage, and environmental factors (Hessami et al. 2021). For example, pavement and bridge management systems that have been developed over several decades are gaining acceptance as management tools (Wu et al. 2014). The sections that follow will discuss the types of deterioration models used in some infrastructure management:

2.6.1 Deterioration Types

According to Kuhn and Madanat (2005), various models have been developed to predict the deterioration of infrastructure assets, including deterministic models and statistical or stochastic models. Furthermore, artificial intelligence and other techniques have also been used to develop deterioration models (Ens, 2012). The following section will provide an overview of the different types of deterioration as well as an in-depth look at an example of each type.

Deterministic Model of Deterioration

Deterministic models are based on regression analysis of condition data and assume that the infrastructure deterioration process has a predictable trend. These models rely on an empirical relationship between one dependent variable and one or more independent variables that affect the infrastructure condition (Ens, 2012). In contrast to non-linear regression models, linear regression models do not provide enough accuracy for long-term infrastructure performance and may underestimate or overestimate infrastructure conditions at a specific time (Srikanth and Arockiasamy, 2020: Ens, 2012).

Multiple Linear Regression

According to Ens (2012), multiple linear regression is one of the simplest methods of a deterministic model and is utilized when more than one factor influences the dependent variable. The equation 2-1 is used to estimate the deterioration.

$$\hat{Y} = b_0 + b_1 x_1 + \ldots + b_k x_k \quad \text{Equation 2-1}$$

where $b_0, b_1, \ldots, b_k$ are the valuations of the regression coefficients, $\hat{Y}$ is the predicted value of the dependent variable, and $x_1, \ldots, x_k$ are the values of the independent variables. In the case of infrastructure deterioration, the dependent variable $\hat{Y}$ is mostly the condition state of the asset while independent variables, $x_1, \ldots, x_k$ are the factors that affect the asset's condition (e.g. age, material, location, etc). To estimate coefficients values, $b_0, b_1, \ldots, b_k$, the least-squares method is generally used.

2.6.2 Statistical and Stochastic Models

Stochastic models consider the deterioration of infrastructure assets as one or more random variables (e.g., time, condition state of infrastructure components) and can therefore capture the deterioration process's uncertainty and randomness (Rajani and Kleiner, 2001). Moreover, Frangopol and Neves (2004), explain that stochastics models are frequently used to model infrastructure deterioration, and there are different types of these models. The two types of stochastic models are state-based stochastic models and time-based stochastic models (Srikanth and Arockiasamy, 2020).

Markov Chain Model

The Markov Chain model is the most used technique for modeling infrastructure deterioration. Some of the authors who have used the Markov deterioration model include Black et al. (2005), Gharehbaghi and Georgy (2015), Madanat et al. (1997), Wirahadikusumah et al. (2012), Nesbitt et al. (1993), Edirisinghe et al. (2015), Kleiner et al. (1998), and Kleiner (2001) among others. According to Madanat and Ben-Akiva (1994), a Markov Chain is a finite-state probability model for describing a particular type of stochastic process that moves through discrete points in time in a sequence of phases based on fixed probabilities. The process is stochastic because it changes unpredictably over time. Future states in this chain are only dependent on the current state and are unaffected by any previous state.

Markov-Chain models focus on the concept of probabilistic cumulative damage, which forecasts changes in infrastructure conditions over the transition periods (Morcous and Lounis, 2005). The following are some advantages of the Markov Chain models:

- have the capability to reveal the uncertainty in the model from different sources like the uncertainty in the initial condition and inherent uncertainty of the deterioration process
- have the ability to forecast future conditions while accounting for the current condition
- have the capacity to manipulate networks with numerous components due to its high computational efficiency

Artificial Intelligence Methods

Artificial intelligence (AI) models make use of computer techniques aimed at automating intelligent actions (Morcous et al. 2002). Natural processes, such as the brain or natural selection, are frequently used to model soft computing methods. Uncertain, imprecise, and ambiguous data are no problem for soft computing techniques. Soft computing methods have been used to create infrastructure deterioration models, as this frequently describes asset inventories and condition information (Flintsch and Chen 2004). Some AI models include expert systems, artificial neural networks, fuzzy logic, etc (Morcous et al. 2002). Tran et al. (2007), used a neural network to predict the deterioration of buried infrastructure (stormwater). Liang et al. (2001) developed a multi-layer fuzzy method for concrete bridge health monitoring.

Other AI methods commonly used in infrastructure deterioration modeling include genetic algorithms (Chang et al. 2008; Raja Shekharan 2000), and fuzzy logic systems (Shen et al. 2019; Kleiner et al. 2006; Najjaran et al. 2004)

2.7 Challenges of Infrastructure Management

Infrastructure management has emerged as a strategy for achieving greater value with fewer resources in the public infrastructure sector (Moon et al. 2009). Switzer and McNeil (2004) highlighted that infrastructure management principles are progressively being incorporated into the working practices of government agencies and a growing body of practice to provide models and tools to aid in infrastructure decision-making. Despite the widespread interest in infrastructure management, little attention has been given to the challenges that agencies face when attempting to improve the effectiveness of their decision-making processes.

The main challenge with infrastructure assets has always been the difficulty to observe and measure the present condition of the infrastructure. It is during recent times that new technology for remote sensing, non-destructive measurement, pattern recognition, statistical inference, and the like has started to allow for sufficiently sophisticated data collection (Halfawy et al., 2002). In spite of these challenges, most municipal agencies continue to look for more efficient ways of allocating their municipal infrastructure resources (Jha et al., 2010). Funding is a major area of concern when it comes to stormwater infrastructure management (Marzouk and Osama, 2017). Upadhyaya (2013), stated that the deficits in funding have an impact on the maintenance and renewal of aging stormwater infrastructure systems.

In 2007, the Federation of Canadian Municipalities conducted a nationwide survey, estimating a $31 billion deficit in stormwater infrastructure across the country (InfraGuide, 2006). The cost of maintaining and upgrading water infrastructure, which includes stormwater management systems, is factored into the estimate (Dávila Aquije 2016; Mirza 2007). Dávila Aquije (2016), presented that municipalities are forced to delay infrastructure maintenance due to stiff budgets and funding cuts. However, other infrastructure development such as roads and bridges that can be seen and appreciated by all is of political interest. Carlson et al. (2015) stated that stormwater infrastructure systems do not get the same attention as other types of infrastructure. The aforementioned concerns indicate some of the challenges municipalities are facing in managing their infrastructure systems.

2.8 Decision-Making for Stormwater Infrastructure Management

Asset managers in government and private agencies are tasked to make technical and financial decisions daily about "what, how, and when" to maintain, repair, or renew municipal assets. This is done to maintain acceptable levels of infrastructure performance, given that infrastructure efficiency is closely linked to social and economic implications within a local community (Sivo and Daniela, 2011). Grigg (2012) suggests that it is significant to decide on a maintenance policy that could substantially improve the stormwater infrastructure. To accomplish this goal, it is important to prepare and execute a variety of activities, including identifying the qualitative and quantitative characteristics, determining the deterioration state, defining alternative technical and economic policies, evaluating risks, and determining priority maintenance actions.

According to Chen and Bai (2019), decision-making (DM) is an important component of stormwater infrastructure management because it determines the intervention plan for the infrastructure asset. Furthermore, Chen and Bai (2019) stated that management outcomes such as managing infrastructure costs and conditions differ when different management plans are generated. A study conducted by InfraGuide (2018), suggests that decision-makers must formulate a management strategy that meets stormwater infrastructure management's objectives. That notwithstanding, in present-day society, DM is difficult due to a variety of obstacles, including large infrastructure asset networks, limited resources, a wide range of outcomes, competing goals, and uncertainty (Haghighi and Bakhshipour, 2012). As a result, optimization is used, and it has gained popularity in DM in recent years.

2.8.1 Optimization of Infrastructure Assets

There are many potential selections for maintenance activities such as repairing and replacing an infrastructure asset in a municipality. The applicable selection procedures depend on their efficiency and economic analyses due to a limited budget (Swamee and Sharma, 2013). To choose the best set of maintenance activities, the implementation of an optimization model is required (Marzouk and Osama 2017). The use of optimization methodologies for infrastructure assets management has received increasing awareness in the last few decades due to more stringent budgets, increasing demands, and stricter accountability in civil infrastructure investments and policy-setting decisions (Wu et al. 2012). Moreover, optimization-based tools have been included in many engineering management systems for individual infrastructure asset classes such as pavement management systems (PMS) and bridge management systems (BMS).

According to Wu et al. (2012) the use of mathematical programming techniques like linear and non-linear programming is the fundamental bedrock of the optimization approach. However, these approaches are capable of handling single objective optimization (SOO) problems. Wu et al. (2012) posited that real-world decision-making in infrastructure asset maintenance and renewal often comprises more than one objective. Therefore, multi-objective optimization (MOO) is required to handle multiple objectives problems. Chen and Bai (2019) argue that MOO is a program that optimizes multiple objectives while adhering to optimization constraints. It aims for Pareto solutions, where each produces the best objective values that cannot be improved without lowering the value of another.

In contrast to the linear and non-linear optimization algorithms, heuristic algorithms based on evolutionary strategies like Genetic Algorithms (GA), simulated annealing (SA), and tabu search (TS) are suitable for practical infrastructure maintenance scheduling problems (Grefenstette, 1993). Most importantly, GAs are general-purpose stochastic search-based optimization techniques that can provide a comparable level of accuracy while being more efficient than traditional optimization techniques (Chow et al. 2004). GA techniques appeared to be appropriate and robust search techniques given the enormous size and combinatorial nature of the solution space, as well as the complexity of the defined objectives and constraints. GAs have been used for several maintenance scheduling purposes in stormwater infrastructure due to its capability of providing efficient Pareto optimal solutions. Several studies have utilized GAs to develop optimal maintenance and renewal planning for stormwater infrastructure systems (Marzouk and Omar 2013; Haghighi and Bakhshipour 2012; Halfawy et al. 2008)

2.9 Summary

The relevance of stormwater infrastructure management will grow as aged stormwater systems and pressing adaptation considerations become more prevalent. As a result, most municipalities are embracing more proactive and optimal approaches to managing stormwater infrastructure and planning for their short- and long-term renewal in a more sustainable manner. These approaches are largely aimed at maximizing the return on investment through budget allocation optimization. The aforementioned features of stormwater infrastructure management were identified through a comprehensive literature review. This review aided in identifying the research gap for this study.

3 A FRAMEWORK FOR PREDICTIVE MAINTENANCE PLANNING FOR STORMWATER INFRASTRUCTURE MANAGEMENT

3.1 Introduction

Conventional decision-making in infrastructure management has been based on a subjective condition assessment. Maintenance decisions made solely on the basis of physical condition may not obtain the best value (Frangopol and Liu, 2007). In recent times, innovative maintenance management techniques have been developed to maintain civil infrastructure. Some of these maintenance techniques include predictive, preventive, and corrective maintenance (Strauss and Wadzuk, 2022; Frangopol and Liu, 2007; Morcous and Lounis, 2005). Traini et al. (2021) indicated that the predictive maintenance approach enables detecting trends, anomalies, and deterioration of infrastructure assets. This enables identifying potential failures in advance and facilitates planning for repair and maintenance activities strategically (Pech et al., 2021). Moreover, predictive maintenance forms the basis for a proactive infrastructure management system.

Lee et al. (2021) stated that the implementation of a proactive infrastructure management system could prevent the failure of stormwater infrastructure systems. Ruwanpura et al. (2004) revealed that proactive infrastructure management is a cost-effective approach for stormwater infrastructure systems. Strauss and Wadzuk (2022) developed a predictive maintenance model for stormwater infrastructure systems using IoT. This study proposed a vulnerability assessment model for stormwater systems with real-time data acquisition. Although previous research looks at predictive maintenance, digitalization of the stormwater infrastructure has been overlooked.

This chapter presents a methodological framework for predictive maintenance planning of stormwater infrastructure. The proposed framework includes a deterioration model that combined a risk model, an LCC model, and an optimization model. This framework will aid in developing a comprehensive stormwater infrastructure management tool.

3.2 Methodology

A comprehensive literature review was used to collect the municipal reports, condition data and GIS shapefiles on stormwater infrastructure systems. These data on the stormwater infrastructure were collected from the Windsor Municipality. The data collection step involves building a comprehensive dataset on stormwater infrastructure. This includes information such as stormwater pipe data (e.g., material and diameter), deterioration data (for developing transition probability matrices) cost data, and risk data. This information serves as the central database for computational models. The above data were used for developing the deterioration model, LCC model, and risk model. Figure 3-1 illustrates the methodology framework.

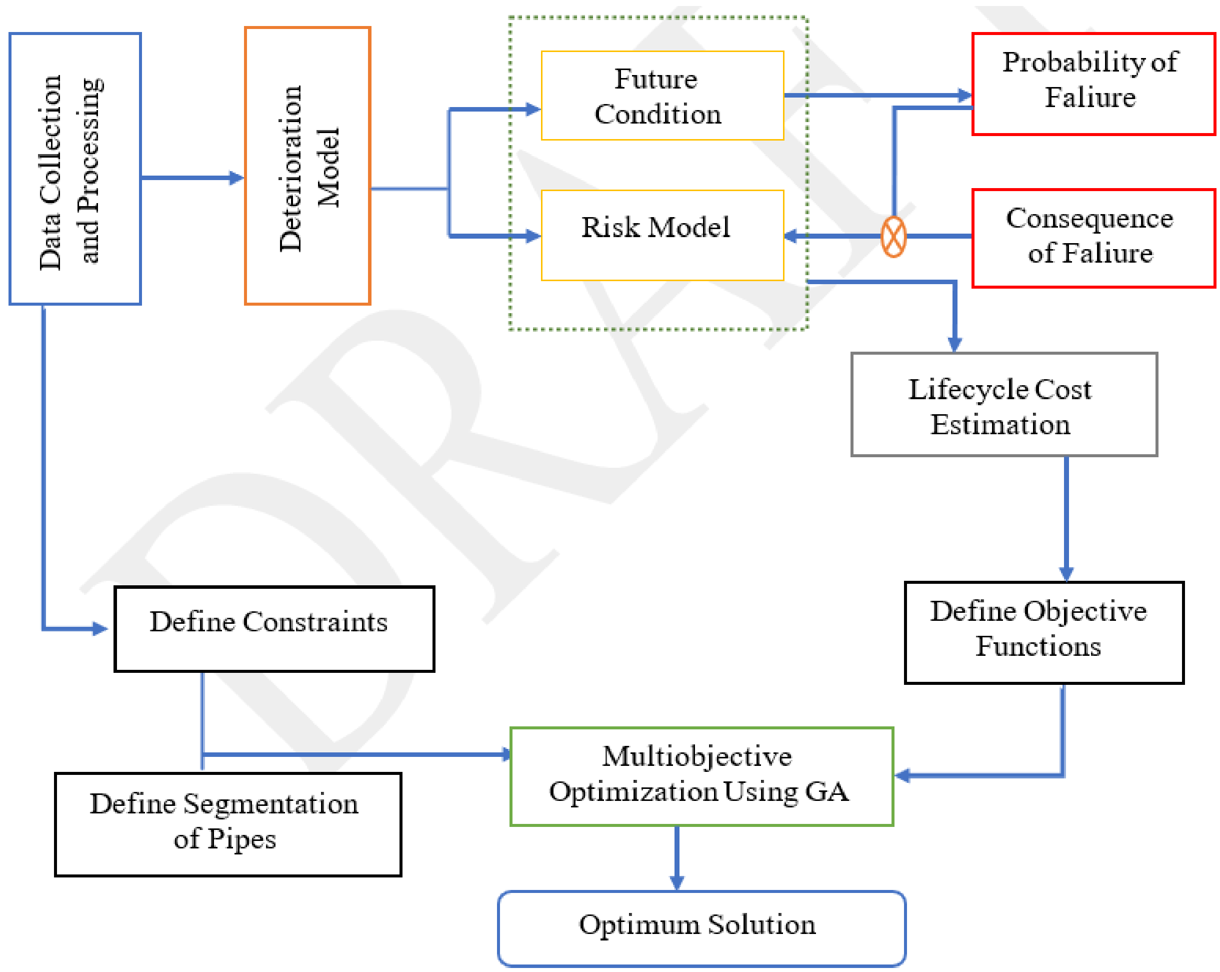


Figure 3-1: Methodology Framework

3.2.1 Methodological Framework

A methodological framework was formulated by using the above data. The methodological framework comprises of three steps; thus (1) segmentation model, (2) deterioration model, and (3) multiobjective optimization model. Figure 3-2 represents the methodological framework. Details of each component are explained in the following sections.

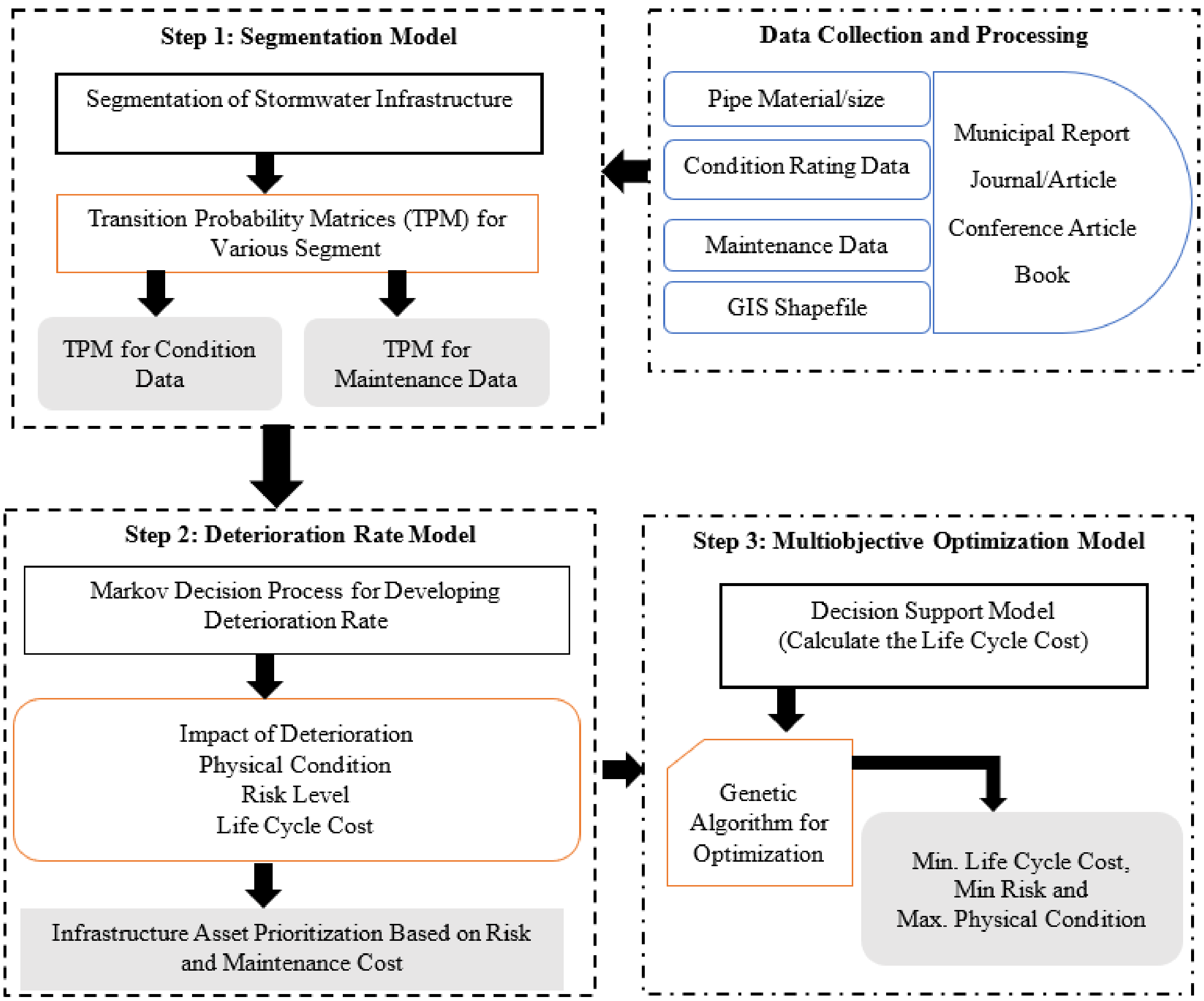


Figure -3-2: DS-Based Methodological Framework

3.3 Step 1: Establishment of Stormwater Infrastructure Segments

With linear infrastructure systems, it is common to break the network into smaller, more controllable components (Shahata and Zayed, 2016). To best describe this smaller unit, the term segments has been used. The segmentation of a stormwater line primarily consists of the pipe length (links) and manholes (nodal). Shehata and Zayed (2016) stated that many municipalities in recent times split their stormwater pipes into a segment, based on manhole-to-manhole separation. Therefore, this study adopted the manhole-to-manhole approach in defining the stormwater segments. Further to the manhole-to-manhole segmentation approach, this study factored in pipe material, pipe diameter, and year of installation. Equation 3-1 and Equation 3-2 define how the segmentation will be done.

First, the algorithm identifies the upstream and downstream manholes ID and filters through it to aid identify the pipe segment ID

$$Manhole\ types = filters\ (manhole\ ID) \qquad \text{Equation 3-1}$$

Second, the algorithm then identifies the external id of the pipes between the manholes and assigns the pipe segment ID for reference.

$$If\ \{\ External\ ID\ of\ pipe = N\ and$$

$$Distance\ between\ upstream\ and\ downstream\ manhole = \ M\ then$$

$$Pipe\ segment\ ID = K\} \qquad \text{Equation 3-2}$$

$External\ ID$: $Pipe\ network\ External\ ID\ in\ the\ BIM\ model$

N_i: $First\ column\ in\ the\ database\ (Pipe\ \ Segment\ ID)$

M: $Distance\ between\ upstream\ and\ downstream\ manhole\ defined\ in\ the\ BIM\ model$

K_i: $segment\ id\ in\ the\ database$

i: $Number\ of\ iteration\ of\ the\ total\ number\ of\ pipes\ in\ the\ model$

3.3.1 Establishment of Stormwater Infrastructure Condition Rating

Municipalities currently follow different management practices for their stormwater infrastructure systems, which causes inconsistent condition assessments (Zhao et al., 2010). Due to this challenge some municipalities have carried out extensive work to assess the condition of their stormwater infrastructure systems of Saskatchewan municipality is no exception. This study adopts an ordinal condition rating system currently used by the Ministry of Municipal Affairs of Saskatchewan where the asset condition is described in terms of integers (Table 3-2)

(Saskatchewan Ministry of Municipal Affairs 2006)**.** The best condition state is defined as C_{max}= 5. The worst condition state is $C_{min} = 1$**.**

Table 3-1: Condition rating adapted for stormwater infrastructure system

Condition Rating	**Linguistic Condition**	**Condition Description**	**Action Required**
5	Excellent	Very good condition	Normal maintenance required
4	Good	Only minor defects	More maintenance required (5%)
3	Fair	Maintenance required to return to an acceptable level of service	Significant maintenance required (10-20%)
2	Poor	Renewal required	Significant renewal/upgrade required (20-40%)
1	Critical/failed	Unserviceable assets	Over 50% of asset needs replacement

3.4 Step 2: Deterioration Rate Model

The Markov Chain is the most widely used stochastic technique for predicting the future condition of various infrastructure classes (e.g., highways, bridges, sewer pipes, and water pipes) (Edirisinghe et al., 2015). The Markov Chain is a stochastic process that moves from one state to the next in state space. This property of the Markov Chain states that the next state is determined solely by the current state and not by the preceding state's sequence (Ens, 2012). This property can be expressed for a discrete stochastic process X_t with a discrete state space as illustrated in Equation 3-3

$$P(X_{t+1} = i_{i+1} \mid X_t = i_t, X_{t-1} = i_{t-1}, \dots, X_0) = P(X_{t+1} = i_{t+1} \mid X_t = i_t) \quad \text{Equation 3-3}$$

where i_t = state of the process at time t; and P = conditional probability of any future event given the present and past events.

Markov Chains are used as performance prediction models for infrastructure components by defining discrete condition states and accumulating the probability of transition from one condition state to another over multiple time intervals (Madanat et al. 1997). The transition probabilities are embodied by a matrix of order (*m x m*) called the transition probability matrix *P*, where *m* is the number of possible condition states. Each element $P_{i,j}$ in this matrix embodies the probability that the condition of an infrastructure component will change from state *i* to state *j* during a certain time interval called the transition period. According to Madanat et al. (1997), the transition probability should satisfy the following constraints:

$$\mathrm{P_{ij}} > 0 \text{ and } \sum \mathrm{P_{ij}} \leq 1 \quad \text{Equation 3-4}$$

If the initial condition vector $C_{(0)}$ that describes the present condition of an infrastructure component is known, the future condition vector $C(ij)$ at any number of transition periods, P^t can be obtained as shown in Equation 3-5,

$$\mathrm{C(ij)} = C_{(0)} \times \mathrm{P}^t \qquad \text{Equation 3-5}$$

Where the transition probability matrix (TPM) is defined as:

$$\mathrm{TPM} = \begin{pmatrix} \mathrm{P_{11}} & \dots & \mathrm{P_{1j}} \\ \vdots & \dots & \vdots \\ \mathrm{P_{i1}} & \dots & \mathrm{P_{ij}} \end{pmatrix}$$

${P_{ij}}^{(t)}$ is the probability of the asset with a condition rating, $C_{i(t)}$ (for i = 1, 2, 3, 4, 5) after t years.

Condition rating of a component/system at time t is expressed as a condition state vector $(C_{(t)})$

$$(C_{(t)}) = \left[C_{1(t)}, C_{2(t)}, C_{3(t)}, C_{4(t)}, C_{5(t)}\right] \qquad \text{Equation 3-6}$$

Condition rating at the early state is defined as the initial condition state vector $(C_{(0)})$ for a new stormwater infrastructure system (Karunarathna et al., 2013).

$$(C_{(0)}) = [1\ 0\ 0\ 0\ 0] \quad \text{Equation 3-7}$$

When the initial condition states vector ($C_{(0)}$) and TPM are known condition states, after time t (C(t)) can be obtained by the Chapman-Kolmogorov formula (Equation 3-8).

$$\mathrm{C}_{(\mathrm{t})} = \mathrm{C}_{(0)} \times \mathrm{P}^{\mathrm{t}} \qquad \text{Equation 3-8}$$

Because the conditions of stormwater systems have been divided into five different states for this study, the Markov Chain model from state *i* to state *j* is represented by a 5 x 5 transition probability matrix. A one-year condition rating was utilized for developing the transition probability matrices.

Reinforced Concrete Pipe

$$\begin{bmatrix} 0.98 & 0.02 & 0 & 0 & 0 \\ 0 & 0.58 & 0.42 & 0 & 0 \\ 0 & 0 & 0.79 & 0.21 & 0 \\ 0 & 0 & 0 & 0.99 & 0.01 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Asbesto Cement

$$\begin{bmatrix} 0.80 & 0.20 & 0 & 0 & 0 \\ 0 & 0.70 & 0.30 & 0 & 0 \\ 0 & 0 & 0.60 & 0.40 & 0 \\ 0 & 0 & 0 & 0.10 & 0.90 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Concrete Pipe

$$\begin{bmatrix} 0.84 & 0.16 & 0 & 0 & 0 \\ 0 & 0.72 & 0.28 & 0 & 0 \\ 0 & 0 & 0.51 & 0.49 & 0 \\ 0 & 0 & 0 & 0.82 & 0.18 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Vitrified Clay

$$\begin{bmatrix} 0.75 & 0.25 & 0 & 0 & 0 \\ 0 & 0.86 & 0.14 & 0 & 0 \\ 0 & 0 & 0.67 & 0.33 & 0 \\ 0 & 0 & 0 & 0.80 & 0.20 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

After the TPM was built, it was then utilized to predict the future condition for 20 years. Table 3-2 shows an example of the Excel-built future condition assessment model for 20-year period for a segment (RCP) in this study for illustrative purposes.

Table 3-2: Depicts a condition assessment model

TIME	5	4	3	2	1	FUTURE CONDITION	ROUNDED CONDITION
0	1.00	0.00	0.00	0.00	0.00	5.00	5.00
1	0.75	0.25	0.00	0.00	0.00	4.75	4.00
2	0.56	0.40	0.04	0.00	0.00	4.53	4.00
3	0.42	0.49	0.08	0.01	0.00	4.32	4.00
4	0.32	0.52	0.12	0.04	0.00	4.12	4.00
5	0.24	0.53	0.15	0.07	0.01	3.92	3.00
6	0.18	0.51	0.18	0.11	0.02	3.72	3.00
7	0.13	0.49	0.19	0.14	0.04	3.52	3.00
8	0.10	0.45	0.20	0.18	0.07	3.33	3.00
9	0.08	0.41	0.19	0.21	0.11	3.14	3.00
10	0.06	0.37	0.19	0.23	0.15	2.96	2.00
11	0.04	0.34	0.18	0.25	0.20	2.78	2.00
12	0.03	0.30	0.17	0.26	0.25	2.62	2.00
13	0.02	0.27	0.15	0.26	0.30	2.46	2.00
14	0.02	0.23	0.14	0.26	0.35	2.31	2.00
15	0.01	0.21	0.13	0.25	0.40	2.18	2.00
16	0.01	0.18	0.11	0.24	0.45	2.05	2.00
17	0.01	0.16	0.10	0.23	0.50	1.94	1.00
18	0.01	0.14	0.09	0.22	0.55	1.84	1.00
19	0.00	0.12	0.08	0.21	0.59	1.74	1.00
20	0.00	0.10	0.07	0.19	0.63	1.66	1.00

3.4.1 Development of Risk Assessment Model

Risk has been used as the basis for the prioritization of infrastructure components for MR&R (Halfawy et al., 2008). InfraGuide (2006) defines risk as the combination of Probability of Failure (PoF) and Consequences of Failure (CoF). The risk assessment model formulated for this study is illustrated in Equation 3-9

$$Risk\ =\ Probabilty\ of\ Failure\ (PoF) \times Consequenceof\ Failure\ (CoF) \qquad \text{Equation 3-9}$$

The approach used to develop the PoF and the CoF of the stormwater infrastructure management is explained below.

3.4.2 Determining PoF

The PoF of the stormwater infrastructure system is determined based on the condition of the infrastructure asset at the period of transition. Thus, the PoF is defined as the inverse of the condition rating (Ruparathna, 2017). Table 3-3 shows the range of PoF scores from 0.20 to 1 based on the condition rating. The PoF model formulated for the study is illustrated in Equation 3-10

$$\text{Probability of Failure (PoF)} = \frac{1}{\text{condition rating}} \qquad \text{Equation 3-10}$$

Table 3-3: Range of probability of failure for stormwater infrastructure system

Asset Condition	POF	POF (description)	Remaining life
5	0.20	Rare	This means there is no minor defect, and failure is unlikely.
4	0.25	Unlikely	This means there is a minor defect, and the pipe may deteriorate or fail in (20 +) years.
3	0.33	Likely	This means there is a moderate defect, and the pipe is likely to fail between 10 to 20 years
2	0.5	Highly likely	This means there is a severe defect, and the pipe is likely to fail between 5 to 10 years
1	1	Almost certain	This means that failure has occurred or is likely to happen in a few years

3.4.3 Determining CoF

The failure of stormwater pipes can cause massive damage to a municipality and endanger the health and safety of the public because the stormwater pipes are closely connected to buildings and other critical infrastructure (Baik et al., 2006). A qualitative and quantitative technique was used to assess the CoF of stormwater infrastructure. A scale was used to linguistically rate the

CoF in Table 3-4 based on Shahata and Zayed (2016). Five (5) was used as the highest CoF score which indicates a catastrophic impact while one (1) was used as the lowest CoF score which indicates an insignificant impact.

Table 3-4: Adapted scale for the consequence of failure

Score	Consequence level	Description
1	Insignificant	There is no noticeable impact. There has been little or no public exposure. There is no risk to one's health. It is tolerable indefinitely.
2	Minor	There has been little public exposure. Minor health risks exist. Can be tolerated for a reasonable period
3	Moderate	Minor public exposure. A small portion of the population faces health risks. Can be tolerated for a short period (i.e., sufficient to plan and take action)
4	Major	A large proportion of the population is at risk. To address this, expeditious and/or emergency measures are required.
5	Catastrophic	A large proportion of the population is at risk, which has a significant impact. Complete system failure Extreme emergency measures are required.

The combination of the qualitative and quantitative factors forms the basis of the CoF for this study. Table 3-5 indicates the modified impact factors considered to determine the CoF (Baah et al., 2015). This study evaluates the distance between the stormwater pipe and the land use type to ascertain the CoF.

Table 3-5: CoF assessment of stormwater infrastructure

Land-use	Proximity	Consequence level
Proximity to hospital	Pipe distance ≤ 20 m	5
	Pipe distance > 20 ≤ 50 m	4
	Pipe distance > 50 ≤ 80 m	3
	Pipe distance > 80 ≤ 100 m	2
	Pipe distance > 100 m	1
Proximity to school	Pipe distance ≤ 500 m	5
	Pipe distance > 50 ≤ 100 m	4
	Pipe distance > 100 ≤ 150 m	3
	Pipe distance > 150 ≤ 2000 m	2
	Pipe distance > 200 m	1
Proximity to buildings	Pipe distance ≤ 5 m	5
	Pipe distance > 5 ≤ 10 m	4
	Pipe distance > 10 ≤ 15 m	3
	Pipe distance > 15 ≤ 20 m	2
	Pipe distance > 20 m	1
Proximity to parks or recreational areas	Pipe distance ≤ 80 m	5
	Pipe distance > 80 ≤ 100 m	4
	Pipe distance > 100 ≤ 120 m	3
	Pipe distance > 120 ≤ 150 m	2
	Pipe distance > 150 m	1
Proximity to river body	Pipe distance ≤ 100 m	5
	Pipe distance > 100 ≤ 125 m	4
	Pipe distance > 125≤ 150 m	3
	Pipe distance > 150 ≤ 175 m	2
	Pipe distance > 175 m	1

3.5 Life Cycle Cost (LCC) Model

The LCC model focuses on the operational stage of stormwater infrastructure systems. For this study, LCC is defined as the costs that arise after post-construction. The LCC of a stormwater infrastructure system depends on the selected MRR options (Nesbitt et al. 1993). The cost of a stormwater segment primarily consists of the link (segment length) costs and nodal (manhole) costs. Hence, the initial cost is defined as shown in Equation 3-11 (Swamee and Sharma, 2013).

$$C_p = \sum(C_i \times l_i) + (k_{hi} \times d_i) \qquad \text{Equation 3-11}$$

Where, C_p is the initial construction cost of the stormwater pipe length and stormwater manhole; C_i is the cost of the pipe per unit; and l_i is the length of the pipe to the next manhole; $k_{hi} = cosy\ of\ the\ manhole\ per\ unit\ depth;$ k_{hi} is the co-efficient of the manhole; and d_i is the depth of the manhole; The coefficient k_{hi} depends on the d_i and the maximum stormwater pipe diameter D connecting the manhole as there will be two or more pipes connected at a manhole.

Given the uncertainty of future costs, interest rates, and even future events, predicting the operational and maintenance costs can be challenging (Rahman and Vanier, 2004). However, an accurate prediction approach of the future condition can be used to estimate the operation and maintenance cost. Hence, this study used the Markov Chain model to predict the future condition in order to determine the maintenance requirement. The deterministic discounted rate method was used to convert all the future cost to the present value. This was based on the economic analysis of time value of money. In this study, the operation and maintenance cost has been defined as (Equation 3-12)

$$\left[\frac{C_t}{(1+i)^n}\right] \qquad \text{Equation 3-12}$$

Equation 3-13 was used to calculate the net present value of the total LCC (Riggs, 1977): Thus, the initial cost is summed with the operation and maintenance cost.

$$\text{NPV} = C_p + \left[\frac{C_t}{(1+i)^n}\right] \qquad \text{Equation 3-13}$$

Where,

NPV: net present value

C_p: initial cost or construction cost;

C_t: sum of maintenance activities that is repair and replacement /rehabilitation

i: discounted rate

n: asset service life

The LCC is defined as the sum of the NPV for all segments of the stormwater infrastructure system (Equation 3-14).

$$LCC = \sum_{i}^{j} NPV \qquad \text{Equation 3-14}$$

The initial cost values for the installation of the pipe network were ascertained from RS Means cost data book (R.S.Mean, 2007). Table 3-6 presents the initial cost for four separate pipe materials of about 1.4 km long installed in the study area.

Table 3-6: Initial installation cost

Pipe material	Reinforced concrete	Polyvinyl chloride	Concrete	Vitrified Clay
Cost ($)	CAD 20,000	CAD 16,500	CAD 18,500	CAD 20,000

According to Wood (2020), the routine inspection cost, minor repair cost, major repair cost, and replacement cost are 10%, 25%, 50%, and 100% of the initial cost, respectively.

3.6 Step 3: Optimization Model

This study uses an evolutionary genetic algorithm (GA) technique to find Pareto fronts and identify a set of feasible renewal solutions for the MOO problem. The optimization model was built in a programming environment. Standard operating conditions were assumed, and four different maintenance options were considered (do nothing, minor repair, major repair, and replace). Regarding the maintenance action data, TPM from Morcous and Lounis (2005), thus the minor repair and major repair, replace were adopted. The do-nothing is considered regular deterioration.

Do-Nothing: A do-nothing policy means that no significant rehabilitation is carried out on the stormwater, and its condition deteriorates until it is abandoned. The stormwater pipes will be inspected on a regular basis.

Minor and Major Repair: The stormwater pipes will be improved as a result of the repair options, which will result in a better condition rating lower than the highest condition rating. The minor repair options target stormwater flushing and root cutting. The flushing is usually done to clean out materials that have been deposited in the stormwater pipe. Similarly, major repair options target pipe defects such as leakages and repair of property damages associated with flooding

Replace: The stormwater will be replaced as part of the replacement policy, which takes the stormwater pipes to its pristine state. This maintenance action includes excavation and total overhaul of the pipe material.

Therefore, the following TPMs for the maintenance actions were used in the MOO algorithm during the study.

Minor Repair	Major Repair	Replace
$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}$	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$

Three opposing objectives were considered in the optimization. The first and second objectives were to minimize the LCC and risk level, while the third was to improve the condition rating for the stormwater system. Equation 3-15 to 3-16 presents a mathematical representation of the MOO formulation:

$$\text{Min LCC} = \sum_{ij}^{t}(\text{NPV}_{\text{stormwater}}) \qquad \text{Equation 3-15}$$

$$\text{Min RI} = \sum_{ij}^{t}\left(\frac{1}{\text{Condition Rating}}\right) \times \text{COF} \ \text{Equation 3-16}$$

$$\text{Max Physical Condition} = \sum_{ij}^{t} \text{TPM} \times \text{CR} \quad \text{Equation 3-17}$$

Subject to;

Maintenance $\text{cost}_{\text{segment ij}} \leq$ Annual budget for stormwater

$1 \leq$ Preferred retrofit action for stormwater network ≤ 4

$CR_{ij} \geq$ Acceptable condition rating for stormwater network,

$RI_{ij} \geq$ Acceptable risk level for stormwater network,

Where $\text{NPV}_{\text{Segment ij}}$ is the net present value for the stormwater network

$\text{RI}_{\text{segment ij}}$ is the risk level for the stormwater network

$CR_{segment\ ij}$ is the condition rating for the stormwater network.

3.6.1 Overview of the optimization

Figure 3-4 depicts the algorithm for the optimization. Deterioration rate models are used to predict the physical condition of segments of the stormwater infrastructure system. The optimization was programmed by using a macro-driven program to translate the TPMs of the various segment into a format that allows the assignment of rehabilitation solutions to each segment of the stormwater network. This program undertakes the process by selecting the upstream manhole and downstream manhole and evaluating the distance between them. In this study, the distance between the two manholes is defined as the pipe segment. The algorithm starts at a defined manhole and observations are reported until the end manhole is reached, or the algorithm is terminated. The objective function formula which is embedded in the optimization environment then updates itself to encompass the cell ranges for each segment length. Thus, permitting the evaluation of the objective function(s) at the segment level, that is, improving the condition and minimizing the lifecycle costs and risk of failure per individual segment length.

The optimization model sorts out the numerous rehabilitation solutions within the optimization environment using a multiobjective GA. Upon establishing the optimization environment, the GA assigns an initial random population of solutions, as a string of 1's and 0's, against each segment. These 1's and 0's become the decision variables in the problem which represent the rehabilitation action; either rehabilitate (minor and major repair or replace) (1) or do nothing (0) based on the available budget. After an initial random population of decision variables is assigned, the GA evaluates the fitness of each solution based on the objective function scores which are calculated dependent on the decision variable values. If the fitness of the solution meets the stopping criteria for the algorithm, then the optimal solution is said to be found. However, if the solution falls short of the criteria then the following GA operators are performed: selection, cross-over, mutation, and the new solutions are re-evaluated (Ward and Savić, 2012). The main advantage of this approach is the ability of a GA to find a set of Pareto-optimal (trade-off) solutions in a single run of the algorithm.

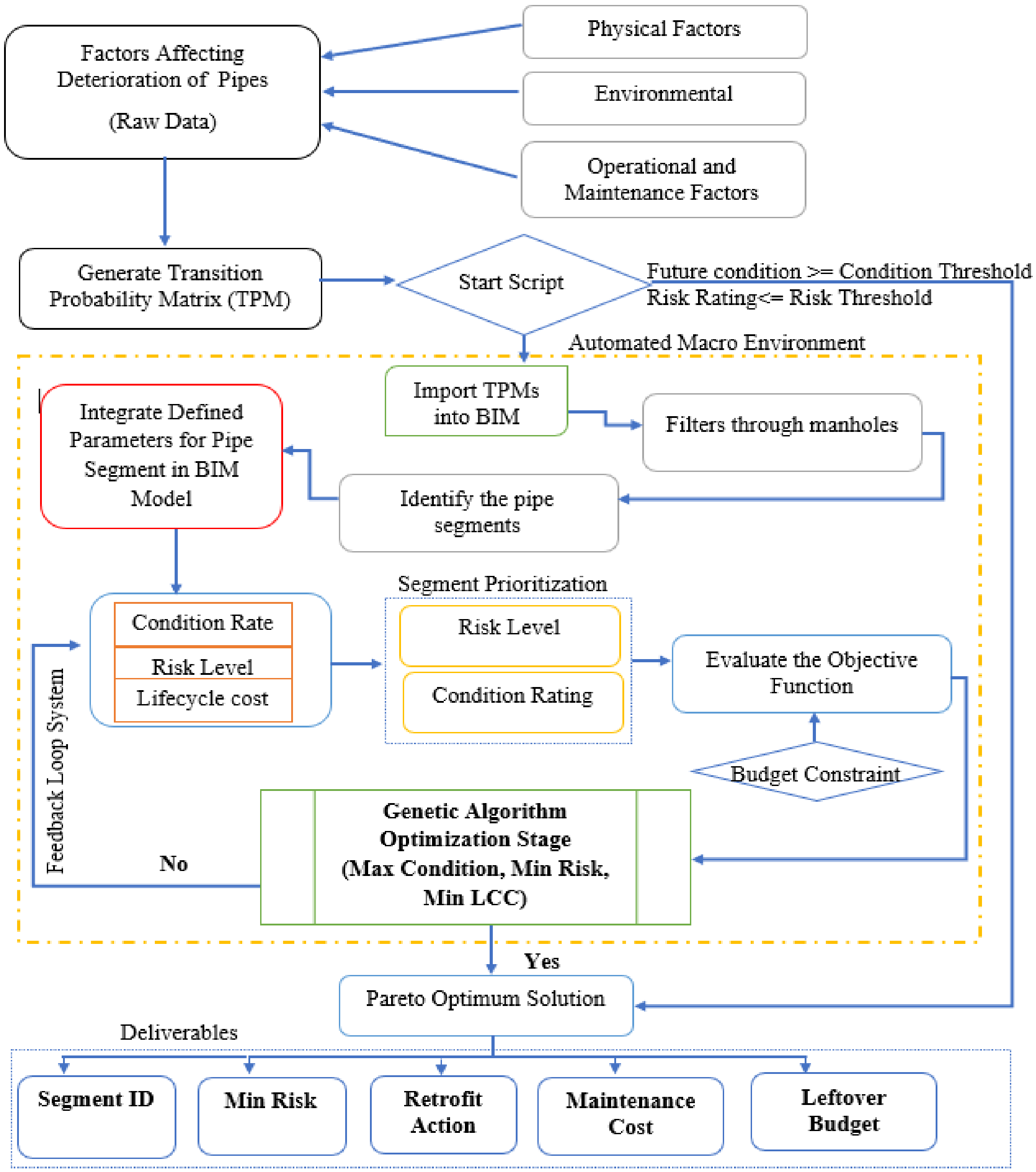


Figure 3-3: GA Optimization Algorithm

3.6.2 Integration of Renewal Activities

Integrating a renewal planning model will allow for a specific planning perspective that would optimize the allocation of the renewal budget by improving the stormwater network’s condition and minimizing both lifecycle cost and risk of failure. This problem is tackled by adopting a prioritization approach for the network. For a given year, renewal planning approach would be established for each segment based on the condition score and risk level. This planning approach would further be used to update the stormwater segment (i.e., manhole to manhole) according to the most appropriate and cost-effective renewal action if any for subsequent years. At the beginning of each planning period, stormwater segment condition ratings are re-evaluated using the deterioration model, taking into consideration any renewal actions that have been planned in previous years. Further, the risk level is estimated, then in combination with the current condition, a prioritization approach of the various segment is planned for renewal action implementation. For each stormwater segment on the priority list, the most cost-effective and feasible renewal actions are selected.

The plans are further evaluated according to the budget constraints. Then, a feedback loop was built on the risk constraint, condition rating, and the annual budget available for undertaking a maintenance action. The following mathematical formulation details how the feedback loop works:

$$IF\{$$

$$Result\ RI_{segment\ i} > \cdots \ldots RI\ threshold$$
$$Result\ CR_{segment\ i} < \cdots ..CR\ threshold$$

$$Then\ select\ segment\ with\ highest\ RI\ and\ lowest\ CR\ value\ for\ maintenance$$

$$\}$$ Equation 3-18

Subject to this constraint:

$MC_t \leq$ Annual budget.

Where RI and CR are the risk level and condition rating of the various segment under consideration respectively. MC_t is the maintenance cost at time t, i-n represents the number of segments in the network.

The decision-maker then carries out several iterations to evaluate the various alternatives through the GA model until the renewal plan meets the objectives. Moreover, in multi-year planning scenarios, this process is repeated for each period in the planning perspective.

3.7 Benefits of the methodological framework

The benefits of the proposed framework are as follows:

I. *It is capable of predicting the condition and optimizing the performance of the stormwater infrastructure*: Infrastructure management relies on accurate and precise data. Given that most municipalities have several condition monitoring approaches adopted, there is yet the difficulty in the acquisition of quality data for developing condition assessment of their infrastructure (Bukhsh and Stipanovic, 2020). To resolve this, a predictive tool that can forecast the condition of the infrastructure based on the available data is required. Therefore, the proposed methodology makes use of the Markov Chains model to develop a deterioration model that can predict the current and future condition of the infrastructure for infrastructure management. Moreover, it helps in optimizing the infrastructure performance by indicating the deterioration pattern of the asset which can be used to develop a renewal plan.

II. *It is capable to forecast the Life Cycle Cost (LCC) for a planning period*: The significance of LCC in infrastructure management is recognized worldwide by several standards and guidelines, such as the ISO 5500x series and the British Institute of Asset Management (ISO, 2014). The proposed methodology, therefore, incorporated the ISO 5500x series in developing the LCC model for the management of stormwater infrastructure by discounting the future cost to the present.

III. *Implementation of Optimization model*: Stormwater infrastructure management has multiple conflicting objectives. Therefore to obtain a balance, there is the need to implement an optimization model (Chen and Bai, 2019). This study makes use of a Genetic Algorithm (GA) to optimize the multiple objectives that are physical condition, risk level, and LCC. Thus, GA optimization allows the search for the decision variable that needs to be optimized and also satisfies all the constraints.

IV. *Linked with a digital model of the stormwater infrastructure*: The data obtained from the municipality was used to develop the digital model of the stormwater infrastructure. Thus, a mathematical model was developed to reflect the physical properties of the stormwater infrastructure. The digital model allows for visualization of the stormwater infrastructure and enhances collaboration among stakeholders.

3.8 Summary

This chapter presented a methodological framework for Stormwater infrastructure management. This framework includes a deterioration model, risk model, LCC model, and MOO model. In order to define, evaluate and predict the probability of stormwater failure, a stormwater deterioration model was first developed. The deterioration model was then utilized to investigate the impact of the deterioration on future conditions, risk level, and lifecycle cost. Furthermore, a MOO was used to optimize the future condition, risk level, and lifecycle cost to improve the performance of stormwater infrastructure.

4 A DIGITAL SHADOW (DS)-BASED DECISION SUPPORT TOOL FOR STORMWATER INFRASTRUCTURE MANAGEMENT

4.1 Background

Proactive management is a strategic approach to minimizing the LCC of infrastructure. Furthermore, this will enable reducing the risk of failure, prolonging asset life, increasing reliability, and ensuring the stakeholder's satisfaction (Teicholz, 2012). To develop a proactive management approach, infrastructure managers need to collect key infrastructure performance data. Grigg (2012) stated that the key to successful stormwater infrastructure management is accurate information management.

DS provides a platform for a thorough examination of an infrastructure system. A DS can serve as the foundation for proactive stormwater infrastructure decision-making. A DS can be used to predict past, present, and future condition of the asset thereby aiding to resolve the data challenges in infrastructure management.

Previous researchers have used BIM to address the operation and maintenance of buildings (Heaton et al., 2019), subways (Marzouk and Abdel Aty, 2012), and airports (Neath et al., 2014). The advent of BIM technology has provided a new platform for information management during the operation and maintenance stage (Eadie et al., 2013).

This chapter presents a DS-based predictive maintenance planning tool for stormwater infrastructure maintenance. The proposed DS is developed in the BIM platform. The proposed DS provides an asset management information system for the municipalities.

4.2 Methodology

The methodological framework developed in chapter 3 was used in creating the DS-based tool. This study has identified Autodesk Infrawork software as a BIM software for managing stormwater infrastructure projects. The Autodesk Infrawork software has some unique in-built features like javascript for application programming interface (API) and ArcGIS component that allows handling and analyzing geographic information through the OpenStreet Maps.

The collected condition data, cost data, and maintenance data were processed in a .CSV file which was later linked to the BIM platform. These data were obtained with the help of an expert from the City of Windsor. The data collected were used to develop the tool and also investigate its capability through the case study.

4.2.1 Linking the methodological framework with BIM

The javascript programming language in Autodesk Infraworks provides a user interface for scripting. This inherent programming language of the tool was used to import the data from the .CSV file, and a mathematical algorithm was written for the optimization of the results. The mathematical algorithm was used to execute the methodology framework proposed in Chapter 3. The code used here is presented in the Appendix. The specific methods used for obtaining specific data for the methodological framework are explained below.

4.2.2 Data flow of the tool

This study uses the InfraWorks model to create the digital counter of the stormwater infrastructure. Figure 4-1 illustrates the data flow chart for the DS-based model. To do this, the following steps were followed:

Step 1: Create a BIM map: In this phase, a map is created using the model builder in the Infraworks to serve as the platform to host the stormwater pipes for analysis.

Step 2: Create extended attributes: In this phase, the stormwater condition, stormwater retrofit action, stormwater risk level, and stormwater lifecycle cost was created as an add-on tool kit using the extended schema function in the InfraWorks platform.

Step 3: Import the GIS shapefiles into the BIM platform: During this phase, the GIS shapefiles comprising the stormwater pipes and stormwater manholes are imported. The imported shapefiles are configured for analyzing the various segments.

Step 4: Start scripting: In this phase, the code for running the programming is written in the InfraWorks environment using the in-built javascript. The code is then run-in order to investigate the stormwater parameters for decision-making.

Step 5: Optimization of results: In this phase, a GA optimization algorithm is used to obtain Pareto optimal results for decision-making in the InfraWork environment. The final output of an optimized condition, risk, and lifecycle cost is obtained.

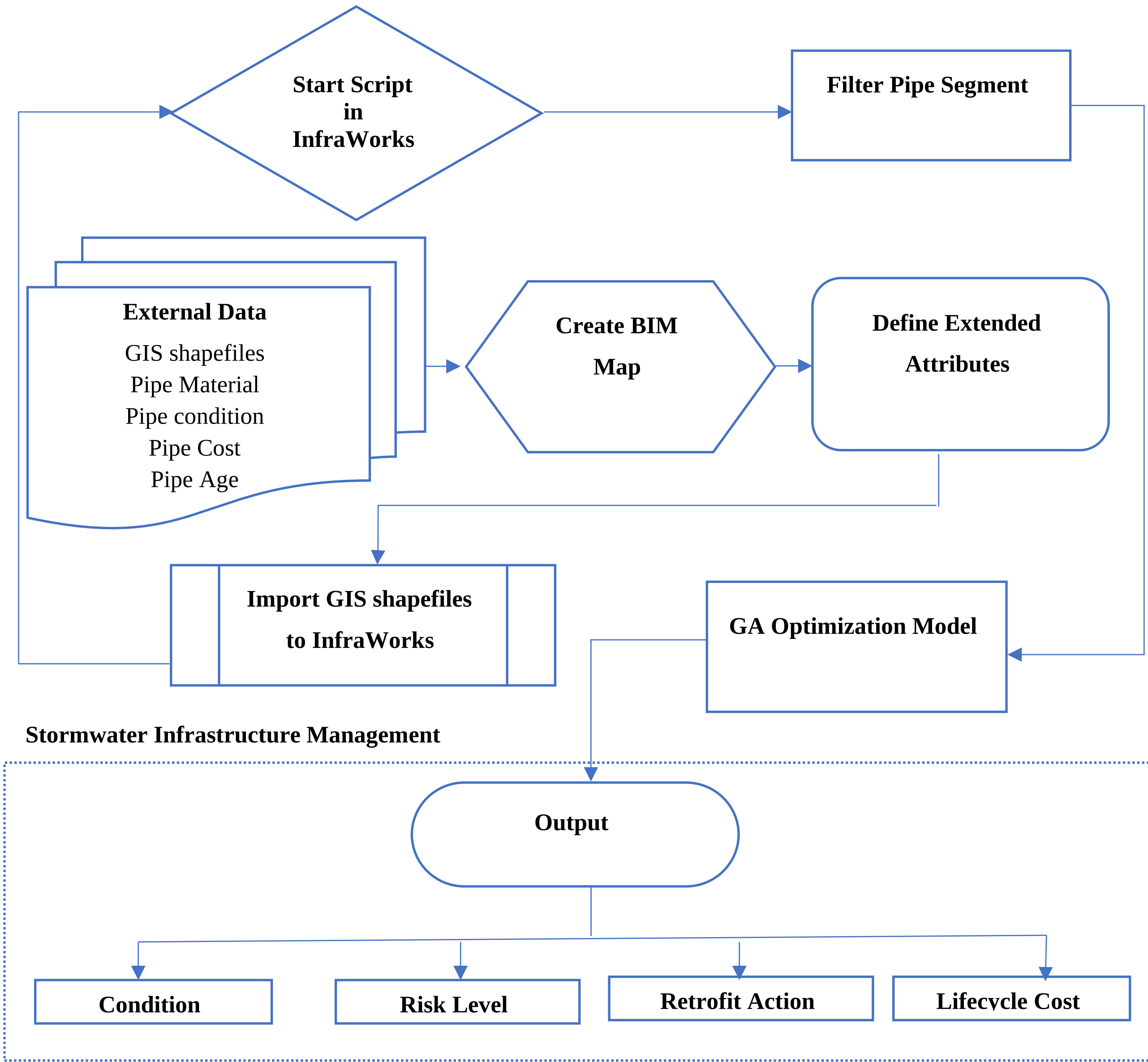


Figure 4-1:Depicts the data flow of the DS-based model

4.3 Overview of the DS-Based Decision Support Tool

The proposed DS-based decision support tool will enhance the decision-making process regarding stormwater infrastructure management. The general overview of the DS-based decision support tool is presented in the following sub-sections.

The user initially starts by creating a BIM map using the Autodesk InfraWorks software. The model builder in InfraWorks was used to create the Map for the case study area as shown in Figure 4-2.

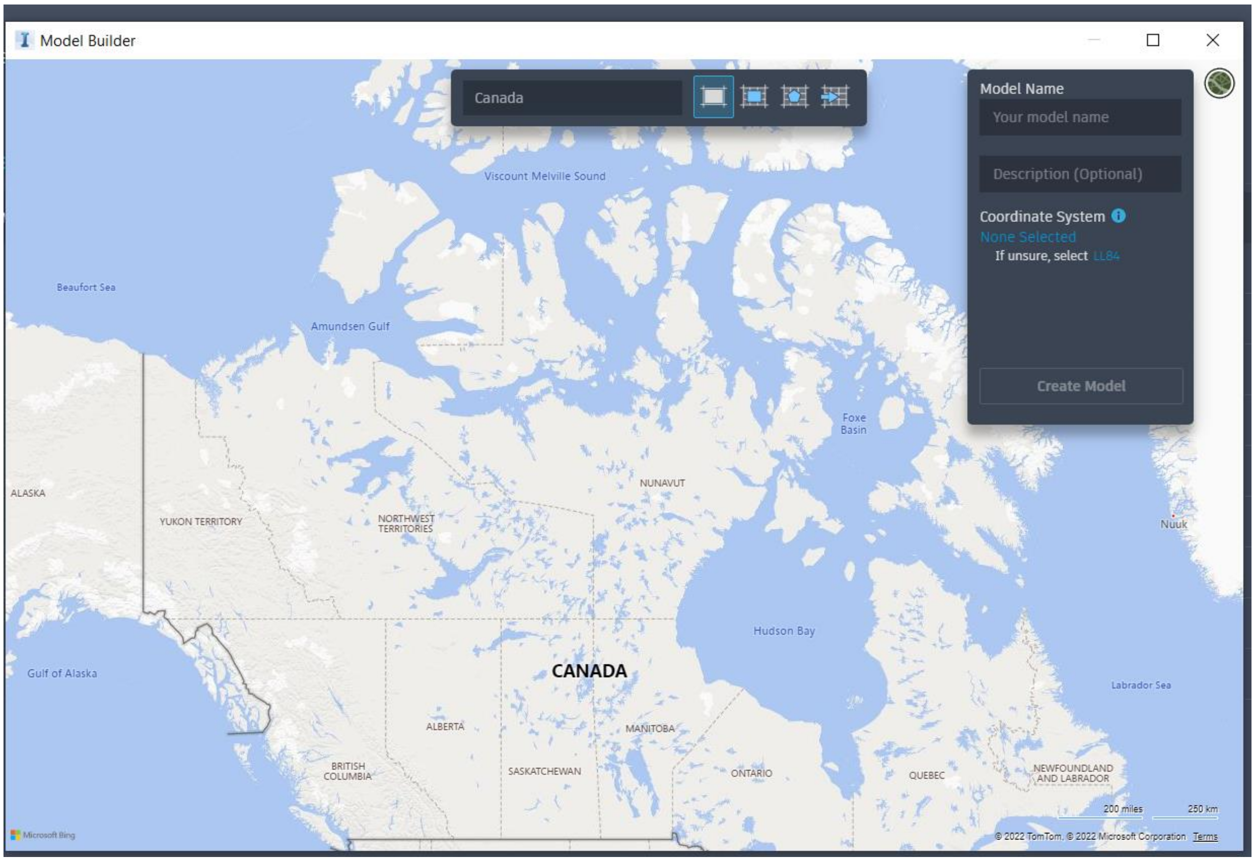


Figure 4-2: Illustrates a BIM map creation

Figure 4-3 displays how the extended attribute function was created. The addition of extended attributes was possible because the Infraworks software has such a unique feature as an add-on kit.

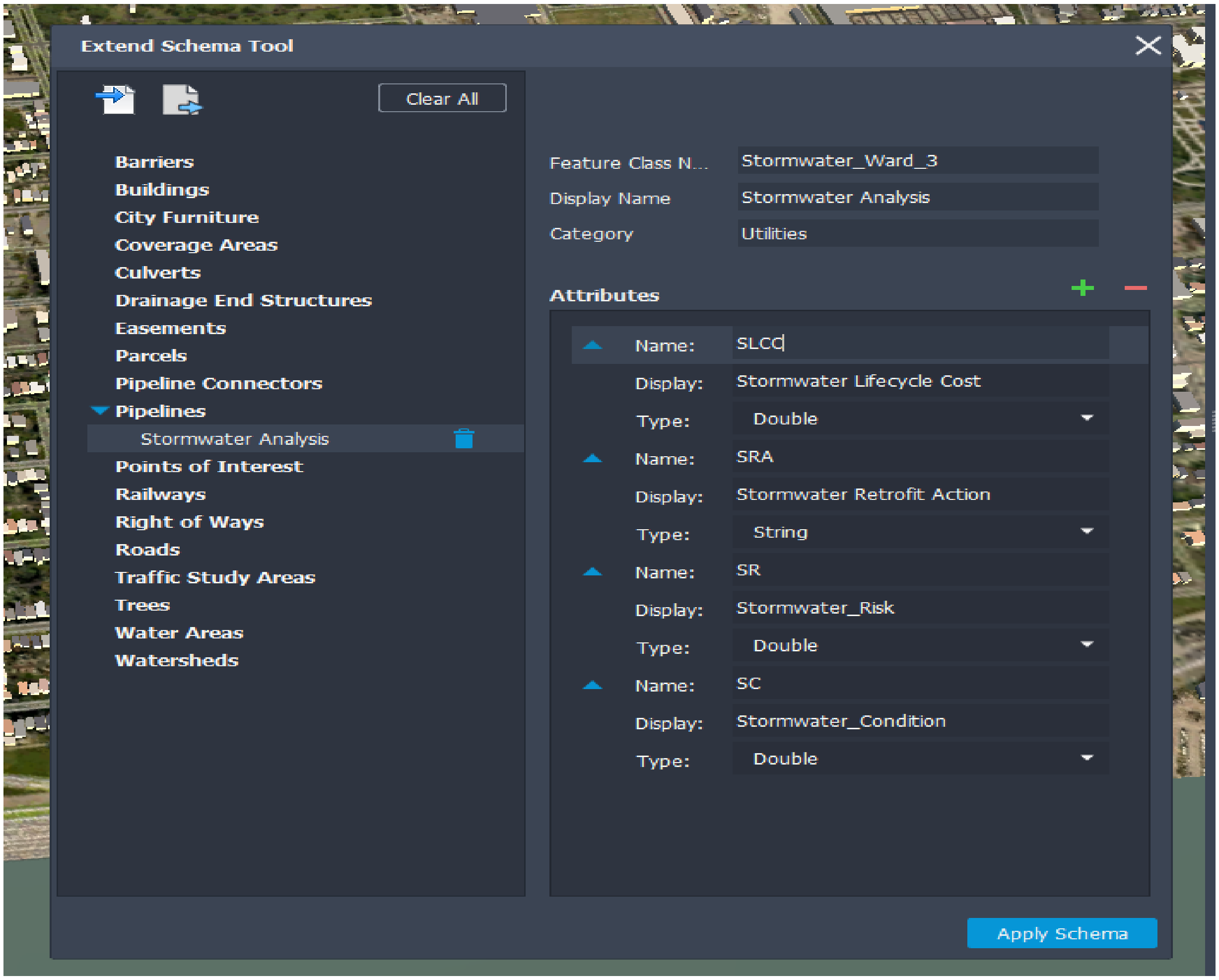


Figure 4-3: Illustrate the creation of the extended schema process

After the creation of the extended attributes, the .shp files are uploaded and configured, and all the pipe segments in the model shall be linked with the external databases and then exported to their respective parameters as defined in the extended attributes. In order to select the appropriate parameters, the tool will loop through the algorithm several times. The tool will then use the segment ID and stormwater manhole ID as filters to investigate the various stormwater segments for the decision-making process. Figure 4-4 presents a pictograph of the developed code for assessing the KPIs for decision making.

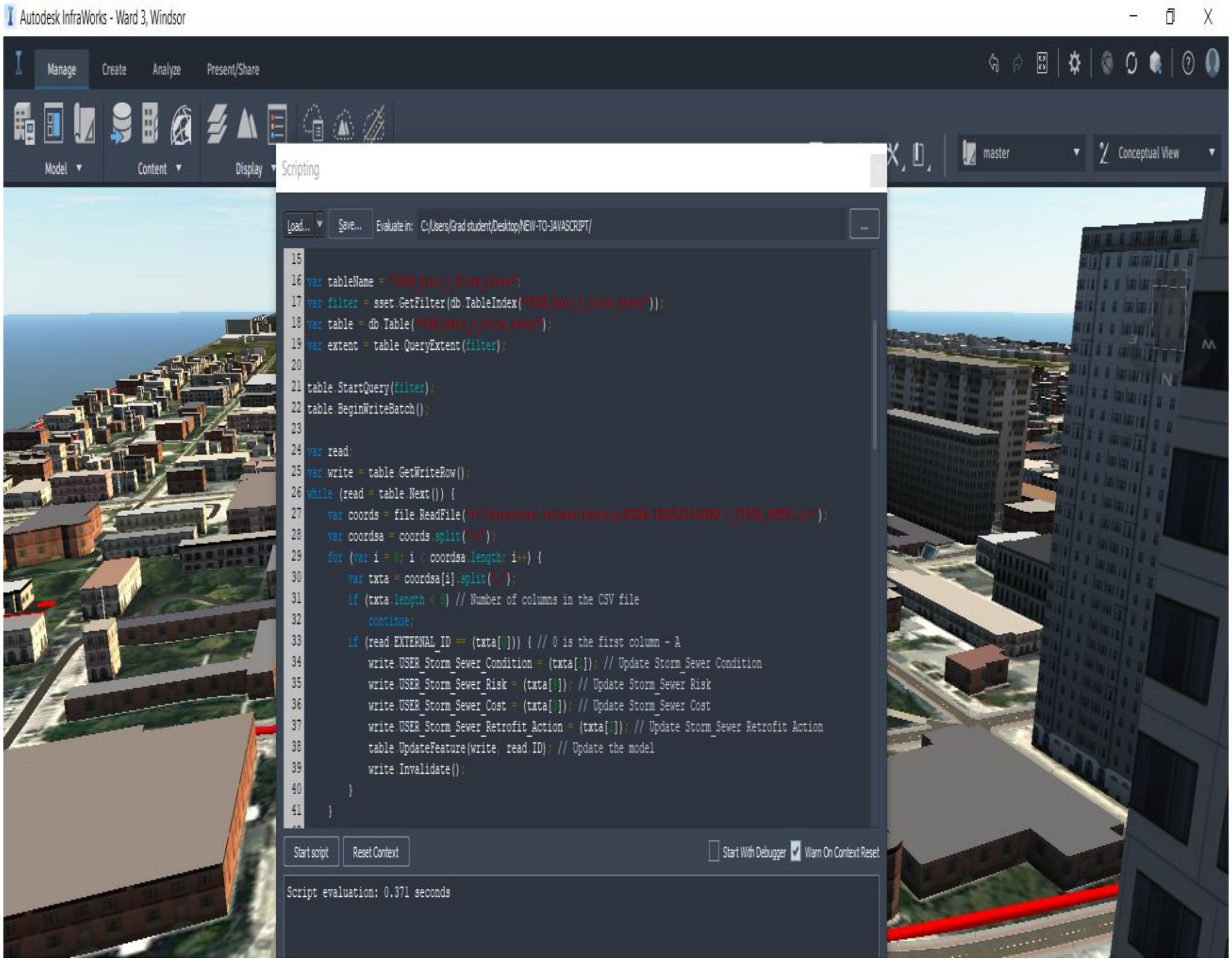


Figure 4-4: Illustrates assessment of KPIs for decision-making

4.3.1 Guidelines for DS-based tool

User Information

Figure 4-5 presents the detailed information required for decision-making. To obtain the required user information, the following steps were followed:

Step 1: The user shall import the TPMs of the various segment, stormwater shapefiles, and stormwater manhole shapefiles into the model as indicated in section 4.2.2. The TPMs are used to develop the deterioration pattern and facilitate the decision-making process. Also, the .shp files allowed the user to visualize, analyze the patterns, and monitor the changes that occur in the various pipe segments.

Step 2: The user shall run the developed script/ code to investigate the necessary information needed for the decision-making as indicated in Figure 4-5. This information is required to indicate the state of the municipal stormwater and also inform the municipality of the required action to be undertaken in the year of inspection and the proceeding years.

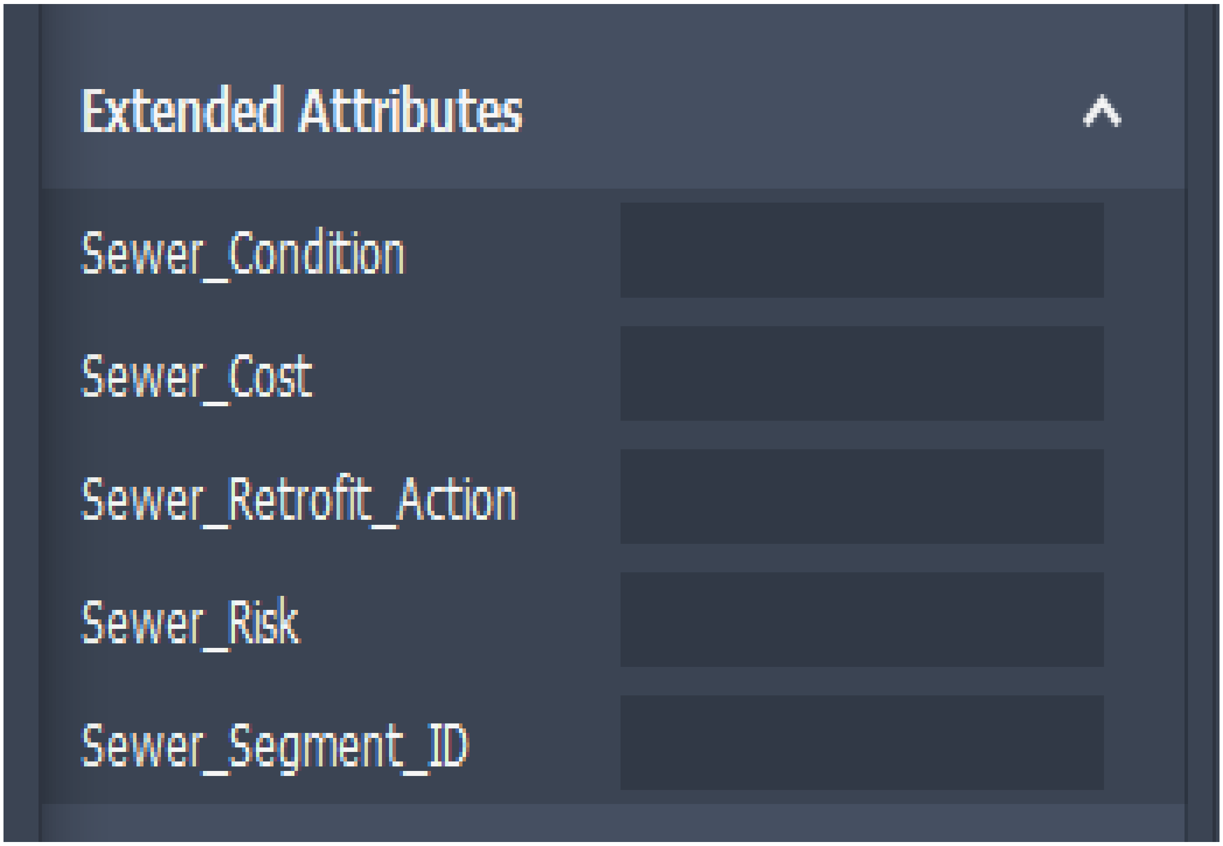


Figure 4-5: Stormwater information for decision-making

Furthermore, the result will indicate the segment's properties such as the condition score, risk level, maintenance action required, and LCC of the stormwater. Figure 4-6 demonstrates an example of a selected segment and its properties at the time of assessment.

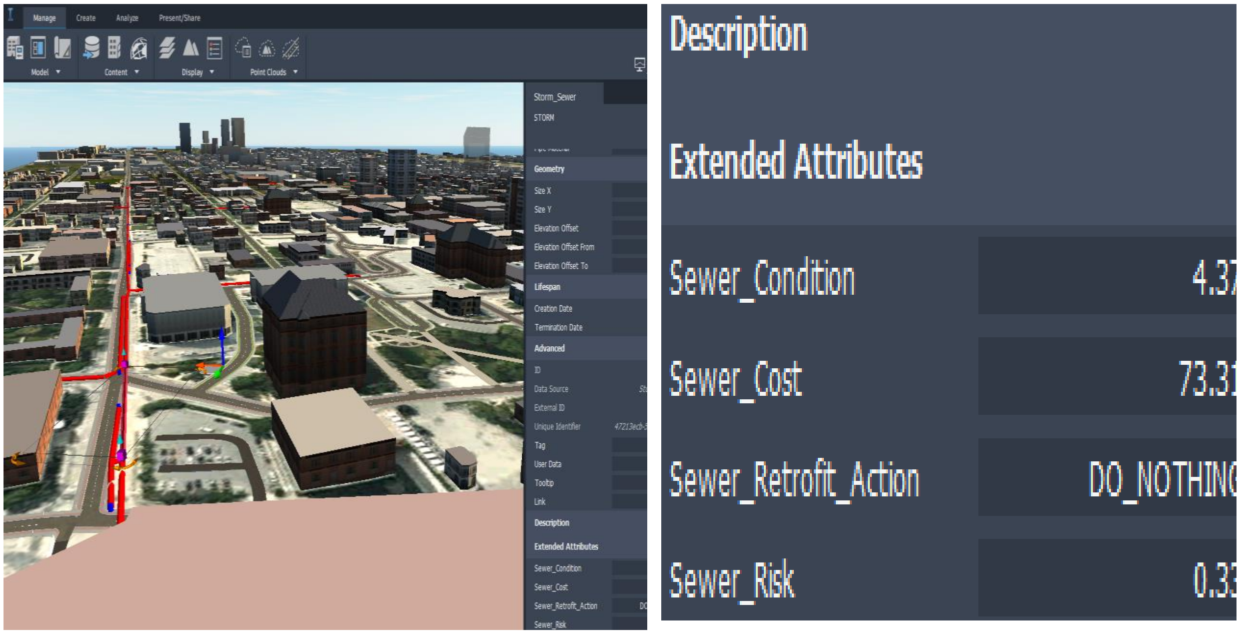


Figure 4-6: Depicts DS-Based results

4.4 Unique Features of the proposed tool

Unique features of the proposed decision support tool are as follows:

- **Predicts the maintenance requirements at the lowest life cycle cost:** This study proposed a DS-based tool that can forecast the maintenance action required to keep the stormwater infrastructure at the expected condition before the asset fails. The proposed DS-based tool uses the Evolutionary GA algorithm in conjunction with the Markov Chain model in a holistic manner to address the short-and long-term budget planning of stormwater infrastructure which aid in minimizing the LCC of the stormwater infrastructure over its planning horizon.
- **Enhance infrastructure decision-making:** The proposed DS tool improves the decision-making for the stormwater infrastructure network. As the stormwater infrastructure ages, the condition score, and risk of failure level need to be assessed. Upon the assessment, a budget must be allocated to implement any retrofit action required to keep the condition and the risk level of the infrastructure at an acceptable level. Therefore, the DS tool developed has the capability to address these challenges thereby ensuring efficient and effective decision making.

- **Easy to use:** The DS-based tool is a user-friendly decision support tool for infrastructure managers in the stormwater domain. There is a lack of digitalization in stormwater infrastructure which hinders DS-based decision-making. Therefore, developing a DS-based tool will make it easy for infrastructure management. This tool, however, allows experts and non-experts in the construction industry to investigate the condition, risk, and LCC of their stormwater infrastructure through the implementation of DS.

4.5 Summary

Most municipalities in Canada are looking for a tool that aids in a proactive infrastructure management approach. Therefore, the proposed DS-based tool has the capability of catering to such demand. In this chapter, a javascript was used to write a script in InfraWorks. This tool enables identifying the best maintenance plan by considering each component of the stormwater infrastructure system. This information can be used for capital budget planning in municipalities.

5 A CASE STUDY FOR DS-BASED STORMWATER INFRASTRUCTURE MANAGEMENT

5.1 Introduction

Digitalization of infrastructure enables the management of an infrastructure project from conception to completion (Tchana et al., 2019). The emergence of smart information technologies, such as digital shadow, IoT, machine learning, and BIM have been accelerating the digital transformation of the AEC sector.

Several studies have developed tools for the proactive management of civil infrastructure systems. As an example, Sanchez et al. (2014) used BIM to develop a tool for entire sustainable lifecycle management for transportation infrastructure, Vitásek and Matějka (2017) utilized BIM to develop an automatic tool for quantity takeoffs and cost estimation in transport infrastructure, Neves et al. (2019) utilized BIM to develop a tool for the implementation of rail track rehabilitation., Wang et al. (2019) used BIM and GIS to develop an integrated decision support tool for underground utility management, (Oreto et al., 2021) developed a BIM-based pavement management tool for scheduling urban road maintenance. Although previous researchers have developed a proactive management tool for the above civil infrastructure classes, stormwater infrastructure has been overlooked.

This chapter describes how the proposed DS-based decision support tool was applied to the stormwater infrastructure system in the Ward 3 area of the Canadian city of Windsor. The proposed proactive infrastructure management method was compared with the conventional approach.

5.2 Methodology

The City of Windsor does not maintain digital models of its civil infrastructure. Hence, required data was collected for creating the digital shadow. The properties of stormwater pipe design such as the pipe material, pipe diameter, length, and storm manhole diameter were identified and further formulated for simulations and calculations purposes during the study. Table 5-1 illustrates the stormwater pipe data used for preparing the digital shadow. Once these preliminary design parameters were identified, the layout of the 2D model of the stormwater pipes was generated as shapefiles from the Windsor mappmycity webpage *"opendata.citywindsor.ca"*. These data were exported into the InfraWorks software. The 2D shapefile format was refined into 3D models in the BIM platform for instinctive purposes as shown in Figure 5-1. Moreover, shapefiles in the form of 2D are graphical entities only, such as lines, arcs and circles while the 3D models define objects in an intelligent contextual semantic manner such as the space, size and the depth. The extended attributes created using the extended schema function were used to integrate the stormwater condition, stormwater retrofit action required, stormwater risk level, and stormwater lifecycle cost into the digital shadow model.

Table 5-1: Sample condition assessment data

Segment_Id	**Pipe Material**	**Pipe Size**	**Condition**
934	Asbestos Cement **(AC)**	200	5
935	Asbestos Cement **(AC)**	200	5
944	Concrete Pipe **(CONC)**	300	4
945	Reinforced Concrete Pipe **(RCP)**	675	5
946	Concrete Pipe **(CONC)**	200	3
954	Vacuum Insulated Tubing **(VIT)**	200	1
960	Vacuum Insulated Tubing **(VIT)**	300	1
7145	Concrete Pipe **(CONC)**	200	4
6511	Asbestos Cement **(AC)**	300	5
7150	Asbestos Cement **(AC)**	300	5
1065	Concrete Pipe **(CONC)**	500	4
1116	Asbestos Cement **(AC)**	300	3
1114	Reinforced Concrete Pipe **(RCP)**	675	4
1118	Reinforced Concrete Pipe **(RCP)**	675	5
1108	Asbestos Cement **(AC)**	300	3
1115	Asbestos Cement **(AC)**	300	4
1117	Asbestos Cement **(AC)**	300	2
10001	Vacuum Insulated Tubing **(VIT)**	300	2
6511	Vacuum Insulated Tubing **(VIT)**	150	5

Figure 5-1: depicts a 3D representation of the stormwater infrastructure

Figure 5-2 displays a map of the study area as well as a BIM model of Ward 3. The research area covered a total area of 6.27 km^2. McDougall street was chosen as a specific network for the study. The network was delineated into a catchment of three land-uses, that is buildings, recreational/parks, and river body. Given that stormwater pipe network is constructed with reference to zoning to in the vicinity. For the buildings, a sub-catchment was created and grouped into two types, that is, commercial and residential buildings. The commercial buildings include hospitals, factories and schools. The stormwater pipes in this area were built over a range of years, from 1910 to 2012. The digital model included actual land use in this area. Google maps were used to identify and indicate the specific land use in the digital model.

Figure 5-2: A graphical representation of Ward 3

As indicated in Chapter three of this study, the Markov Chain was used to forecast the future condition of the stormwater pipes. Mailhot et al. (2000) and Wirahadikusumah et al. (1999) developed a 20-year condition prediction model for stormwater pipes. Marzouk & Omar, (2013) endorsed a condition prediction model for stormwater should be 20 years. Hence, this study establishes a 20-year evaluation period for the stormwater pipes to predict condition. The current physical condition of each of the four segments during the time of study has been displayed in Table 5-2. This information was obtained after consulting engineers from the municipality.

Table 5-2: indicates the current physical condition of each stormwater segment

Segment	Current Physical Condition
943	4
944	5
945	4
946	5

InfraWorks model has an in-built measure tool that is capable of measuring point-to-point distance. This feature will be used in automating the distance measurement in the algorithm. Table 5-3 presents the distances to main land use types in the study region.

Table 5-3: Illustrates samples of 10 different segment distances measured to the land use

Storm sewer ID	Land Use Type	Distance of Pipe (m)
943	Building	11.50
944	Building	11.40
945	Building	11.70
946	Building	10.70
954	Building	10.60
960	Building	2.60
7145	Commercial Building	64.90
6511	Commercial Buildings	50.20
7150	Commercial Buildings	14.90
1118	Commercial Building	9.80
1108	Commercial Building	4.0

5.2.1 Benchmarks for stormwater systems

To determine the physical condition of stormwater pipes, a set of constraints were defined after consulting an engineer from the City of Windsor. Table 5-4 presents the constraint sets for this study. A retrofit action is implemented before/after the threshold for repair have been met.

Table 5-4: Benchmarks for each criterion

Criteria	Threshold	Target
Condition	3.5	5
Risk	0.80	0.10
Annual budget	CAD 5,000	N/A

5.3 Results

Table 5-5 and Table 5-6 present the recommended maintenance actions and optimal solutions for 4 selected segments in the research area. With respect to prioritization in the DS-based model, the tool predicted the maintenance actions to be undertaken by the decision-maker. Figure 5-3 shows the prioritization based on the risk and condition of the various segment as well as the cost of budget constraint for decision making. Table 5-6 presents the minimum condition rating, maximum risk level, and minimum LCC for each segment for the 20-year horizon. For segment 943, the minimum condition rating was 4.21 maximum risk was 0.71, and the minimum LCC was CAD 30,500. For segment 944, the minimum condition rating was 3.58, a maximum risk level of 0.83, and LCC is CAD 57,800. In addition, a minimum suggested condition rating for segment 945 was 357 whilst the maximum risk and minimum LCC were 0.84 and CAD 65,200 respectively. Again, for segment 946, the minimum condition rating is 3.51, a maximum risk level is 0.85, and LCC is CAD 45,400

Table 5-5: DS-based maintenance plan for the 20-year planning horizon

Year	Segment 943	Segment 944	Segment 945	Segment 946
1	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
2	MINOR REPAIR	DO_NOTHING	MINOR_REPAIR	DO_NOTHING
3	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
4	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
5	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
6	DO_NOTHING	REPLACE	DO_NOTHING	DO_NOTHING
7	DO_NOTHING	DO_NOTHING	REPLACE	MAJOR_REPAIR
8	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
9	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
10	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
11	DO_NOTHING	MAJOR_REPAIR	DO_NOTHING	DO_NOTHING
12	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
13	DO_NOTHING	DO_NOTHING	MAJOR_REPAIR	DO_NOTHING
14	DO_NOTHING	MINOR_REPAIR	DO_NOTHING	MINOR_REPAIR
15	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
16	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
17	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
18	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
19	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
20	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING

Table 5-6: DS-based optimal result for the 20-year planning horizon

Segment _ID	Minimum Condition Rating	Maximum Risk Level	Minimum LCC (CAD)
943	4.21	0.71	$30,500
944	3.58	0.83	$57,800
945	3.56	0.84	$65,200
946	3.51	0.85	$45,400

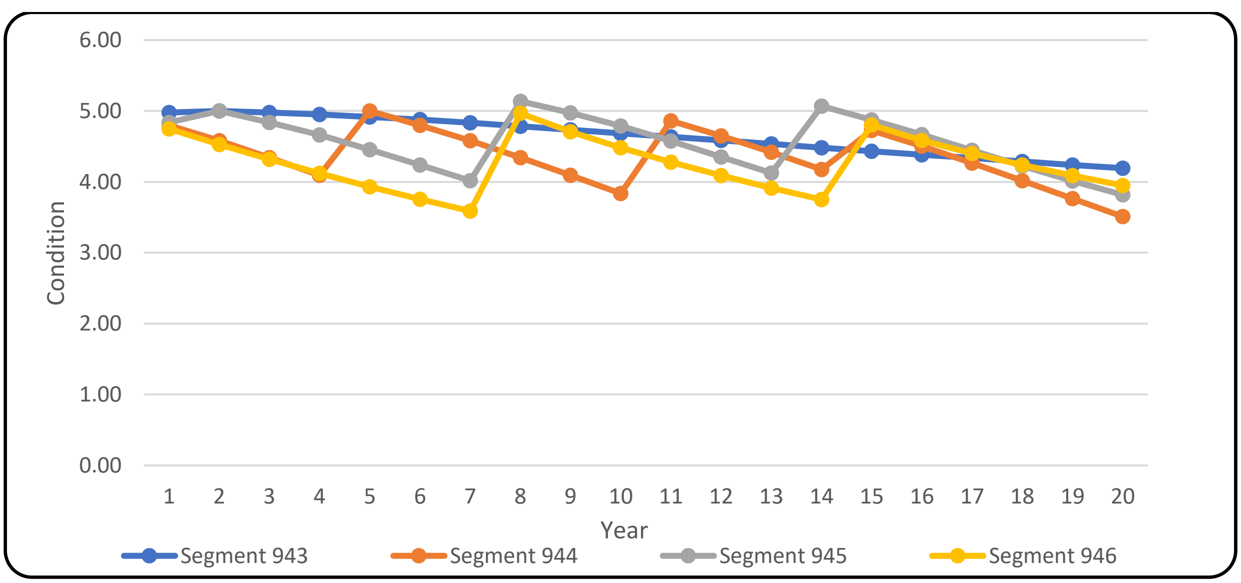
As shown in Figure 5-3, the segment with the initial highest risk is given priority before the other segments. A notable example is segment 943 and segment 945. These two segments have been selected for maintenance since they have the highest risk level in year 1 and year 2 respectively. However, in years 3 and 4, all the segments were within the acceptable limit, hence, no retrofit action was implemented. The DS-based does the prioritization based on the annual budget available while considering the risk level and condition rating. The DS-based tool forecast the cost associated with each maintenance action thereby informing the decision-maker about the funds required should any decision be taken. As result, the proposed DS-based model makes prioritization in stormwater asset management decision-making easy and quick.

```
Year 1
******************************
Segment: 943 | Risk:0.75 | Retrofit Action: 2.00 | Maintenance Cost: 5000.00 | 1
Segment: 945 | Risk:0.75 | Retrofit Action: 1.00 | Maintenance Cost: 165.00 | 0
Segment: 946 | Risk:0.60 | Retrofit Action: 1.00 | Maintenance Cost: 200.00 | 0
Segment: 946 | Risk:0.60 | Retrofit Action: 1.00 | Maintenance Cost: 185.00 | 0

Year 2
******************************
Segment: 945 | Risk:0.81 | Retrofit Action: 2.00 | Maintenance Cost: 4763.75 | 1
Segment: 944 | Risk:0.62 | Retrofit Action: 1.00 | Maintenance Cost: 169.95 | 0
Segment: 946 | Risk:0.63 | Retrofit Action: 1.00 | Maintenance Cost: 206.00 | 0
Segment: 943 | Risk:0.60 | Retrofit Action: 1.00 | Maintenance Cost: 206.00 | 0
```

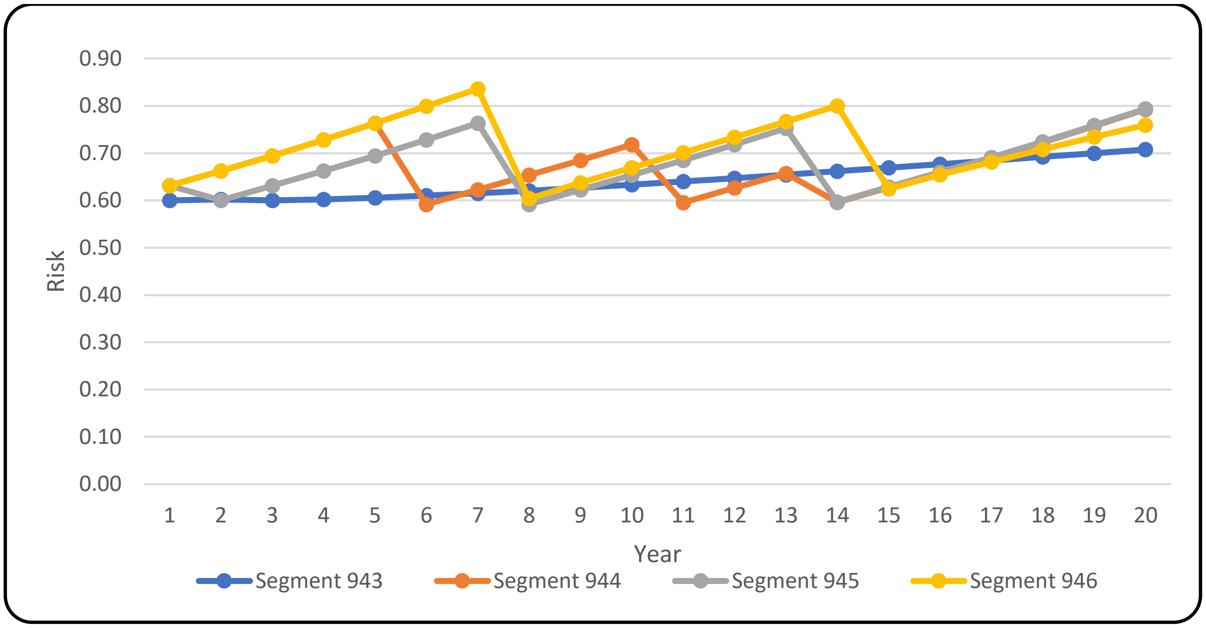
```
Year 3
******************************
Segment: 944 | Risk:0.66 | Retrofit Action: 1.00 | Maintenance Cost: 175.05 | 0
Segment: 946 | Risk:0.66 | Retrofit Action: 1.00 | Maintenance Cost: 212.18 | 0
Segment: 943 | Risk:0.60 | Retrofit Action: 1.00 | Maintenance Cost: 212.18 | 0
Segment: 945 | Risk:0.64 | Retrofit Action: 1.00 | Maintenance Cost: 196.27 | 0

Year 4
******************************
Segment: 944 | Risk:0.69 | Retrofit Action: 1.00 | Maintenance Cost: 180.30 | 0
Segment: 946 | Risk:0.69 | Retrofit Action: 1.00 | Maintenance Cost: 218.55 | 0
Segment: 943 | Risk:0.61 | Retrofit Action: 1.00 | Maintenance Cost: 218.55 | 0
Segment: 945 | Risk:0.66 | Retrofit Action: 1.00 | Maintenance Cost: 202.15 | 0
```

Figure 5-3: Illustration of the prioritization approach for the DS-based tool

Figure 5-4 illustrates how the optimized physical condition and risk of failure changes for the different segments over the years for the stormwater infrastructure. As illustrated in Figure 5-4, physical condition (Figure 4-5(a)), and risk (Figure 4-5(b)), of stormwater infrastructure systems change annually based on the constraints set for the algorithm. Thus, a threshold of 3.5 was set for the physical condition and 0.80 for the risk level. However, the relative risk levels remain the same despite the scenario. This is due to the assumption that the consequences of failure do not change with time for the various segments. Hence, in a budget-constrained scenario, it is important to identify stormwater infrastructure systems with the highest risk at a specific period to prioritize the systems which require urgent interventions.



(a) Physical condition



(b) Risk level

Figure 5-4: Physical condition and Risk of failure states of optimal DS-based model result

5.3.1 Conventional Method of Stormwater Infrastructure Management

Table 5-7 and Table 5-8 present the recommended maintenance actions and optimal solutions for 4 selected segments in the research area for the conventional model respectively. This model was developed in an excel platform to enable the comparison with the DS-based model in this study. A replacement of the asset is recommended as the maintenance action for the various segment upon failure of the pipe as shown in Table 5-7. Therefore, depending on the implementation of the recommended maintenance action within 20 years, Table 5-8 results suggested the minimum condition rating, maximum risk level, and minimum LCC that the various segments experienced. The results indicated that segment 943 experienced a minimum condition rating of 2.01, a maximum risk level of 1.49, and a minimum LCC of CAD 36,900 throughout the 20-year planning horizon. Similarly, a minimum condition rating of 2.07, a maximum risk level of 1.45, and a minimum LCC of CAD 29,800 was suggested for segment 944. Again, the suggested minimum condition rating for segment 945 was 2.54 whilst the suggested maximum risk and minimum LCC were 1.18 and CAD 21,300 respectively. For segment 946, a minimum condition rating of 2.60, a maximum risk level of 1.15, and a minimum LCC of CAD 23,000 was suggested.

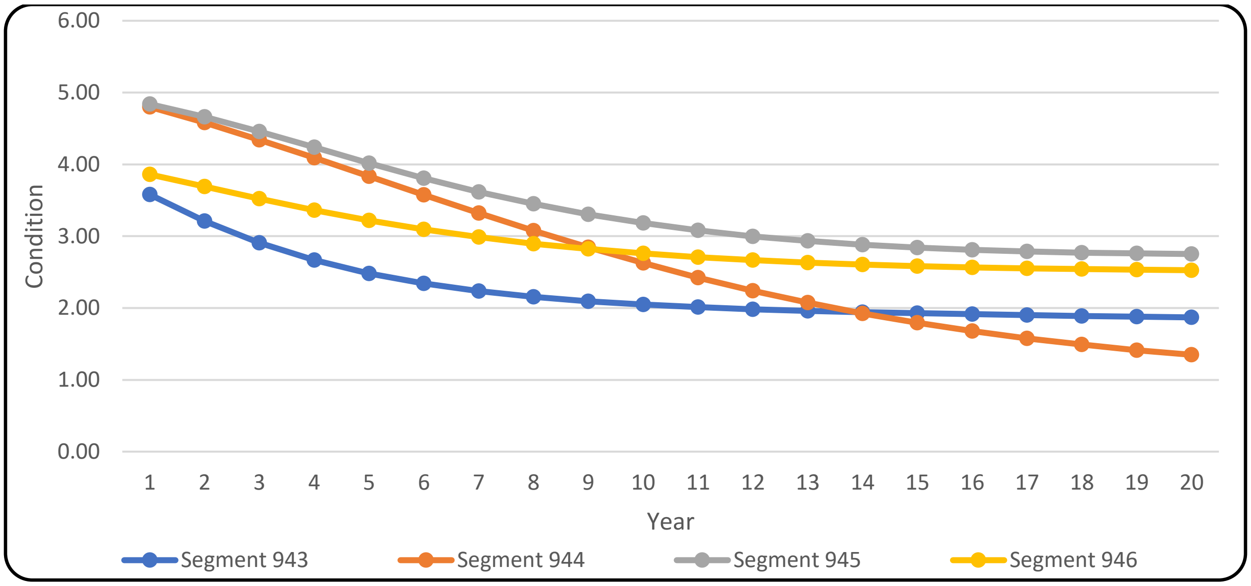
Table 5-7: Conventional maintenance plan for the 20-year planning horizon

Year	Segment 943	Segment 944	Segment 945	Segment 946
1	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
2	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
3	DO_NOTHING	REPLACE	DO_NOTHING	DO_NOTHING
4	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
5	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
6	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
7	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
8	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
9	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
10	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
11	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
12	REPLACE	DO_NOTHING	DO_NOTHING	DO_NOTHING
13	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
14	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
15	DO_NOTHING	REPLACE	DO_NOTHING	DO_NOTHING
16	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
17	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
18	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
19	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING
20	DO_NOTHING	DO_NOTHING	DO_NOTHING	DO_NOTHING

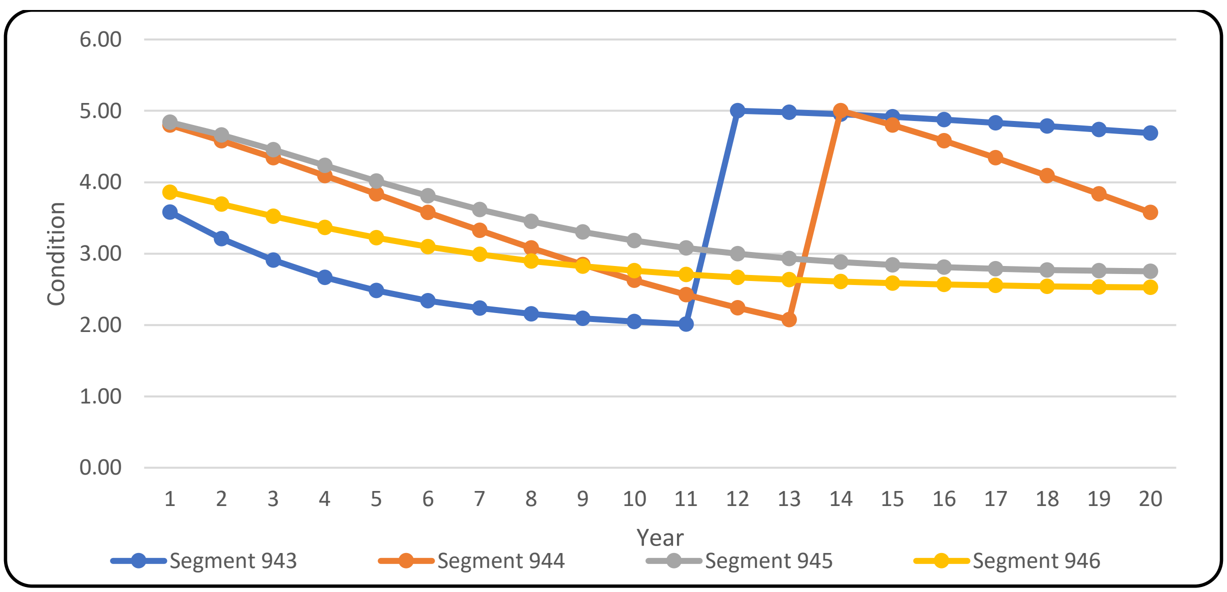
Table 5-8: Conventional method result for a 20-year planning horizon

Segment _ID	Minimum Condition Rating	Maximum Risk Level	Minimum LCC (CAD)
943	2.01	1.49	$ 36,900
944	2.07	1.45	$ 29,800
945	2.54	1.18	$ 21,300
946	2.60	1.15	$ 23,000

Figure 5-5 illustrates how the physical condition changes for the different segments over the years for the stormwater infrastructure without intervention. As illustrated in Figure 5-5 (a), the physical condition deteriorates without any intervention until the asset fails. Based on Figure 5.5 (a), segment 943 failed in year 12 while segment 944 failed in year 14. Similarly, Figure 5-5 (b) presents a scenario where interventions are implemented for segment 943 and segment 944, leading to an improved physical condition. Thus, it takes the physical condition from 2 which is the failed state to 5 which is the pristine state. However, such an approach to managing stormwater infrastructure systems can lead to disruptions like flooding, sudden collapse, and damage to businesses and stakeholders. Therefore, it is recommended to adopt a proactive way that can keep the stormwater operational without such disruptions.



(a) Routine inspection without intervention



(b) Routine inspection with interventions

Figure 5-5: Routine inspection with/out intervention of the Conventional model

5.3.2 Cost of Damage of Conventional Model

Defective stormwater pipes may lead to flooding and contamination of drinking water sources (Baah et al., 2015). Flooding mostly occurs when a pipe network fails. Flooding is one of the most expensive risks for Canadian municipalities, which recently surpassed fire and theft as the leading causes of property insurance claims (KPMG, 2014). According to the Insurance Bureau of Canada (2022), the average cost of repair of an average flooded basement is CAD 43,000. For this study, a pipe segment was considered to cover 5 lots, indicating that 5 properties are within the segment. Segment 943 and segment 944 failed at year 12 and 14 respectively. Since, flooding is mostly associated to pipe failure, it implies that an extra cost of damage would be incurred upon the pipe segment failure. The total cost of damage used in this study was CAD 430,000. This was calculated as a product of the damage cost and the 10 properties within the two-pipe segment.

5.3.3 Analyzing DS-based Model and Conventional Model Results

Table 5-9 presents the various LCCs of the selected segments for a 20-year planning period for both approaches. Further, the total network's LCC was calculated. Based on the result presented in Table 5-9, the total LCC of the selected stormwater segment for the DS-based model was CAD 198,900 while the conventional model was CAD 111,00. However, since segment 943 and segment 944 failed, the extra cost incurred was added to the conventional network LCC. Therefore, the total LCC for the conventional model network is CAD 541,000. This indicated that the DS-based model is about 63% more cost-efficient than the conventional approach.

Table 5-9: Analyzing LCC of DS-based model and Conventional model

Segment_ID	LCC of DS-Based Approach	LCC of Conventional Approach
943	$30,500	$36,900
944	$57,800	$29,800
945	$65,200	$21,300
946	$45,400	$23,000
Damage Cost	-	$430,000
Network Total	**CAD** 198,900	**CAD** 541,000

Based on the recommended solutions, the DS-based outperformed the conventional model. This was because maintenance actions were implemented only when the asset had failed. Thus, it does not consider periodic maintenance during the planning horizon. Moreover, the recommended solution for the conventional model has the condition rating and risk level below the acceptable limits. Hence, the poor condition rating and low-risk level indicate that the various segments might not meet the stakeholder's requirements. Additionally, the conventional model which represents a reactive approach to the management of infrastructure is fading out and it is much recommended to tackle such a problem from proactive management. Thus, it is best recommended to keep the infrastructure system at an acceptable threshold where the asset will meet the user's demand.

5.4 Summary

The proposed DS-based predictive maintenance planning tool for stormwater infrastructure was demonstrated using a case study. This assessment was conducted on selected stormwater pipes located in Ward 3, City of Windsor. The physical condition inspection report and maintenance data were initially used to develop the digital shadow of the stormwater infrastructure.

The outcome of the DS-based model had an average condition rating of 3.72 and an average risk level of 0.81 during the planning period. Unlike the DS-based model, the conventional model had an average condition rating and risk rating of 2.31 and 1.32 respectively. The result has shown that the DS-based model maintains an acceptable condition rating and risk level throughout the planning horizon while the conventional model does otherwise. However, due to the periodic maintenance occurring in the DS-based model the total network LCC was about 63% less than a conventional model. Although the DS-based LCC is moderately low, the condition rating and risk level of the pipe network were within acceptable limits.

6 CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

Proactive stormwater infrastructure management is an integrated data-driven decision-making process. This research developed a methodological framework and a DS-based decision support tool for stormwater infrastructure management. The proposed method was demonstrated by using a case study where traditional and proposed methods were compared. The main conclusions of this research are as follows:

- The proposed methodological framework and decision support tool can predict the maintenance requirements of stormwater infrastructure systems. A case study was conducted to verify the proposed methodological framework's capabilities. The case study revealed that the DS-based model was more cost efficient than the conventional approach. Moreover, the DS-based model prevented the extra damage cost that was incurred in the conventional model due to it preventative maintenance schedule.
- The following conclusions can be made based on the comparison of the DS-based proactive asset management method versus the traditional infrastructure management method.
    - The LCC of the DS-based method is about 63% less than the conventional stormwater infrastructure management in long-term planning. This can be attributed to the fact that the DS-based model keeps the asset in a good condition all the time based on the timely implementation of the maintenance action thereby avoiding the cost of damaged incurred in the conventional model.
    - The physical condition of the DS-based model was better than the conventional method. Similarly, the DS-based model was capable of maintaining an average condition rating of 3.72 when implementing the recommended maintenance actions.
- The DS-based model kept the average risk of failure at a 0.81 rating. The reduction in risk of failure by the DS-based model boosts the stakeholder's confidence compared to the conventional approach where the risk of failure is high. Also, research has shown that a high risk of failure results indicates a sudden interruption in the infrastructure asset performance. Hence, the conventional model would be experiencing intermittent flooding or collapse due to the high risk of failure level.

- Unlike the conventional approach, the proposed DS-based approach can simulate the planning, design, construction and operation of an infrastructure by using computer generated models. This will aid municipal asset managers to eliminate data fragmentation challenges in infrastructure management. Other operational benefits of the proposed approach are as follows:
    - The DS-based model also provides a digital visualization (3D) of the stormwater infrastructure system as compared to conventional practice.
    - The DS-based model provides long-term maintenance data for the planning horizon.
    - The DS-based model provides data on the risk level and LCC for the planning horizon
    - The DS-based model aids in maintaining the physical condition of the infrastructure while ensuring its performance.

6.2 Contributions

The main contributions of this research are as follows:

Using a digital shadow for proactive stormwater infrastructure management: In the context of smart infrastructure management, predictive maintenance planning is vital. Previous researchers have developed various predictive maintenance tools that have used GIS data. The proposed study uses a digital shadow for a predictive maintenance planning approach that facilitates proactive management of the stormwater infrastructure. The implementation of the proposed tool will answer the questions: which should be the maintenance strategy? What funds are required to maintain the infrastructure system? The outcome of the model can help capital budget planning for stormwater infrastructure and boost stakeholders' confidence. Furthermore, the proposed DS-based tool advocates and promotes the digitalization of stormwater infrastructure.

An automated tool for proactive infrastructure management: Literature has revealed the lack of automation in the construction industry. Although there have been several tools developed for the management of stormwater infrastructure, these tools are yet to be automated. However, the proposed DS-based model was developed to function as an automated tool that can automatically forecast the maintenance action required, future conditions, and risk level throughout the estimated lifecycle of the stormwater infrastructure.

The proposed tool is a user-friendly decision support tool for proactive management of stormwater infrastructure and other linear infrastructures. Moreover, the integration of DS with the BIM model provides the users with a visualization feature that makes infrastructure analysis easy. This makes the DS-based model more comprehensive for proactive management strategy compared to the conventional approaches.

6.3 Limitations

The following are the limitations of the deliverables of this research:

Data unavailability and uncertainty: There was a lack of physical condition data to develop the TPMs of the various segment. Hence, literature-based data was used for TPM. Therefore, the simulated TPMs may not have accurately represented the local context of the study. Moreover, the data unavailability could have affected the optimal maintenance plan.

Limitations with risk assessment: Due to the data unavailability, the study ignored some factors that can influence the risk assessment such as the catchment area, hydrological flow, and rainfall intensity within the area of study. It is necessary to incorporate such parameters into the model and determine the potential consequences of flooding.

***Interoperability issues in the BIM platform*:** Given that the GIS shapefile was not developed as Industry Foundation Classes (IFCs) or XML spec, importing it into the BIM environment resulted in some data fragmentation. Therefore, it is recommended to create the stormwater shapefiles in the IFCs and XML formats to allow for data exchange in the BIM model.

6.4 Recommendation and Future Research

The following research will further enhance the DS-based tool and the methodological framework proposed in this research:

- Several factors that affect the deterioration of stormwater pipes were ignored due to data unavailability. It is recommended to investigate the various factors that affect the deterioration of stormwater infrastructure with a suitable mathematical method.
- It is recommended that an uncertainty analysis approach such as fuzzy set theory should be utilized to investigate the impact of data uncertainties on the results. This approach can help resolve data ambiguity in this research.

- It is recommended that the level of the service of stormwater infrastructure be integrated into the model. This will enable ensuring a satisfactory service level.
- The study ignored watersheds in the study area. It is recommended to include a watershed in the research area since it influences the volume of water that runs through the stormwater pipe thereby impacting the deterioration rate and risk.
- It is recommended to collect condition data of infrastructure to enhance the accuracy of TPM. This will increase the accuracy of the predictive maintenance plan.

REFERENCES/BIBLIOGRAPHY

Abbasnejad, B., Nepal, M. P., Ahankoob, A., Nasirian, A., & Drogemuller, R. (2021). Building Information Modelling (BIM) adoption and implementation enablers in AEC firms: a systematic literature review. *Architectural Engineering and Design Management*, *17*(5–6), 411–433.

Abraham, D. M., Wirahadikusumah, R., Short, T. J., & Shahbahrami, S. (1998). Optimization modeling for sewer network management. *Journal of Construction Engineering and Management*, *124*(5), 402–410.

Abu-Samra, S., Ahmed, M., & Amador, L. (2020). Asset management framework for integrated municipal infrastructure. Journal of Infrastructure Systems, 26(4), 04020039.

Abu Samra, S., Ahmed, M., Hammad, A., & Zayed, T. (2018). Multiobjective Framework for Managing Municipal Integrated Infrastructure. *Journal of Construction Engineering and Management*, *144*(1), 04017091.

Afsari, K., & Eastman, C. M. (2016). A comparison of construction classification systems used for classifying building product models. *52nd ASC Annual International Conference Proceedings*, 1–8.

Akcamete, A., Akinci, B., & Garrett, J. H. (2010). Potential utilization of building information models for planning maintenance activities. *Proceedings of the International Conference on Computing in Civil and Building Engineering*, *2010*, 151–157.

Alavi, A. H., Jiao, P., Buttlar, W. G., & Lajnef, N. (2018). Internet of Things-enabled smart cities: State-of-the-art and future trends. *Measurement*, *129*, 589–606.

Alavi, H., Bortolini, R., & Forcada, N. (2022). BIM-based decision support for building condition assessment. *Automation in Construction*, *135*, 104117.

Alegre, H., & Coelho, S. T. (2012). Infrastructure asset management of urban water systems. *Water Supply System Analysis-Selected Topics*, 49–73.

Ammar, M., Zayed, T., & Moselhi, O. (2013). Fuzzy-Based Life-Cycle Cost Model for Decision Making under Subjectivity. *Journal of Construction Engineering and Management*, *139*(5), 556–563.

Ana, E., Bauwens, W., Pessemier, M., Thoeye, C., Smolders, S., Boonen, I., & De Gueldre, G. (2009). An investigation of the factors influencing sewer structural deterioration. *Urban Water Journal*, *6*(4), 303–312.

Ani, A. I. C., Johar, S., Tawil, N. M., Abd Razak, M. Z., & Hamzah, N. (2015). Building information modeling (BIM)-based building condition assessment: A survey of water ponding defects on a flat roof. *Jurnal Teknologi*, *75*(9).

Ariaratnam, S. T., El-Assaly, A., & Yang, Y. (2001). Assessment of infrastructure inspection needs using logistic models. *Journal of Infrastructure Systems*, *7*(4), 160–165.

Arif, F., Bayraktar, M. E., & Chowdhury, A. G. (2016). Decision support framework for infrastructure maintenance investment decision making. *Journal of Management in Engineering*, *32*(1), 4015030.

Water Authorities Association. (1990). Sewerage rehabilitation manual. Water Research Center: London, UK.

Atef, A., Osman, H., & Moselhi, O. (2012). Multiobjective genetic algorithm to allocate budgetary resources for condition assessment of water and sewer networks. *Canadian Journal of Civil Engineering*, *39*(9), 978–992. https://doi.org/10.1139/L2012-049

Baah, K., Dubey, B., Harvey, R., & McBean, E. (2015). A risk-based approach to sanitary sewer pipe asset management. *Science of the Total Environment*, *505*, 1011–1017.

Baik, H.-S., Jeong, H. S., & Abraham, D. M. (2006). Estimating Transition Probabilities in Markov Chain-Based Deterioration Models for Management of Wastewater Systems. *Journal of Water Resources Planning and Management*, *132*(1), 15–24.

Barbosa, A. E., Fernandes, J. N., & David, L. M. (2012). Key issues for sustainable urban stormwater management. *Water Research*, *46*(20), 6787–6798.

Baur, R., & Herz, R. (2002). Selective inspection planning with ageing forecast for sewer types. *Water Science and Technology*, *46*(6–7), 389–396.

Beitelmal, W., Molenaar, K. R., Javernick-Will, A., & Pellicer, E. (2017). Challenges and barriers to establishing infrastructure asset management: A comparative study between Libya and the USA. *Engineering, Construction and Architectural Management*.

Ben-Akiva, M., & Gopinath, D. (1995). Modeling infrastructure performance and user costs. *Journal of Infrastructure Systems*, *1*(1), 33–43.

Bengassem, J., & Bennis, S. (2000). Fuzzy expert system for sewer networks diagnosis. *Proceedings of the International Conference on Decision Making in Urban and Civil Engineering*.

Bhave, P. R., & Gupta, R. (2006). *Analysis of water distribution networks*. Alpha Science Int'l Ltd.

Black, M., Brint, A. T., & Brailsford, J. R. (2005). A semi-Markov approach for modelling asset deterioration. Journal of the Operational Research Society, 56(11), 1241-1249.

Boulos, B. P. F. (2010). *Using Risk-Based GIS Modeling Software to Optimize Sewer Renewal Planning*.

Butt, A. A., Shahin, M. Y., Feighan, K. J., & Carpenter, S. H. (1987). Pavement performance prediction model using the Markov process (No. 1123).

Callcut, M., Cerceau Agliozzo, J.-P., Varga, L., & McMillan, L. (2021). Digital Twins in Civil Infrastructure Systems. *Sustainability*, *13*(20), 11549.

Carlson, C., Barreteau, O., Kirshen, P., & Foltz, K. (2015). Storm water management as a public good provision problem: Survey to understand perspectives of low-impact development for urban storm water management practices under climate change. *Journal of Water Resources Planning and Management*, *141*(6), 4014080.

Castro-Lacouture, D., Quan, S. J., & Yang, P. P.-J. (2014). GIS-BIM framework for integrating urban systems, waste stream and algal cultivation in residential construction. *ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction*, *31*, 1.

Chang, J.-R., Chen, S.-H., Chen, D.-H., & Liu, Y.-B. (2008). Rutting prediction model developed by genetic programming method through full scale accelerated pavement testing. *2008 Fourth International Conference on Natural Computation*, *6*, 326–330.

Chappell, E. (2015). *Autodesk InfraWorks 360 and autodesk InfraWorks 360 LT essentials*. John Wiley & Sons.

Chen, L., & Bai, Q. (2019). *Optimization in Decision Making in Infrastructure Asset Management : A Review*.

Chen, Z., Liang, Y., Wu, Y., & Sun, L. (2019). *Research on Comprehensive Multi-Infrastructure Optimization in Transportation Asset Management : The Case of Roads and Bridges*.

Cheng, J. C. P., Chen, W., Tan, Y., & Wang, M. (2016). A BIM-based decision support system framework for predictive maintenance management of building facilities. *Proceedings of the 16th International Conference on Computing in Civil and Building Engineering (ICCCBE2016)*.

Chong, H. Y., Lopez, R., Wang, J., Wang, X., & Zhao, Z. (2016). Comparative analysis on the adoption and use of BIM in road infrastructure projects. *Journal of Management in Engineering*, *32*(6), 5016021.

Chow, C. K., Tsui, H. T., & Lee, T. (2004). Surface registration using a dynamic genetic algorithm. *Pattern Recognition*, *37*(1), 105–117.

Chughtai, F., & Zayed, T. (2008). Infrastructure condition prediction models for sustainable sewer pipelines. *Journal of Performance of Constructed Facilities*, *22*(5), 333–341.

CIRC. (2019). Canada Infrastructure Report Card 2019. *Circ*, 1–56. http://canadianinfrastructure.ca/en/about.html

Cook, L. M., McGinnis, S., & Samaras, C. (2020). The effect of modeling choices on updating intensity-duration-frequency curves and stormwater infrastructure designs for climate change. Climatic Change, 159(2), 289-308.

Council, N. R. (1995). *Measuring and improving infrastructure performance*. National Academies Press.

Daher, S., Zayed, T., & Hawari, A. (2021). Defect-Based Condition Assessment Model for Sewer Pipelines Using Fuzzy Hierarchical Evidential Reasoning. *Journal of Performance of Constructed Facilities*, *35*(1), 4020142.

Dávila Aquije, D. (2016). *Paying for stormwater management: What are the options?* Institute on Municipal Finance and Governance.

De Gueldre, G., Herzeele, F. Van, Boonen, I., Thoeye, C., & Steene, B. Van De. (2007). Hydroplan-EU : An integrated approach for sewer asset management Hydroplan-EU : Un outil intégré pour la gestion des égouts. *Novatech*, 1–8.

De Paola, F., Giugni, M., Pugliese, F., & Romano, P. (2018). Optimal design of LIDs in urban stormwater systems using a harmony-search decision support system. *Water Resources Management*, *32*(15), 4933–4951.

Demello, J. (2017). *Using Stormwater Compliance to Drive Better Sewer System Planning - Woodard & Curran*. https://www.woodardcurran.com/using-stormwater-compliance-to-drive-better-sewer-system-planning-2/

Dirksen, J., Clemens, F., Korving, H., Cherqui, F., Le Gauffre, P., Ertl, T., Plihal, H., Müller, K., & Snaterse, C. T. M. (2013). The consistency of visual sewer inspection data. *Structure and Infrastructure Engineering*, *9*(3), 214–228.

Eastman, C. M., Eastman, C., Teicholz, P., Sacks, R., & Liston, K. (2011). *BIM handbook: A guide to building information modeling for owners, managers, designers, engineers and contractors*. John Wiley & Sons.

Eastman, C., Teicholz, P., Sacks, R., & Liston, K. (2008). BIM Tools and Parametric Modeling.

BIM Handbook, 25–64.

Ebtehaj, I., & Bonakdari, H. (2013). Evaluation of sediment transport in sewer using artificial neural network. *Engineering Applications of Computational Fluid Mechanics*, *7*(3), 382–392.

Edirisinghe, R., Setunge, S., & Zhang, G. (2015). Markov Model—Based Building Deterioration Prediction and ISO Factor Analysis for Building Management. *Journal of Management in Engineering*, *31*(6), 04015009.

Eggimann, S., Mutzner, L., Wani, O., Schneider, M. Y., Spuhler, D., Moy de Vitry, M., Beutler, P., & Maurer, M. (2017). The potential of knowing more: A review of data-driven urban water management. *Environmental Science & Technology*, *51*(5), 2538–2553.

Elbeltagi, I. A., Elbeltage, E. E., & Dawood, M. A. (2013). Frame Work of Condition Assessment for Sewer Pipelines. International Journal of Engineering Research and Applications (IJERA), 3, 1833-1844.

Elhakeem, A. A. M. (2006). An asset management framework for educational buildings with life -cycle cost analysis. In *ProQuest Dissertations and Theses* (p. 152).

Ens, A. (2012). Development of a flexible framework for deterioration modelling in infrastructure asset management (Doctoral dissertation, University of Toronto).

Environmental Commission of Ontario (ECO). 2016. Urban Stormwater Fees: How to Pay for What We Need. Toronto, ON: ECO. https://media.assets.eco.on.ca/web/2016/11/Urban-Stormwater-Fees.pdf

EP-C, E. C. N. (2017). Asset Management Programs for Stormwater and Wastewater Systems: Overcoming Barriers to Development and Implementation.

Fane, S., Willetts, J., Abeysuriya, K., Mitchell, C., Etnier, C., & Johnstone, S. (2004). Evaluating reliability and life-cycle cost for decentralized wastewater within the context of asset management. *Proceedings of 6th Specialist Conference on Small Water & Wastewater Systems and 1st International Conference on Onsite Wastewater Treatment & Recycling*.

Fanning, B., Clevenger, C. M., Ozbek, M. E., & Mahmoud, H. (2015). Implementing BIM on infrastructure: Comparison of two bridge construction projects. *Practice Periodical on Structural Design and Construction*, *20*(4), 4014044.

Fares, H., & 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.

FCM. (2018). *Asset Management 101*, 1–32.

Fenner, R. A. (2000). Approaches to sewer maintenance: a review. *Urban Water*, *2*(4), 343–356.

Flintsch, G. W., & Chen, C. (2004). Soft Computing Applications in Infrastructure Management. *Journal of Infrastructure Systems*, *10*(4), 157–166.

Franco-Duran, D. M., & Mejia A, G. (2016). Construction Research Congress 2016 2039. *PROCEEDINGS Construction Research Congress 2016*, *2008*, 2039–2049.

Frangopol, D., Bocchini, P., Kim, S., & Okasha, N. M. (2012). *Integrated Life-Cycle Framework for Maintenance , Monitoring , and Reliability of Naval Ship Structures*. *January 2015*.

Frangopol, D. M., & Neves, L. C. (2004). *Probabilistic maintenance and optimization strategies for deteriorating civil infrastructures*.

Geem, Z. W., Tseng, C.-L., Kim, J., & Bae, C. (2007). Trenchless water pipe condition assessment using artificial neural network. In *Pipelines 2007: Advances and Experiences with Trenchless Pipeline Projects* (pp. 1–9).

Gharehbaghi, K and Georgy, M. (2015). Utilization of Infrastructure Gateway System (IGS) as a transportation infrastructure optimization tool. *International Journal of Traffic and Transportation Engineering*, *4*(1), 8.

Grefenstette, J. J. (1993). Genetic algorithms and machine learning. *Proceedings of the Sixth Annual Conference on Computational Learning Theory*, 3–4.

Grigg, N. S. (2006). Condition Assessment of Water Distribution Pipes. *Journal of Infrastructure Systems*, *12*(3), 147–153.

Grigg, N. S. (2012). Water, Wastewater, and Stormwater Infrastructure Management. In *Water, Wastewater, and Stormwater Infrastructure Management*.

Grilo, A., & Jardim-Goncalves, R. (2010). Value proposition on interoperability of BIM and collaborative working environments. *Automation in Construction*, *19*(5), 522–530.

Grimsey, D., & Lewis, M. K. (2002). Accounting for public private partnerships. *Accounting Forum*, *26*(3–4), 245–270.

Group, B. I. M. T. (2012). *The government soft landings policy*. Cabinet Office London.

Grussing, M. N. (2015). *Risk-based facility management approach for building components using a discrete markov process - Predicting condition, reliability, and remaining service life*.

Guzmán-Fierro, J., Charry, S., González, I., Peña-Heredia, F., Hernández, N., Luna-Acosta, A., & Torres, A. (2020). Bayesian network-based methodology for selecting a cost-effective sewer asset management model. *Water Science and Technology*, *81*(11), 2422–2431.

Haghighi, A., & Bakhshipour, A. E. (2012). Optimization of sewer networks using an adaptive genetic algorithm. *Water Resources Management*, *26*(12), 3441–3456.

Hahn, M. A., Palmer, R. N., Merrill, M. S., & Lukas, A. B. (2002). Expert system for prioritizing the inspection of sewers: Knowledge base formulation and evaluation. *Journal of Water Resources Planning and Management*, *128*(2), 121–129.

Haider, A. (2012). *Information systems for engineering and infrastructure asset management*. Springer Science & Business Media.

Halfawy, M. R. (2008). Integration of Municipal Infrastructure Asset Management Processes: Challenges and Solutions. *Journal of Computing in Civil Engineering*, *22*(3), 216–229.

Halfawy, M. R., Dridi, L., & Baker, S. (2008). Integrated decision support system for optimal renewal planning of sewer networks. *Journal of Computing in Civil Engineering*, *22*(6), 360–372.

Halfawy, M. R., Pyzoha, D., & El-Hosseiny, T. (2002). An integrated framework for GIS-based civil infrastructure management systems. *Proceedings, Annual Conference - Canadian Society for Civil Engineering*, *2002*(January 2015), 83–92.

Harral, C., & Asif, F. (1998). *Road Deterioration in Developing Countries: Causes and Remedies. World Bank.*

Harvey, R., de Lange, M., McBean, E., Trenouth, W., Singh, A., & James, P. (2017). Asset condition assessment of municipal drinking water, wastewater and stormwater systems–Challenges and directions forward. *Canadian Water Resources Journal/Revue Canadienne Des Ressources Hydriques*, *42*(2), 138–148.

Hawari, A., Alkadour, F., Elmasry, M., & Zayed, T. (2020). A state of the art review on condition assessment models developed for sewer pipelines. *Engineering Applications of Artificial Intelligence*, *93*, 103721.

Heaton, J., Parlikad, A. K., & Schooling, J. (2019). Design and development of BIM models to support operations and maintenance. *Computers in Industry*, *111*, 172–186.

Hess, J. (2015). Assessing the condition and consequence of failure of pipes crossing major transportation corridors. In *Pipelines 2015* (pp. 1750–1761).

Hessami, A. R., Anderson, S. D., & Smith, R. E. (2021). Levels of Uncertainty in Infrastructure Asset Management. In *Transportation Research Record: Journal of the Transportation Research Board* (p. 036119812199184).

Horoshenkov, K. V, Long, R. J., & Tait, S. J. (2010). Improvements in and relating to apparatus for the airborne acoustic inspection of pipes. *Patent Application WO2010020817, 25/02/2010*.

Hudson, W. R., & Hudson, S. W. (1994). Pavement management systems lead the way for infrastructure management systems. *Proceedings - 3rd International Conference on Managing Pavements*, *2*, 99–112.

InfraGuide. (2004). Assessment and evaluation of storm and wastewater collection systems. In *InfraGuide: The national guide to sustainable municipal infrastructure*. Centre for

Sustainable Community Development.

InfraGuide. (2018). Decision Making and Information. *The Economics of Risk and Time*.

InfraGuide, N. G. (2006). Managing risk. *Decision Making and Investment Planning*.

Infrastructure, C. (2016). *Canadian infrastructure report card-informing the future*.

IPWEA. (2006). Asset Performance Guidelines Practice Notes. *International Infrastructure Management Manual*, 1–26.

ISO, I. (2014). 55000 Asset management-Overview principles and terminology. Geneva2014.

Jafari, M., Parlikad, A., Robazetti-Concho, L., & Jafari, B. (2014). *Review of asset hierarchy criticality assessment and risk analysis practices.*

Jha, M. K., Udenta, F., Chacha, S., & Abdullah, J. (2010). *The Sixth International Conference on City Logistics Formulation and solution algorithms for highway infrastructure maintenance optimisation with work-shift and overtime limit constraints*. *2*, 6323–6331.

Jin, Y., & Mukherjee, A. (2014). Markov chain applications in modelling facility condition deterioration. *International Journal of Critical Infrastructures*, *10*(2), 93–112.

Kabir, G., Balek, N. B. C., & Tesfamariam, S. (2018). Sewer Structural Condition Prediction Integrating Bayesian Model Averaging with Logistic Regression. *Journal of Performance of Constructed Facilities*, *32*(3), 04018019.

Kabir, G., Sadiq, R., & Tesfamariam, S. (2014). A review of multi-criteria decision-making methods for infrastructure management. In *Structure and Infrastructure Engineering* (Vol. 10, Issue 9, pp. 1176–1210). Taylor & Francis.

Karl, T. R., Meehl, G. A., Miller, C. D., Hassol, S. J., Waple, A. M., & Murray, W. L. (2008). *Weather and climate extremes in a changing climate*. US Climate Change Science Program.

Keady, R. (2009). Financial Impact and analysis of equipment inventories. *Facilities Engineering Journal*, *27*(5), 13–17.

Kelly, G., Serginson, M., Lockley, S., Dawood, N., & Kassem, M. (2013). BIM for facility management: a review and a case study investigating the value and challenges. *Proceedings of the 13th International Conference on Construction Applications of Virtual Reality*, *5*.

Kleiner, Y. (2001). *Scheduling Inspection and Renewal of Large Infrastructure Assets*. December.

Kleiner, Y., Adams, B. J., & Rogers, J. S. (1998). Selection and scheduling of rehabilitation alternatives for water distribution systems. *Water Resources Research*, *34*(8), 2053–2061.

Kleiner, Y., Sadiq, R., & Rajani, B. (2006). Modelling the deterioration of buried infrastructure as a fuzzy Markov process. *Journal of Water Supply: Research and Technology—AQUA*, *55*(2), 67–80.

Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2018). Digital Twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine*, *51*(11), 1016–1022.

Kuhn, K. D., & Madanat, S. M. (2005). Model uncertainty and the management of a system of infrastructure facilities. *Transportation Research Part C: Emerging Technologies*, *13*(5–6), 391–404.

Langston, C. (2013). *Life-cost approach to building evaluation*. Routledge.

Le, H. T. T., Likhitruangsilp, V., & Yabuki, N. (2020). A BIM-integrated relational database management system for evaluating building life-cycle costs. Engineering Journal, 24(2), 75-86.

Lee, J., Park, C. Y., Baek, S., Han, S. H., & Yun, S. (2021). Risk-based prioritization of sewer pipe inspection from infrastructure asset management perspective. *Sustainability (Switzerland)*, *13*(13).

Lee, S.-K., An, H.-K., & Yu, J.-H. (2012). An extension of the technology acceptance model for BIM-based FM. *Construction Research Congress 2012: Construction Challenges in a Flat World*, 602–611.

Lemer, A. C., & Wright, J. R. (1997). Developing a Comprehensive Infrastructure Management System. *APWA International Public Works Congress: NRCC/CPWA Seminar Series Innovations in Urban Infrastructure*.

Liang, M. T., Wu, J. H., & Liang, C. H. (2001). Multiple layer fuzzy evaluation for existing reinforced concrete bridges. Journal of Infrastructure Systems, 7(4), 144-159.

Liao, C. Y., Tan, D. L., & Li, Y. X. (2012). Research on the Application of BIM in the Operation Stage of Green Building. *Applied Mechanics and Materials*, *174*, 2111–2114.

Madanat, S. M., Karlaftis, M. G., & McCarthy, P. S. (1997). Probabilistic infrastructure deterioration models with panel data. Journal of infrastructure systems, 3(1), 4-9.

Madanat, S., & Ben-Akiva, M. (1994). Optimal Inspection and Repair Policies for Infrastructure Facilities. In *Transportation Science* (Vol. 28, Issue 1, pp. 55–62).

Malek Mohammadi, Mohammadreza, Najafi, M., Kaushal, V., Serajiantehrani, R., Salehabadi, N., & Ashoori, T. (2019). Sewer pipes condition prediction models: A state-of-the-art review. *Infrastructures*, *4*(4), 64.

Malek Mohammadi, M., Najafi, M., Salehabadi, N., Serajiantehrani, R., & Kaushal, V. (2020). Predicting condition of sanitary sewer pipes with gradient boosting tree. In Pipelines 2020 (pp. 80-89). Reston, VA: American Society of Civil Engineers.

Marmo, R., Nicolella, M., Polverino, F., & Tibaut, A. (2019). A methodology for a performance information model to support facility management. *Sustainability*, *11*(24), 7007.

Marzouk, M., Hisham, M., Ismail, S., Youssef, M., & Seif, O. (2010). On the use of building information modeling in infrastructure bridges. *Proceedings of the 27th International Conference on Applications of IT in the AEC Industry, Cairo, Egypt*, 16–18.

Marzouk, M., & Omar, M. (2013). Multiobjective optimisation algorithm for sewer network rehabilitation. *Structure and Infrastructure Engineering*, *9*(11), 1094–1102.

Marzouk, M., & Osama, A. (2017a). Fuzzy-based methodology for integrated infrastructure asset management. *International Journal of Computational Intelligence Systems*, *10*(1), 745–759.

Marzouk, M., & Osama, A. (2017b). *Fuzzy-Based Methodology for Integrated Infrastructure Asset Management*. *10*, 745–759.

Mashford, J., Marlow, D., Tran, D., & May, R. (2011). Prediction of sewer condition grade using support vector machines. *Journal of Computing in Civil Engineering*, *25*(4), 283–290.

Mathew, J., Ma, L., Tan, A., Weijnen, M., & Lee, J. (2011). Engineering asset management and infrastructure sustainability. *Proceedings of the 5th World Congress on Engineering Asset Management (WCEAM 2010), Cincinnati, OH, USA*, 3–5.

McDonald, S. E., & Zhao, J. Q. (2001). Condition assessment and rehabilitation of large sewers. *Underground Infrastructure Research*, 361–369.

Micevski, T., Kuczera, G., & Coombes, P. (2002). Markov Model for Storm Water Pipe Deterioration. *Journal of Infrastructure Systems*, *8*(2), 49–56.

Mirza, S. Danger Ahead: the Coming Collapse of Canada's Municipal Infrastructure. A Report for the Federation of Canadian Municipalities. November 2007. Режим доступа: https://www.fcm.ca/Documents/reports/Danger_Ahead_The_coming_collapse_of_Canadas _municipal_infrastructure_E N. pdf.(дата обращения: 23.10. 2018).

Montoya Montoya, A. (2019). *The influence of different characteristics on the probabilities of failure of sewer pipes*.

Moon, F. L., Aktan, A. E., Furuta, H., & Dogaki, M. (2009). Governing issues and alternate resolutions for a highway transportation agency’s transition to asset management. *Structures & Infrastructure Engineering*, *5*(1), 25–39.

Morcous, G. (2006). Performance Prediction of Bridge Deck Systems Using Markov Chains. *Journal of Performance of Constructed Facilities*, *20*(2), 146–155.

Morcous, G. & Lounis, Z. (2005). Maintenance optimization of infrastructure networks using genetic algorithms. *Automation in Construction*, *14*(1), 129–142.

Morcous, G., Rivard, H., & Hanna, A. M. (2002). Modeling bridge deterioration using case-based reasoning. *Journal of Infrastructure Systems*, *8*(3), 86–95.

Muhlbauer, W. K. (2004). *Pipeline risk management manual: ideas, techniques, and resources*. Elsevier.

Nafi, A., Werey, C., & Llerena, P. (2008). Water pipe renewal using a multiobjective optimization approach. *Canadian Journal of Civil Engineering*, *35*(1), 87–94.

Najafi, M., & Kulandaivel, G. (2005). Pipeline condition prediction using neural network models. In *Pipelines 2005: Optimizing Pipeline Design, Operations, and Maintenance in Today's Economy* (pp. 767–781).

Najjaran, H., Sadiq, R., & Rajani, B. (2004). Modeling pipe deterioration using soil properties-an application of fuzzy logic expert system. In *Pipeline Engineering and Construction: What's on the Horizon?* (pp. 1–10).

Nesbitt, D. M., Sparks, G. A., & Neudorf, R. D. (1993). Semi-Markov formulation of the pavement maintenance optimization problem. *Canadian Journal of Civil Engineering*, *20*(3), 436–447.

Nikolaidis, E., Ghiocel, D. M., & Singhal, S. (2004). *Engineering design reliability handbook*. CRC press.

N. R. C. C.-C. national de recherches C. (2003). *Deterioration and inspection of water distribution systems, a best practice by the national guide to sustainable municipal infrastructure*.

Obaidat, M. T., & Al-Kheder, S. A. (2006). Integration of geographic information systems and computer vision systems for pavement distress classification. *Construction and Building Materials*, *20*(9), 657–672.

PAS, B. S. (2008). 55: Asset Management. *British Standards Institutes. London. UK*.

Patacas, J., Dawood, N., Vukovic, V., & Kassem, M. (2015). BIM for facilities management: Evaluating BIM standards in asset register creation and service life planning. *Journal of*

Information Technology in Construction, *20*(August), 313–331.

Perrin Jr, J., & Dwivedi, R. (2006). Need for culvert asset management. *Transportation Research Record*, *1957*(1), 8–15.

Plihal, H., Kretschmer, F., Bin Ali, M. T., See, C. H., Romanova, A., Horoshenkov, K. V, & Ertl, T. (2016). A novel method for rapid inspection of sewer networks: combining acoustic and optical means. *Urban Water Journal*, *13*(1), 3–14.

Rahman, S., & Vanier, D. J. (2004a). Life cycle cost analysis as a decision support tool for managing municipal infrastructure. *CIB 2004 Triennial Congress*, *January*, 13.

Rahman, S., & Vanier, D. J. (2004b). Life cycle cost analysis as a decision support tool for managing municipal infrastructure. *CIB 2004 Triennial Congress*, *2*(1), 11–18.

Raja Shekharan, A. (2000). Solution of pavement deterioration equations by genetic algorithms. *Transportation Research Record*, *1699*(1), 101–106.

Rajani, B., & Kleiner, Y. (2001). Comprehensive review of structural deterioration of water mains: Physically based models. *Urban Water*, *3*(3), 151–164.

Rama, D., & Andrews, J. (2013). A system-wide modelling approach to railway infrastructure asset management. *Proceedings of the 20th Advances in Risk and Reliability Technology Symposium*, 7–22.

Riggs, J. L. (1977). Engineering economics (No. TA177. 4 R53)..

Rodrigues, F., Teixeira, J., Matos, R., & Rodrigues, H. (2019). Development of a web application for historical building management through BIM technology. *Advances in Civil Engineering*, *2019*.

Rosen, R., Von Wichert, G., Lo, G., & Bettenhausen, K. D. (2015). About the importance of autonomy and digital twins for the future of manufacturing. *Ifac-Papersonline*, *48*(3), 567–572.

Ruparathna, V. K. R. J. (2017). *Climate-driven asset management of public buildings: a multi-*

period maintenance planning framework. University of British Columbia.

Saback de Freitas Bello, V., Popescu, C., Blanksvärd, T., & Täljsten, B. (2021). Framework for facility management of bridge structures using digital twins. *IABSE Congress Ghent 2021, Structural Engineering for Future Societal Needs, Ghent, Belgium, 22-24 September, 2021*, 629–637.

Sacks, R., Eastman, C., Lee, G., & Teicholz, P. (2018). *BIM handbook: A guide to building information modeling for owners, designers, engineers, contractors, and facility managers*. John Wiley & Sons.

Salman, B., & Salem, O. (2012). Risk Assessment of Wastewater Collection Lines Using Failure Models and Criticality Ratings. *Journal of Pipeline Systems Engineering and Practice*, *3*(3), 68–76. https://doi.org/10.1061/(asce)ps.1949-1204.0000100

Saskatchewan Ministry of Municipal Affairs. (2006). *Condition grading / rating standards are often used to identify and prioritize the renewal requirements for infrastructures such as roads , sewers , and water mains . This rating standard typically includes a point scoring system for each performance indi*. *2006*, 1–7.

Scheidegger, A., Hug, T., Rieckermann, J., & Maurer, M. (2011). Network condition simulator for benchmarking sewer deterioration models. *Water Research*, *45*(16), 4983–4994.

Schraven, D., Hartmann, A., & Dewulf, G. (2011). Effectiveness of infrastructure asset management: Challenges for public agencies. *Built Environment Project and Asset Management*, *1*(1), 61–74. https://doi.org/10.1108/20441241111143786

Šelih, J., Kne, A., Srdić, A., & Žura, M. (2008). Multiple-criteria decision support system in highway infrastructure management. *Transport*, *23*(4), 299–305. https://doi.org/10.3846/1648-4142.2008.23.299-305

Semadeni-Davies, A., Hernebring, C., Svensson, G., & Gustafsson, L.-G. (2008). The impacts of climate change and urbanisation on drainage in Helsingborg, Sweden: Combined sewer system. *Journal of Hydrology*, *350*(1–2), 100–113.

Shahata, K., & Zayed, T. (2016). Integrated risk-assessment framework for municipal infrastructure. *Journal of Construction Engineering and Management*, *142*(1), 4015052.

Shahrour, I., Alileche, L., & Alfurjani, A. (2017). Smart cities: System and tools used for the digital modelling of physical urban systems. *2017 Sensors Networks Smart and Emerging Technologies (SENSET)*, 1–4.

Shen, Y., Goodall, J. L., & Chase, S. B. (2019). Condition State–Based Civil Infrastructure Deterioration Model on a Structure System Level. *Journal of Infrastructure Systems*, *25*(1), 4018042.

Shou, W., Wang, J., Wang, X., & Chong, H. Y. (2015). A comparative review of building information modelling implementation in building and infrastructure industries. *Archives of Computational Methods in Engineering*, *22*(2), 291–308.

Singh Ahluwalia, S. (2008). *A framework for efficient condition assessment of the building infrastructure*.

Sivo, D., & Daniela, L. (2011). *Procedia Computer Decision-support tools for municipal infrastructure maintenance management*. *3*, 36–41.

Smith, D. K., & Tardif, M. (2009). *Building information modeling: a strategic implementation guide for architects, engineers, constructors, and real estate asset managers*. John Wiley & Sons.

Spedding, A. (1994). *CIOB handbook of facilities management*. Longman Scientific and Technical.

Srikanth, I., & Arockiasamy, M. (2020). Deterioration models for prediction of remaining useful life of timber and concrete bridges: A review. In *Journal of Traffic and Transportation Engineering (English Edition)* (Vol. 7, Issue 2, pp. 152–173).

STORM. (2022). *Storm Sewer vs. Sanitary Sewer*. https://www.azstorm.org/stormwater-101/storm-vs-sanitary-sewer/storm-sewer-vs-sanitary-sewer

Strauss, M., & Wadzuk, B. (2022). Predictive Maintenance of Stormwater Infrastructure Using Internet-of-Things Technology. *Journal of Environmental Engineering*, *148*(2), 4021084.

Sunil, K., Pathirage, C., & Underwood, J. (2015). The importance of integrating cost management with building information modeling (BIM). *International Postgraduate Research Conference* (IPGRC 2015).

Swamee, P. K., & Sharma, A. K. (2013). Optimal design of a sewer line using linear programming. *Applied Mathematical Modelling*, *37*(6), 4430–4439.

Switzer, A., & McNeil, S. (2004). Developing a road map for transportation asset management research. *Public Works Management & Policy*, *8*(3), 162–175.

Syachrani, S., Jeong, H. D., & Chung, C. S. (2013). Advanced criticality assessment method for sewer pipeline assets. *Water Science and Technology*, *67*(6), 1302–1309.

Tchana, Y., Ducellier, G., & Remy, S. (2019). Designing a unique Digital Twin for linear infrastructures lifecycle management. *Procedia CIRP*, *84*, 545–549.

Teicholz, E. (2012). *Technology for Facility Managers: The Impact of Cutting-edge Technology on Facility Management*. John Wiley & Sons.

Too, E. G. (2012). Strategic infrastructure asset management: the way forward. In Engineering Asset Management and Infrastructure Sustainability (pp. 945-958). Springer, London..

Tran, D. H., Ng, A. W. M., & Perera, B. J. C. (2007). Neural networks deterioration models for serviceability condition of buried stormwater pipes. *Engineering Applications of Artificial Intelligence*, *20*(8), 1144–1151.

TRB. (2006). *Maintenance and operations of transportation facilities 2005 strategic vision*.

Tscheikner-Gratl, F., Caradot, N., Cherqui, F., Leitão, J. P., Ahmadi, M., Langeveld, J. G., Le Gat, Y., Scholten, L., Roghani, B., & Rodríguez, J. P. (2019). Sewer asset management–state of the art and research needs. *Urban Water Journal*, *16*(9), 662–675.

Ugarelli, R., Venkatesh, G., Brattebø, H., Di Federico, V., & Sægrov, S. (2010). Asset management for urban wastewater pipeline networks. *Journal of Infrastructure Systems*, *16*(2), 112–121.

Upadhyaya, J. K. (2013). *A sustainability assessment framework for infrastructure: Application in stormwater systems*.

US Department of Transportation, F. H. A. (FHWA). (2006). *"Asset Management Data Collection for Supporting Decision Processes Asset Management Data Collection for Supporting Decision Processes."* 2–97.

USEPA. (2008). Asset management: A best practices guide. In *EPA 816/F-08/014*. Office of Water Washington.

Vadapalli, V. U. K. (2021). *An Integrated asset management of buried infrastructure: a BIM-based life cycle thinking framework*. University of British Columbia.

Van Auken, M., Ahmed, A., & Slaven, K. (2016). Maximizing Stormwater Program Effectiveness Through Risk-Based Asset Management. *Journal-American Water Works Association*, *108*(9), 20–25.

van der Velde, J., Klatter, L., & Bakker, J. (2013). A holistic approach to asset management in the Netherlands. *Structure and Infrastructure Engineering*, *9*(4), 340–348.

Vladeanu, G. J., & Matthews, J. C. (2019). Consequence-of-Failure Model for Risk-Based Asset Management of Wastewater Pipes Using AHP. *Journal of Pipeline Systems Engineering and Practice*, *10*(2), 04019005. https://doi.org/10.1061/(asce)ps.1949-1204.0000370

Wahida, R. N., Milton, G., Hamadan, N., Lah, N. M. I. B. N., & Mohammed, A. H. (2012). Building condition assessment imperative and process. *Procedia-Social and Behavioral Sciences*, *65*, 775–780.

Wang, L., Li, W., Feng, W., & Yang, R. (2021). Fire risk assessment for building operation and maintenance based on BIM technology. *Building and Environment, 205*, 108188.

Wang, M., Deng, Y., Won, J., & Cheng, J. C. P. (2019). An integrated underground utility management and decision support based on BIM and GIS. *Automation in Construction*, *107*, 102931.

Wei, X., Bonenberg, W., Zhou, M., Wang, J., & Wang, X. (2017). The case study of BIM in urban planning and design. *International Conference on Applied Human Factors and Ergonomics*, 207–217.

Wirahadikusumah, R., Abraham, D., & Iseley, T. (2001). Challenging issues in modeling deterioration of combined sewers. *Journal of Infrastructure Systems*, 7(2), 77-84.

Wirahadikusumah, R., Abraham, D. M., Iseley, T., & Prasanth, R. K. (1998). Assessment technologies for sewer system rehabilitation. *Automation in Construction*, *7*(4), 259–270.

Won, J., Lee, G., Dossick, C., & Messner, J. (2013). Where to focus for successful adoption of building information modeling within organization. *Journal of Construction Engineering and Management*, *139*(11), 4013014.

Wood. (2020). *Stormwater Financing Study*. *December*.

Valderrama, A., & Levine, L. (2012). Financing stormwater retrofits in Philadelphia and beyond.

Wu, S., Bates, B., Zbigniew Kundzewicz, A. W., & Palutikof, J. (2008). Climate change and water. Technical Paper of the Intergovernmental Panel on Climate Change. Geneva.

Wu, Y., Rubin, D. L., Woods, R. W., Elezaby, M., & Burnside, E. S. (2014). Developing a Comprehensive Database Management System. *Cancer Informatics*, *13*(October 2000), 53–62.

Wu, Z., Flintsch, G., Ferreira, A., & Picado-Santos, L. de. (2012). Framework for multiobjective optimization of physical highway assets investments. *Journal of Transportation Engineering*, *138*(12), 1411–1421.

Yazdandoost, F., & Izadi, A. (2018). An asset management approach to optimize water meter replacement. *Environmental Modelling & Software*, *104*, 270–281.

Zhang, Z., Dossey, T., Weissmann, J., & Hudson, W. R. (1994). GIS integrated pavement and infrastructure management in urban areas. *Transportation Research Record*, *1429*, 84–89.

APPENDICES

Appendix A Transition Probability Matrices for testing the initial parameters in the DS-based tool

Segment (943)

Asbesto Cement

$$\begin{bmatrix} 0.98 & 0.02 & 0 & 0 & 0 \\ 0 & 0.58 & 0.42 & 0 & 0 \\ 0 & 0 & 0.79 & 0.21 & 0 \\ 0 & 0 & 0 & 0.99 & 0.01 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Segement (944)

Reinforced Concrete Pipe

$$\begin{bmatrix} 0.80 & 0.20 & 0 & 0 & 0 \\ 0 & 0.70 & 0.30 & 0 & 0 \\ 0 & 0 & 0.60 & 0.40 & 0 \\ 0 & 0 & 0 & 0.10 & 0.90 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Segement (945)

Concrete Pipe

$$\begin{bmatrix} 0.84 & 0.16 & 0 & 0 & 0 \\ 0 & 0.72 & 0.28 & 0 & 0 \\ 0 & 0 & 0.51 & 0.49 & 0 \\ 0 & 0 & 0 & 0.82 & 0.18 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Segment (946)

Vitrified Clay

$$\begin{bmatrix} 0.75 & 0.25 & 0 & 0 & 0 \\ 0 & 0.86 & 0.14 & 0 & 0 \\ 0 & 0 & 0.67 & 0.33 & 0 \\ 0 & 0 & 0 & 0.80 & 0.20 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

C1- Code for Importing data into InfraWorks

```
var db = app.ActiveModelDb;
var sset = app.ActiveSelectionSet;

var formSewer_Segment_ID = ui.LoadForm("Ward_3_Thesis_Project_1_UI.ui");
formSewer_Segment_ID.findChild("Sewer_Segment_ID").clicked.connect(Sewer_Segment_ID);
formSewer_Segment_ID.show();

function Sewer_Segment_ID() {
  var val=[];
val.push(parseFloat(formSewer_Segment_ID.findChild("Sewer_SegmentID").text));

var val1 = (val -1)
//print (val1);


var tableName = "USER_Ward_3_Storm_Sewer";
var filter = sset.GetFilter(db.TableIndex("USER_Ward_3_Storm_Sewer"));
```

```
var table = db.Table("USER_Ward_3_Storm_Sewer");
var extent = table.QueryExtent(filter);

table.StartQuery(filter);
table.BeginWriteBatch();

var read;
var write = table.GetWriteRow();
while (read = table.Next()) {
   var coords = file.ReadFile("c:/Users/Grad student/Desktop/AKANA RESEARCH/WARD
3_STORM_SEWER.csv");
   var coordsa = coords.split("\n");
   for (var i = 0; i < coordsa.length; i++) {
      var txta = coordsa[i].split(",");
      if (txta.length < 5) // Number of columns in the CSV file
         continue;
      if (read.EXTERNAL_ID == (txta[0])) { // 0 is the first column - A
         write.USER_Storm_Sewer_Condition = (txta[1]); // Update Storm_Sewer Condition
         write.USER_Storm_Sewer_Risk = (txta[4]); // Update Storm_Sewer Risk
         write.USER_Storm_Sewer_Cost = (txta[3]); // Update Storm_Sewer Cost
         write.USER_Storm_Sewer_Retrofit_Action = (txta[2]); // Update Storm_Sewer Retrofit Action
         table.UpdateFeature(write, read.ID); // Update the model
         write.Invalidate();
      }
   }
}

var tablePipesl = db.Table("USER_Ward_3_Storm_Sewer");
var filter = "EXTERNAL_ID"; //CREATE FILTER
table.StartQuery(filter); //apply filter
var read;
var id;
var idArr = [];
while (read = tablePipesl.Next()) {
   id = read.EXTERNAL_ID;
   idArr.push(parseFloat(id))
}
table.EndQuery();
// print (idArr[100]);

var tablecondition = db.Table("USER_Ward_3_Storm_Sewer");
var filter = "USER_Storm_Sewer_Condition"; //CREATE FILTER
table.StartQuery(filter); //apply filter
var read;
var cond;
```

```
var condArr = [];
while (read = tablecondition.Next()) {
   cond = read.USER_Storm_Sewer_Condition;
   condArr.push(cond)
}
table.EndQuery();
// print (condArr[100]);

var tablerisk = db.Table("USER_Ward_3_Storm_Sewer");
var filter = "USER_Storm_Sewer_Risk"; //CREATE FILTER
table.StartQuery(filter); //apply filter
var read;
var risk;
var riskArr = [];
while (read = tablerisk.Next()) {
   risk = read.USER_Storm_Sewer_Risk;
   riskArr.push(risk)
}
table.EndQuery();
//  print (riskArr[100]);

var tableretrofitaction = db.Table("USER_Ward_3_Storm_Sewer");
var filter = "USER_Storm_Sewer_Retrofit_Action"; //CREATE FILTER
table.StartQuery(filter); //apply filter
var read;
var retrofitaction;
var retrofitactionArr = [];
while (read = tableretrofitaction.Next()) {
   retrofitaction = read.USER_Storm_Sewer_Retrofit_Action;
   retrofitactionArr.push(retrofitaction)
}
table.EndQuery();
// print (retrofitactionArr[100]);

var tablecost = db.Table("USER_Ward_3_Storm_Sewer");
var filter = "USER_Storm_Sewer_Cost"; //CREATE FILTER
table.StartQuery(filter); //apply filter
var read;
var cost;
var costArr = [];
while (read = tableretrofitaction.Next()) {
   cost = read.USER_Storm_Sewer_Cost;
   costArr.push(cost)
}
table.EndQuery();
```

```
// print (costArr[100]);



;

alert(condArr[val1] + " , " + riskArr[val1] + " , " + retrofitactionArr[val1] + " , " + costArr[val1]);
}
gc();
```

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