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Moving towards a proactive sewer pipe inspection approach: a state-of-the-art analysis.

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a state-of-the-art analysis.

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Abstract

The failure of sewer pipes is a significant issue that can adversely affect the environment and public health. The problem is exacerbated by the additional burden it places on treatment plants, which must work harder to process the increased sewage flow resulting from pipe failures. The research in this thesis is based on an extensive review of the existing literature on sewer pipe failure and inspection, focusing on the proactive approach that can predict pipe failures to assist in effective maintenance.

The study finds that several predictive models can accurately predict sewer deterioration with high accuracy (up to 95 % precision), making it possible to identify potential failures and address them before they cause significant damage or disruption. However, the research indicates that there has been relatively little work done on predicting blockage and CSO, two critical aspects of sewer pipe management that could be addressed more to manage sewer systems effectively.

The thesis discusses that by developing an effective predictive model for prioritisation of monitoring sewer pipes, planners can save time and money on individual inspections while planning well ahead to avoid any service disruption. The study also summarised the data needs for the predictive models and found pipe age, material, diameter depth, and length to be the most commonly used input parameters by the existing model developers. The finding of this research can guide decision support in future efforts to improve sewer pipe inspection practices.

Keywords: Sewer failure, Inflow, and infiltration, CSO, Blockage, prediction model, proactive

Abstrakt

Fel på avloppsrör är en viktig fråga som kan påverka miljön och folkhälsan negativt. Problemet förvärras av den extra börda det innebär för reningsverken, som måste arbeta hårdare för att hantera det ökade avfallsflödet till följd av rörbrott. Forskningen i denna avhandling baseras på en omfattande genomgång av den befintliga litteraturen om fel på avloppsrör och inspektion, med fokus på det proaktiva tillvägagångssättet som kan förutsäga rörfel för att bidra till effektivt underhåll.

Studien visar att flera prediktiva modeller kan förutsäga försämring av avlopp med hög noggrannhet (upp till 95 % precision), vilket gör det möjligt att identifiera potentiella fel och åtgärda dem innan de orsakar betydande skador eller störningar. Forskningen visar dock att det har gjorts relativt lite arbete för att förutsäga blockering och CSO, två kritiska aspekter av hantering av avloppsrör som skulle kunna hanteras mer för att hantera avloppssystemet effektivt.

I avhandlingen diskuteras att genom att utveckla en effektiv prediktiv modell för prioritering av övervakning av avloppsrör kan planerare spara tid och pengar på enskilda inspektioner och samtidigt planera i god tid för att undvika eventuella driftstörningar. Studien sammanfattade även data behovet för de prediktiva modellerna och fann att röra ålder, material, diameter, djup och längd var de mest använda ingångs parametrarna av de befintliga modellutvecklare. Resultatet av denna forskning kan vägleda beslutsstöd i framtida ansträngningar för att förbättra praxis för inspektion av avloppsrör.

Nyckelord: Avlopps Fel, Inflöde och infiltration, CSO, Blockering, prediktionsmodell, proaktiv

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1.Introduction

1.1 Context of the research

Wastewater collection systems, also known as sewer systems, are integral to municipal water distribution and management. A sewer system is a network of buried pipes and structures that transport wastewater, including sewage and other wastewater, from homes, businesses, and industries to a wastewater treatment plant (WWTP) or disposal site. According to Grigg (2003), the major function of the sewer system is collecting wastewater discharged by residential, industrial, and commercial areas and transporting those to treatment plants or disposal points. Sewer systems provide society with vital services.

A well-functioning sewage collection is critical for minimising the potentially hazardous effects of wastewater exposure to nature and human health. Medical associations in Britain and America have acknowledged the significance of wastewater conveyance and treatment for public health and longevity (Lofrano and Brown, 2010). In industrialised societies, the conveyance and treatment of wastewater play a critical role in minimising soil and water contamination. Sewer systems are important for public health and environmental protection because they help prevent disease spread, reduce water pollution, and protect the natural environment.

Worldwide, wastewater systems are in poor condition, with many networks at risk of failure due to inadequate maintenance plans and limited funding. The wastewater pipe network in the United States is rated "D+," and water and wastewater pipe breaks increased by 27% between 2012 and 2018. (ASCE, 2020) European countries, such as Austria and Germany, require significant reinvestment to maintain their networks. In Sweden, wastewater infrastructure has rapidly expanded and requires reinvestment of up to 320 million per year, primarily due to pipe network ageing and deterioration. Municipal budget constraints are a primary cause of poor maintenance plans and contribute to the deterioration of sewage networks. Preventative maintenance and regular inspections are essential for detecting and correcting problems before they occur. (ASCE, 2020)

Maintenance actions are performed, among other things, to maintain an asset's function and extend its remaining service life by improving its condition and reducing its condition deterioration rate and improving performance (Grigg 2003). Maintenance operations are important in ensuring the dependability of urban water infrastructure, particularly sewer pipes. Effective maintenance actions are expected to reduce the frequency of service disruptions and their unfavourable consequences. Due to limited resources and cost constraints, all maintenance cannot be performed concurrently, so the most critical maintenance activities must be prioritised. Sewer failures are one of the most significant challenges that municipalities face in this regard.

In the coming decades, considerable investments will be made globally to repair, replace, and maintain wastewater pipe networks, which raises an essential question. Deciding on which pipes should receive priority to optimise economic investments and service levels is crucial for effective and cost-sensitive maintenance. The pipes in the wastewater network vary in material and dimensions, installation age, and era and are situated in different settings related to land use and soil conditions. Various inspection methods are available to predict pipe conditions, and deterioration prediction models have been created(ASCE, 2020).

In the past, including current time, a reactive approach has been used, with rehabilitation carried out once pipelines had reached the point of failure. The practice of repairing or replacing

sewer network components only after they have failed or malfunctioned is known as reactive sewer maintenance. This approach is frequently used when funding for sewer network maintenance is limited and resources are scarce. While reactive maintenance may be a cost-effective approach in the short term, it has several drawbacks and can lead to long-term issues. Reactive maintenance can result in higher long-term costs because emergency repairs and replacements are often needed. These repairs can be more costly than routine maintenance, resulting in longer downtime and disruptions to the sewer network. (Hawari et al., 2020) Failure of one component can set off a chain reaction that leads to the failure of other components, necessitating more extensive and costly repairs. Reactive maintenance can increase the risk of raw sewage discharge into the environment, seriously affecting public health. Waterborne diseases, pathogen exposure, and environmental damage are all possible outcomes. Raw sewage discharge can harm aquatic life and ecosystems, and sewage network failures can contribute to climate change by releasing greenhouse gases.(Liu et al., 2023)

In recent years, many municipalities worldwide have realised the drawbacks of reactive maintenance and are striving to adopt a proactive approach to sewer maintenance. Proactive maintenance involves regularly inspecting and maintaining sewer network components to prevent failures and other problems before they occur. Proactive maintenance can save money in the long run by reducing the need for emergency repairs and replacements. (Mohamed, Ramadan, and El-Dash, 2023) Routine maintenance can help extend sewer network components' life and lower the risk of system failure, leading to fewer service disruptions and fewer public health and environmental risks. Proactive maintenance can also reduce the risk of raw sewage discharge into the environment, which can seriously affect public health. Regular maintenance can also help ensure that sewer networks are operating properly and are not endangering the public's safety. Hence, proactive maintenance can improve community satisfaction by ensuring sewer networks operate properly and do not cause disruptions or public health and safety risks.(Salihu et al., 2022)

Proactive sewer inspection is critical to meeting the ISO 24510 and ISO 24511 asset management objectives for wastewater systems. Key objectives that proactive sewer inspection can achieve are meeting user expectations and requirements, ensuring workplace safety and health, promoting sustainability, assisting with customary and emergency cases, and preserving the environment. To keep sewage utilities running, it is critical to organise and effectively maintain their facilities in accordance with defined goals based on an assessment and prediction of their condition. Setting asset management objectives and functional requirements allows wastewater utilities to adhere to an agreed-upon and sustainable level of service while considering risks and economic performance. To ensure safe effluent discharge into natural surroundings, functional requirements such as treating and pumping sewage and sludge through treatment facilities and networks must be subject to asset management. Various tools and resources are available to help with the primary functionalities, and proactive sewer inspection can help ensure that system extensions or changes do not jeopardise the overall goal.(Salihu et al., 2022)

According to Wang et al. (2023), sewer pipeline inspection was challenging before the 1960s due to limited access to the inspection area. However, researchers developed methods to overcome this challenge, which led to the emergence of innovative technologies such as Closed Circuit Television (CCTV) cameras, Pipe Penetrating Radar (PPR), laser profilers, Electro Scan, Sonar, Zoom cameras, Gamma-Gamma Logging (GGL), Infrared radiation, and Infrared thermography. These technologies have facilitated less hazardous testing applications to evaluate sewer pipeline conditions (Staufer, Scheidegger, and Rieckermann, 2012).

The selection of the appropriate inspection technology depends on factors such as the pipe material, type of utility, and volume of information available (Koo and Ariaratnam, 2006). However, due to limited resources, such as time, budget, and workers, these technologies can only determine the current condition of a limited part of the sewer network. Therefore, utilities develop deterioration models to predict the condition of sewer pipelines since failures can occur at any time based on multiple factors.

Condition assessment tools are typically used to provide users and planners with sufficient information to determine whether an intervention is required for specific pipes based on their state of deterioration. These tools are essential for identifying potential problems in sewer networks and planning preventative maintenance activities such as sewer pipe inspection, repair, or replacement. Closed-circuit television (CCTV) inspection, acoustic inspection, laser profiling, smoke testing, manhole inspections, and flow monitoring are among the techniques and technologies used to assess the condition of sewer network components such as pipes, manholes, and pumping stations. Municipalities should create condition assessment models by combining data from databases and municipal records to assess asset condition and prioritise inspection, repair, or replacement of sewer pipes. CCTV inspection, acoustic inspection, laser profiling, smoke testing, manhole inspections, and flow monitoring are the most commonly used sewer condition assessment tools (Khan, Zayed, and Moselhi, 2010). These tools can detect cracks, corrosion, blockages, and leaks in pipes, as well as irregularities in pipe diameter that can cause blockages or flow restrictions. Manhole inspections can detect any damage, corrosion, or other issues that may cause sewer network problems. Flow monitoring measures wastewater flows through a sewer network to detect blockages or other issues that may cause backups or overflows.

To reach the goal of proactive maintenance, predictive inspections are an important component of this strategy because they can help identify potential problems before they become severe enough to necessitate costly repairs and environmental damage.(Arthur et al., 2009) Planners can decide when and where to perform maintenance activities by predicting potential sewer failure. Early decision-making based on predictive inspections can help municipalities save money while improving the sewer network's reliability, public satisfaction, reputation, and environmental status. (Arthur et al., 2009).

1.2 Research problem; the knowledge gap

This study addresses a knowledge gap in the understanding of the major issues associated with sewer failure as well as the state of research and implementation of sewer failure prediction models. While sewer failure can have serious consequences such as environmental contamination, infrastructure damage, and community disruption, there is a need for a thorough understanding of the underlying issues as well as effective proactive sewer inspection strategies.

This study aims to bridge the knowledge gap and shed light on the key challenges faced by municipalities by investigating the problems associated with sewer failure that motivate the adoption of proactive sewer inspection. Understanding these challenges is critical for developing targeted and effective strategies to prevent sewer failure, reduce its impact, and improve overall sewer infrastructure management.

Furthermore, the study investigates the current state of sewer failure prediction model research and implementation. This investigation is critical because it provides insights into existing technologies and approaches for predicting and identifying potential sewer failures. The study c

identifies gaps, limitations, and opportunities for improvement in sewer failure prediction models by analysing the current state of research and implementation. This data is critical for informing future research efforts and facilitating the adoption of advanced sewer inspection technologies and models.

1.3 Research questions

To fill the knowledge gap the study intended to find answer to the following two research questions-

1. What problems are associated with sewer failure that motivates proactive sewer inspection?
2. What is the current status of research or implementation of sewer failure prediction models?

1.4 Thesis Organisation

This thesis comprises Seven chapters, each focusing on specific aspects of sewer infrastructure management and proactive sewer inspection. The organisation of the thesis is outlined as follows:

1.Introduction: This chapter presents the background, rationale , research problem and objectives of the thesis.

2. Methodology: the methods involved in the study, literature selection, sorting and theoretical consultancy as well as limitation of the study is presented in this section.

3. Background of the Swedish sewer system: This chapter provides a brief overview of the historical development of the Swedish sewer system, including treatment plants and the pipe network. Furthermore, the regulatory framework governing sewer infrastructure in Sweden will be discussed, offering contextual background information.

4.Sewer failure; characteristics and problems: This chapter is the first part of the literature review, discussing general information on sewer failure and its consequences.

5.Proactive sewer pipe inspection approach: A critical literature review of various sewer failure prediction models are presented in this chapter. Different models are introduced and compared, focusing on their underlying principles, efficiency, and data requirements. This chapter is instrumental in addressing the second research question.

6. Results: Though literature and results are blended in this research, still some most critical information retrieved and organised as a base of discussion is presented here.

7. Discussion and Conclusion: The thesis's final chapter discusses the research questions on the basis of literature review and the key findings shown in chapter six, then conclusive remarks are drawn for future developments.

The organisation of the thesis follows a systematic exploration of sewer failure and proactive inspection, leading to valuable insights and recommendations that can contribute to improving sewer infrastructure management practices.

2. Methodology

2.1 Literature search

This study's methodology was intended to conduct a thorough and systematic search for existing literature on proactive sewer pipe inspection approaches. To ensure a comprehensive collection of relevant literature, several reputable databases, including Google Scholar, ScienceDirect, and Wiley Online Library, were used for the literature search. These databases were chosen for their comprehensive coverage of scholarly articles, conference proceedings, and reports relevant to the research topic. After identifying relevant literature, a thorough analysis was conducted using qualitative content analysis to extract data on proactive sewer inspection technologies, approaches, and their financial and environmental benefits. This analysis aimed to identify common themes and patterns within the literature. The selected literature included peer-reviewed journal articles, conference proceedings, and reports that demonstrated theoretically proven efficiency or precision. Non-peer-reviewed sources and duplicates were excluded, ensuring the inclusion of high-quality studies.

2.2 Relevance sorting

2.2.1 Key words

Specific search terms were used during the literature search to retrieve articles that were most relevant to the study. The terms used in the search were "sewer pipe inspection," "sewer maintenance," "proactive approach," "predictive maintenance," "sewer prediction models," "sewer failure model," and "sewer failure prediction", “deterioration model” “condition assessment” “CSO prediction”, “Blockage prediction” CSO models”, “Blockage models”. These terms were selected with care to capture the key concepts and themes associated with proactive sewer pipe inspection. With these keywords more approximately two hundred relevant literature was collected.

2.2.2 Time frame and language

To ensure that the literature reviewed in this study was both current and relevant to the research objectives, a time frame for the search was established. The study aimed to strike a balance between including recent research and providing a substantial historical context by restricting the search to English-language publications published between 2001 and 2023. Recent research is essential for understanding the current state of knowledge and advancements in proactive sewer pipe inspection methods. The study could incorporate the most recent findings, methodologies, and technologies by looking at literature published up to 2023. This ensures that the literature review's analysis and conclusions accurately reflect the field's current understanding. After scrutinising these two criteria, approximately 130 articles seemed relevant for further study. Around 40 of the articles were for model analysis and rest for introduction, literature and impacts of sewer failure.

2.2.3 Interpretation of results

As the thesis is mostly literature based, hence separating results and literature is quite challenging in this regard. Rather the study presented the literature analysis and key findings as a blended way. Where chapter 3,4, and 5 represents the literature analysis, chapter 6 presents summarisation of some key aspects as results which are adapted from the literature. The results are shown mostly in table and figure and later explained in narrative form in discussion. The analysed and summarised predictive models that were not validated are presented in the appendix (1-4) to provide insight into their existence and to facilitate the discussion.

2.3 Theoretical consultation

In this thesis, the use of theoretical frameworks related to technological evolution serves as a lens to guide critical thinking and improve comprehension of the literature on proactive sewer pipe inspection. The use of these theories is motivated by their ability to provide valuable insights into how technologies change and the factors that have the most significant impact during the transition to new technological approaches. The thesis aims to gain a better understanding of the dynamics and complexities involved in the evolution of proactive sewer pipe inspection technologies by incorporating these theoretical frameworks. These theories provide conceptual frameworks for interpreting and analysing the literature, allowing for a systematic approach to investigating the adoption, usage, and impact of new inspection technologies. Understanding how technologies evolve over time is critical for keeping up with the latest developments and identifying the critical factors that contribute to successful technological advancements. The thesis seeks to shed light on the patterns, challenges, and opportunities inherent in the evolution of proactive sewer pipe inspection approaches by investigating these theories. This understanding is critical for developing effective strategies, policies, and interventions to drive the adoption and implementation of innovative inspection technologies in real-world scenarios.

One of these frameworks is the Technology Acceptance Model (TAM), which explains how users adopt and use new technologies. TAM proposes user acceptance and usage behaviour depending on the technology's perceived usefulness (PU) and perceived ease of use (PEOU). Social influence, system and job characteristics, and individual differences influence PU and PEOU. Attitudes and intentions mediate the relationship between PU, PEOU, and usage behaviour (Johannes Köck, 2017).

The Diffusion of Innovation Theory (Dearing and Cox, 2018) suggests that innovation adoption depends on the characteristics of the innovation itself, the communication channels used to promote the innovation and the characteristics of the adopters. The theory also proposes that the perceived value and credibility of information sources can influence the adoption of an innovation. Effective communication strategies can be critical to promoting the diffusion of innovations (Dearing and Cox, 2018). In the context of proactive sewer pipe inspection, the Diffusion of Innovation Theory can be used to understand the factors influencing the adoption and spread of new inspection technologies among stakeholders.

The Unified Theory of Acceptance and Use of Technology (UTAUT) explains how and why people use technology. The theory suggests that four key factors influence user behaviour: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). UTAUT proposes that these factors interact to determine the user's intention to use the technology and their actual behaviour. In addition, the theory proposes that individual differences may affect the relationships between these factors and user behaviour (Abdulwahab, Ringim, and Lawan, 2012).

The Social-Technical Systems Theory (STS) explains how organisations can optimise their performance by balancing work systems' social and technical components. STS proposes that work systems consist of two interdependent components: social and technical. The social component refers to the human aspect of work, while the technical component refers to the tools and processes used to accomplish the work. STS suggests optimising work systems requires balancing these two components through a participatory design process involving all stakeholders' input. STS also emphasises the importance of continuous organisational

improvement and learning to create a culture of openness, trust, and communication that encourages experimentation, innovation, and adaptation. (S Borras and J Edler, 2015)

In the context of proactive sewer pipe inspection, these theoretical frameworks can be used to understand the factors that influence the adoption and use of new inspection technologies by different stakeholders, including engineers, operators, and maintenance crews. By identifying the key factors that affect technology adoption and use, researchers and practitioners can develop effective strategies to promote their acceptance and enhance the efficiency and effectiveness of sewer pipe inspection and maintenance. Additionally, organisations can optimise their performance in sewer pipe inspection and maintenance by engaging in a participatory design process and creating a culture of openness, trust, and communication.

Analysing the studied theoretical framework, some key points that are common across the four theories and can serve as decision tools when designing and implementing technology or innovation:

- Perceived usefulness: Users are more likely to adopt and use technology or innovation if they perceive it to be useful in achieving their goals or improving their performance.
- Perceived ease of use: Users are more likely to adopt and use technology or innovation if they perceive it to be easy to use and understand.
- Social influence: The attitudes and behaviours of other people (such as peers, leaders, or influencers) can influence users' perceptions and adoption of technology or innovation.
- Facilitating conditions: The presence of necessary resources and infrastructure, such as training, support, and equipment, can facilitate users' adoption and use of technology or innovation.
- Contextual factors: Organisational culture, norms, and infrastructure can shape users' attitudes and behaviours towards technology or innovation and should be considered in the design and implementation process.

By considering these key points, organisations can develop strategies to promote user acceptance and adoption of technology or innovation and create work systems optimised for performance and user satisfaction. The study considered these key points as motivation while analysing the proactive sewer pipe inspection literature.

2.4 Methodological limitation

It is necessary to acknowledge the limitations of this study at the beginning so that readers have a comprehensive idea of what to expect next and to provide a clear understanding of the scope and extent of the research conducted. This research is based on a literature review and includes no primary data collection or analysis.

Secondly, while the study highlights various proactive sewer pipe inspection approaches, it does not validate their efficacy through laboratory analysis or modelling; rather, it depends on the efficiency data provided by the literature.

Thirdly, the study only provides a qualitative overview of the financial and environmental problems associated with sewer failure and assumes those as motivation for introducing a proactive sewer inspection approach. It does not provide an actual calculation of how much a proactive approach can save. Instead, the study discusses the relationship qualitatively.

Furthermore, the study does not thoroughly examine the potential social and political barriers to adopting a proactive approach to sewer pipe inspection. These barriers may include a lack of public awareness, resistance to change, and a lack of resources.

In conclusion, while this study provides valuable insights into the current state of research and implementation of a proactive approach to sewer pipe inspection, it has specific limitations. Future research should consider overcoming these limitations and providing a more comprehensive analysis of the implementation and effectiveness of proactive sewer maintenance in various contexts.

3. Background of Swedish sewer system

3.1 Historical development of wastewater treatment in Sweden

Big cities in Sweden began to build sewage systems in the late nineteenth century. Underground piping was installed to transport wastewater from newly installed modern water closets and kitchens into nearby lakes or coastal waters. This wastewater disposal system eventually replaced the historical latrine management systems in which household waste was collected in pits and barrels and used as fertiliser on local farms. When it was not possible to use this waste for fertilisation, it was simply buried underground. Twelve Swedish cities had underground sewer systems by 1880. Water closets were installed primarily to improve sanitary conditions in homes and cities. Wastewater systems became prevalent in larger cities, first in the 1920s, then in smaller towns.(Bernes and Lundgren, 2009).

Initially, both urban and industrial wastewater was discharged untreated. Lakes, rivers, and coastal areas became increasingly polluted over time. As a result of the discharge of nutrients, oxygen-demanding pollutants, and pathogens, bodies of water in Sweden were experiencing hypoxia and fish death. At times, the discharge caused waterborne epidemics. Until the 1940s, water pollution was considered a municipal concern, limiting the potential for comprehensive action. The construction of new municipal sewage treatment plants moved slowly. Only 15 municipal wastewater treatment plants were in operation nationwide by 1940. By 1955, this figure had doubled to 30, but it was still insufficient (Bernes and Lundgren, 2009).

In the 1960s, public attention was drawn to the eutrophication of bodies of water in Sweden. By then, decades of effluent discharge had severely degraded the water quality of many lakes and streams near larger urban areas. Lakes became overgrown, and algae drifted towards shores that were once considered ideal bathing spots. Heavy metals and other chemicals were discovered in some lakes and rivers sediments, primarily due to historic industrial activities. Environmental alarms were raised regularly, prompting national government action against water pollution. In 1967 the Swedish Environmental Protection Agency (Swedish EPA) was established. A year later, national funding for wastewater treatment was introduced to decontaminate municipal wastewater, and the Environmental Protection Act was enacted in 1969.(Bernes and Lundgren, 2009).

From 1971 to 1979, the national government invested more than SEK 1.5 billion in expanding municipal wastewater treatment capacity (equivalent to approximately SEK 7-8 billion in 2018 value). Several industries received government grants for environmental improvements in the early 1970s. These funds were mostly used to improve wastewater treatment. Since then, industries with wastewater treatment plants have also made significant investments to reduce their discharge. Discharges from small properties with on-site wastewater systems, on the other hand, have not decreased similarly. The extensive investments, mostly made in the 1970s,

resulted in improved water quality in the country's lakes and rivers, the reopening of bathing areas, and the return of fish. (Swedish EPA 2018)

Currently, almost all urban households are connected to municipal wastewater treatment plants. More than 96% of urban wastewater is treated biologically and chemically. Many larger industrial and mining facilities have wastewater treatment plants. In addition, approximately a million households lack municipal water and sewage service. Approximately 718,000 households have water closets, and 141,000 have wastewater facilities for baths, washing-up, and laundry. Furthermore, several properties used primarily for recreation have no water or sewage system. Many small-scale systems do not meet legal requirements and contribute significantly to phosphorus and nitrogen pollution in lakes, rivers, and coastal waters.(Swedish EPA 2022)

3.2 Wastewater sewage systems in Sweden

Wastewater treatment plants with sewage systems and pumping stations have been built throughout Sweden to treat wastewater from urban and built-up areas. In 2019, more than 9 million people in Sweden had access to municipal wastewater treatment, according to Statistics Sweden, SCB (2018). The situation constantly changes as new housing areas are connected, and smaller treatment plants are replaced with pumping stations that transfer sewage to larger treatment plants. As a result, the number of treatment plants is decreasing over time.

In 2017, the total length of Sweden's sewage system exceeded 100,000 km (Lundin, Malm, and Svensson ., 2017). Stormwater and sewage are collected in separate pipes in separate sewage systems, also known as duplicate sewage systems. Stormwater does not enter the sewage system or wastewater treatment plant in this case, meaning it is not polluted "more than necessary." However, there is a high frequency of stormwater leakage into sewage systems. Stormwater is discharged to treatment plants through the same pipes as sewage in combined sewage systems. Combined sewage systems are mostly found in older urban areas and were built until the mid-twentieth century. Combined sewage systems account for approximately 13% of Sweden's sewage system (Svensk Vatten, 2016).

In addition to domestic and industrial wastewater, stormwater and other waters enter the wastewater treatment plant through sewage system leaks. Leakage occurs in municipal sewage systems and private pipes connecting to municipal systems. The amount of stormwater and other water fed into the treatment plant varies depending on the sewage system and the wastewater treatment plant. Stormwater and other waters contribute to the dilution of contaminated wastewater while also increasing the amount of wastewater, which may result in overflows on sewage systems or at treatment plants in heavy precipitation. Because of the lower water temperature, shorter hydraulic retention time, and dilution, the effect of the purification process provided by the wastewater treatment plant is also reduced.

3.3 Discharge quality of treatment plants

Before the 1960s, wastewater was discharged uncontrollably. The measured discharges increased dramatically as urban communities installed wastewater treatment plants. In the late 1960s and early 1970s, the construction of modern treatment plants significantly reduced phosphorus and organic matter discharges. Beginning in the mid-1980s, treatment methods were added to reduce nitrogen levels further.(Swedish EPA 2022)

For the last decade, the degree of purification of phosphorus and biochemically degradable organic matter in wastewater treatment plants larger than 2,000 population equivalents in

Sweden has remained around 97%. The degree of nitrogen purification is lower, but it has recently improved for larger wastewater treatment plants that discharge into nitrogen-sensitive recipients. Despite an increase in input load, total municipal wastewater treatment plant releases decreased in 2020 compared to 2018. The average treatment levels for phosphorus and BOD7 have remained constant, while nitrogen has increased since 2018. Nitrogen and phosphorus discharges to inland waters are significantly reduced by retention, particularly in lakes, so that only a portion of the gross load within a catchment area reaches the sea. (Swedish EPA 2022). Figure 1 shows Himmerfjärdsverket, a wastewater treatment plant in Stockholm.

Figure 1: The purified wastewater from Himmerfjärdsverket is released into Himmerfjärden.(Swedish EPA 2022)

The Swedish EPA (2022) provides important statistics on municipal wastewater treatment plants in Sweden. Table 1 presents statistics from the Swedish EPA (2022), including the number of treatment plants, output volumes (in tonnes), and average concentrations of phosphorus, nitrogen, and organic substances in municipal wastewater treatment plants (mg/l). All wastewater treatment plants requiring permits, i.e., those with at least 2,000 people connected or included in the statistics.

Table 1: Common pollutants and average removal efficiency. (Swedish EPA 2022)

Year	No of WWT P	Water volume (x 1000 m3)	Concentration (mg/l)			Removal Efficiency (%)			Released (Ton/year)		
			P	N	BOD_7	P	N	BOD_7	P	N	BOD_7
2020	429	1,182,957	0.21	12.5	4.9	95	65	97	249	14,779	5,822
2018	426	1,100,444	0.24	13.6	6.0	95	64	97	266	14,982	6,548
2016	416	1,078,652	0.22	14.3	6.1	96	62	97	237	15,414	6,612
2014	431	1,217,093	0.21	12.9	6.2	95	62	96	260	15,743	7,549
2012	411	1,269,131	0.22	13.5	6.3	95	59	96	275	17,120	7,993
2010	467	1,186,767	0.22	14.7	6.7	95	59	96	267	17,419	7,908

3.4 Treatment methods and capacity

Mechanical, biological, and chemical treatment methods are commonly used in Swedish wastewater treatment plants. Mechanical treatment is the first step in the wastewater treatment process, after which various treatment methods are combined. The traditional three-stage treatment, which includes biological and chemical treatments, is the most common treatment combination. Another common method is a biological-chemical treatment followed by denitrification. In addition to biological-chemical treatment, some wastewater treatment plants use additional methods such as filtration. These treatment methods work together to remove impurities and contaminants from wastewater, making it safe to discharge into the environment.(Svensk Vatten, 2016)

The wastewater treatment plants aim to treat substances that cause eutrophication effectively, and they can also help to separate other unwanted particles, such as microplastics. Micropollutant removal techniques are also available. The Swedish government is funding the installation of pharmaceutical residue treatment techniques, which will be used more frequently in wastewater treatment plants in the future.(Svensk Vatten, 2016 and Swedish EPA 2018). Figure 2 depicts the typical treatment steps used in Swedish wastewater treatment plants, as described by the Swedish EPA (2018).

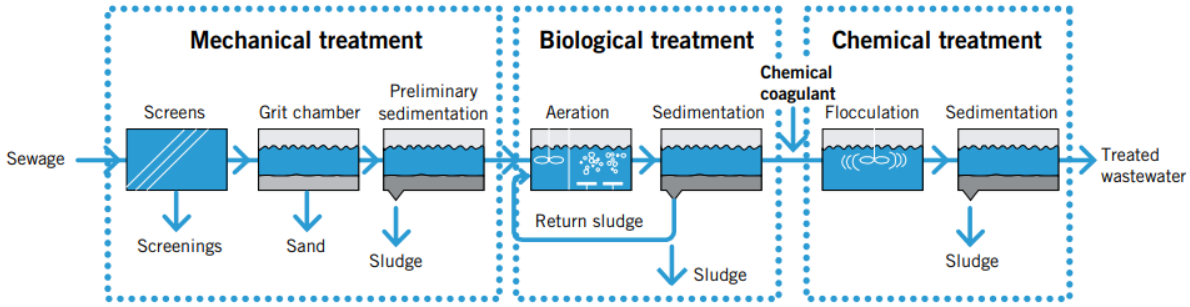

Figure 2: Typical treatment steps in Swedish WWTPs (Swedish EPA, 2018)

Swedish wastewater treatment plants vary greatly regarding total hydraulic and secondary treatment capacity. Any incoming wastewater that exceeds this capacity is released in nature without getting treatment. The treatment capacity of some major Swedish treatment plants is listed in Table 2.

Table 2: Treatment capacity of some Swedish WWTP (Hey et al., 2016)

WWTP	Population Connected (person)	Total hydraulic capacity (m3/day)	Secondary treatment capacity (m3/day)
Bromma	320500	259200	50000
Henriksdal	782600	475200	262000
Gryaab	666441	604800	150700
Syvab	290412	143424	68200
Käppala	454909	432000	187123
Sjölunda	291200	432000	57140
Gässlösa	82600	129600	17080
Umeva	93364	86400	9870
Göviken	50800	59962	16800
Västerås	130333	115197	21810
Kalmar	55880	26160	9860
Sundet	61598	71700	14250

3.5 Regulatory frameworks for wastewater in EU and in Sweden

The EU has enacted several environmental acts. Sweden has gradually incorporated EU directives into national legislation since its accession to the EU in 1995 through law, ordinance, or government regulations. Several EU environmental acts are enforced broadly in the Environmental Code, Sweden's main environmental legislation. The most important EU directives governing wastewater discharge requirements are the Directive on Urban Wastewater Treatment (91/271/EEC) and the Water Framework Directive (2000/60/EG). The Marine Strategy Framework Directive (2008/56/EC), the Directive on bathing water quality and repealing (76/160/EEC), the Directive on the quality of water intended for human consumption (98/83/EC), the Directive on the protection of groundwater against pollution and deterioration (2006/118/EC), the Nitrates Directive (91/676/EEC), the Directive on environmental quality standards are other important directive related to wastewater treatment and disposal.(Swedish EPA 2018)

3.5.1 The Urban Wastewater Treatment Directive

This directive aims to protect the environment from the harmful effects of urban wastewater and wastewater discharges from certain industrial discharge processes. This includes the following specifications (Swedish EPA 2018):

- All agglomerations with more than 2,000 population equivalents must have an urban wastewater collection system. The requirements were gradually introduced for various agglomeration sizes and went into effect by the end of 2005.

- Before discharge, all wastewater entering the collecting system must undergo at least secondary treatment. This means the discharge must meet the requirements to discharge organic matter or other oxygen-consuming substances governed by the BOD and COD parameters. Treatment plants typically use a biological treatment method to accomplish this. There are other options, and they can be used as long as the emission levels are met. There may be some exceptions to this ground rule in coastal areas.
- When wastewater is discharged into sensitive areas identified by the member state, the directive imposes particularly stringent requirements.
- When wastewater is discharged to a sensitive area identified as sensitive to phosphorus or nitrogen or in a drainage area to such a sensitive area, the directive establishes specific requirements for these substances.

Sweden primarily incorporated the Urban Wastewater Directive into Swedish legislation through the Environmental Code and its ordinances and regulations. The directive's concrete requirements for wastewater treatment are largely incorporated into Swedish law by the Swedish EPA's regulations on treating and controlling wastewater discharge from urban areas. The Environmental Assessment Ordinance (2013:251) specifies which wastewater treatment plants must obtain permits. All wastewater treatment plants subject to the requirements of the Urban Wastewater Directive must be licensed. (Swedish EPA 2018). The Swedish EPA's regulations include, among other things, specific requirements for nitrogen and biochemically degradable organic matter (BOD_7) in wastewater discharge, as well as inspection and sampling rules. The regulations contain no phosphorus requirements because phosphorus discharge requirements are determined in wastewater treatment plant permits. In practice, significantly stricter than the requirements of the Urban Wastewater Directive.(Swedish EPA 2018). Sweden has identified areas that are sensitive to nutrient emissions or are at risk of becoming so unless action is taken. All waters in Sweden, including all coastal areas, have been designated phosphorus sensitive.(Swedish EPA 2018 & 2022)

3.5.2 Water Framework Directive

According to the Water Framework Directive 2000, all surface and groundwater bodies in the EU should have achieved "good status" by 2015 if no exceptions are granted. The directive also mandates that decreases in the current status be permitted. The Water Information System in Sweden (VISS) database contains maps and information on the status and environmental quality standards (including exceptions) for all water bodies in Sweden.

The Water Framework Directive has been incorporated into Swedish legislation primarily through provisions of the Environmental Code and the Water Management Ordinance. The SwAM and the Swedish Geological Survey have issued regulations outlining how Sweden's five water authorities should assess the status of surface and groundwater bodies and determine which environmental quality standards will apply to each. Current water status and environmental quality standards are important tools in the licensing process and should be used to determine discharge requirements in wastewater treatment plants' permits, among other things. Depending on the state of the water environment required by the water directive, some wastewater treatment plants may face stricter licensing requirements. These increased requirements may include parameters that are already treated in the treatment plant. Still, they may eventually include additional parameters that aren't addressed by the normal level of emission prerequisites.

3.6 The Swedish wastewater pipe network

In the 1850s, Sweden started being sensitive to nutrient emissions or water pipes. 80 Swedish cities had some form of wastewater drainage system by the early twentieth century. As industrialisation and the use of toilets increased, so did the demand for wastewater pipes. Previously, untreated wastewater was discharged directly into the environment, resulting in negative environmental effects. The first WWTPs were built between the 1930s and the 1950s to address this issue, employing mechanical treatment and combined sensitivity to nutrient emissions or pollution(Lundberg, 2021). However, as the volume of wastewater increased, frequent backflows and overflows were causing nutrient emissions or pollution. Separate systems replaced combined systems in the 1960s and 1970s, and WWTPs began using biological treatment. In the nineteenth century, tree or brick pipes were used for wastewater transportation. However, the introduction of vitrified clay pipes improved pipe quality between 1860 and 1940. From 1870 to the 1990s, concrete pipes were the preferred material, and plastic pipes were introduced in the 1970s and have dominated new installations since the 1990s. Most of the network was built between the 1960s and 1970s (Lundberg, 2021). Figure 3 shows that concrete was the dominant material used in Swedish wastewater pipe networks until the 1990s. Concrete pipes accounted for 66.6% of all pipes in an inventory conducted by Malm et al. (2011). PVC, Polyethylene and Polypropylene, and structure pipes accounted for 23.7% of the total.

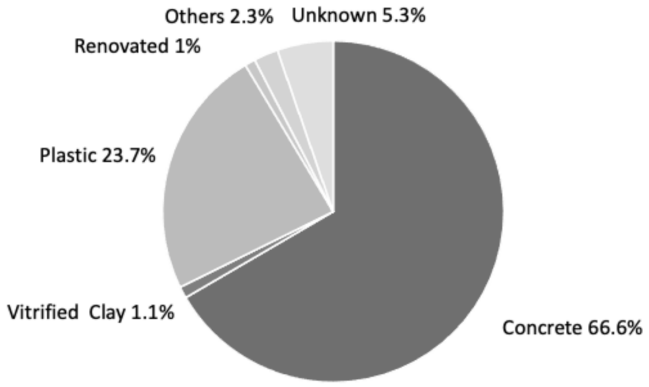

Figure 3: Material used in the Swedish wastewater pipe network. (Malm et al., 2011)

In 2017, more than 8.5 million people in Sweden had access to wastewater treatment facilities. Furthermore, the total length of the wastewater pipes exceeded 100,000 kilometres. According to the Swedish EPA (2016), 8% of these pipes are combined, 57% are separate wastewater pipes, and 35% are runoff water pipes. Figure 4 shows that plastic pipes, particularly Polyethylene and Polypropylene, dominated Sweden's 416 km of newly installed pipe in 2016.

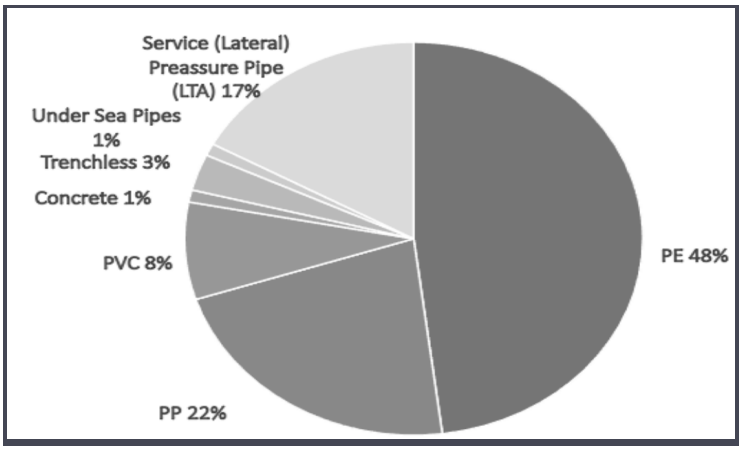

Figure 4: Material of newly installed wastewater pipes in Sweden (Lundberg · 2021).

3.7 Current practice of sewer inspection in Sweden

For many years, CCTV inspection has been the primary method for assessing the condition of sewage pipelines in Sweden due to its numerous advantages. Pushrod cameras mounted on a tractor and remote-controlled crawlers are used to inspect the pipelines. The level of optical control the camera provides varies depending on its type, and some cameras can even tilt and zoom. This enables the operator to obtain a complete circumferential view of the pipe and accurately assess its condition (Svensk Vatten 2016).

Traditionally, CCTV inspection has been used to detect and repair problems in sewer systems that have already occurred. Customers' complaints about sewer leaks, basement flooding, or a lack of water in taps usually prompt this approach. However, there has been a shift in recent years toward using CCTV inspection as a proactive tool to prevent sewer failures. This proactive approach entails inspecting sewer pipes regularly to identify potential problems before they cause significant damage. Using CCTV inspection, municipalities can avoid the negative consequences of sewer failure, such as property damage, environmental contamination, and service disruptions. Furthermore, early detection of potential problems allows for more cost-effective repairs than costly emergency repairs required when problems escalate. (Svensk vatten 2016)

Some municipalities have even begun to go beyond traditional preventative measures, implementing more advanced techniques such as sewer deterioration modelling. This method uses data from different sources, such as GIS databases, municipal databases, and CCTV inspections, to create models that predict the likelihood of sewer failure based on variables such as age, material, and location. Municipalities can use these models to prioritise maintenance and repair activities more efficiently and effectively, extending the life of their sewer systems. For example, Stockholm Vatten & Avfall (SVOA) developed a sewer deterioration model that can predict sewer failure. The model can prioritise sewer pipes needing inspection immediately. However, the model is not validated with real data yet. The company is interested in achieving more development in using Artificial Intelligence to model sewer failure prediction (SVOA 2023).

Overall, a shift toward a proactive inspection system is emerging. As technology and data analytics improve, proactive approaches will likely become more sophisticated and effective.

Municipalities can save money and resources while minimising the negative environmental and public health impact by identifying potential issues before they cause significant damage.

4. Sewer failure; characteristics and problems

4.1 Sewer failure characteristics

Sewer failure can be caused by structural or operational flaws that prevent sewage conveyance. Although pipelines are designed to last for a specific number of years, their deterioration does not follow a predictable pattern. Defects in both new and old pipes can be detected at any time.(Najaf and Kulandaivel 2005). The term "wastewater pipe failure" refers to an event in which the wastewater network does not function as intended in the context of this thesis. Previous research (Hawari et al., 2020; Mohammadi et al., 2019) divides wastewater pipe failure into two categories: operational failure and structural failure.

4.1.1 . Operational failure

The inability of the pipe to perform its operational or hydraulic function, which may or may not be caused by its structural condition or capacity to convey wastewater, is referred to as operational failure. The following sections will describe the various types of failures that can occur due to operational flaws.

Blockage: Operational or structural flaws can cause blockages in wastewater pipes. Root intrusion, sediment, fat, oil, grease, or objects such as rags, forks, or plastics can all cause pipe blockages (Malm et al., 2011). Basement flooding can occur as a result of stoppages and high flows. Extreme weather and heavy precipitation cause high flows. Basement flooding has financial costs for public infrastructure and private residences and the risk of pollution and disease. Basement flooding can also occur due to flooding from nearby bodies of water or stormwater runoff during heavy rain. Due to the increased risk of basement flooding caused by high flows, combined wastewater systems are more vulnerable than separate systems. (Malm et al., 2011). Sewer blockages indicate several problems in sewer networks, such as hydraulic deterioration, structural integrity, and operation and maintenance efficiency. (Van den Berg & Danilenko 2010)

Sewer overflow: Sanitary sewer overflows (SSOs) and combined sewer overflows (CSOs) are primarily influenced by the type of sewer system (combined or separate), pipe dimensions, and precipitation. Overflows are a way to reduce the risk of back flooding during heavy rain. On the other hand, overflows can have serious consequences if the wastewater ends up in the recipient, particularly for the environment. Sewer overflow can hurt public health, the environment, and the economy. When sewage from sanitary sewer systems overflows into the environment without being properly treated or processed, it can release harmful pollutants like bacteria, viruses, and other pathogens into the environment, spreading waterborne diseases and other health problems. Untreated sewage can also harm the environment by reducing oxygen levels, creating hazardous conditions for aquatic life, and encouraging the growth of harmful algae and bacteria. The cost of cleaning polluted waterways, lost tourism and recreational revenue, and damage to industries that rely on clean water can all have an economic impact. Several factors, including the volume of wastewater, the size of the recipient, and the characteristics of the wastewater, determine the severity of the environmental impact. Furthermore, if SSOs or CSOs occur during dry weather, the concentration of wastewater may be higher, exacerbating the consequences. (Malm et al., 2011).

Infiltration & Inflow (I & I): In an ideal situation, the amount of wastewater conveyed to a WWTP should match the amount of water produced at the water supply plants. However, this is not often due to Infiltration and Inflow (I & I). Infiltration occurs when groundwater and precipitation infiltrate the wastewater pipes through fractures, cracks, poor installation, or inadequate joints. Conversely, inflow is the additional water in the system caused by inappropriate connections such as roof or surface drainage (Barton, Yang, and Kelly, 2009). The consequences of high levels of I & I are basement flooding, CSOs or SSOs, and capacity problems at WWTP. This means the WWTP cannot treat all incoming wastewater or may skip certain treatment processes (Cardoso et al., 2006). The amount of I & I also depends on the groundwater table and soil type. If the pipe is located below the groundwater table, the risk of infiltration increases. Soils with high permeability, i.e., the ability for fluids to penetrate the soil, have a higher risk of infiltration (Beheshti and Sægrov, 2018).

4.1.2 . Structural failure

Wastewater pipe failures and breaks are complex phenomena without a clear definition that necessitate additional research. On the other hand, Rajani and Kleiner (2001) proposed physical mechanisms that influence pipe failure, such as:

- Material, interaction with soil type, and installation (e.g., transportation, jointing, bedding, and backfill) are examples of structural properties.
- External loads typically include soil overburden, live loads (e.g., traffic), and frost.
- Chemical processes such as corrosion and sulfuric acid are examples of material deterioration.

It is critical to understand that structural failure in wastewater pipes involves a stepwise deterioration of the pipe's condition. Corrosion, improper joint sealing, soil settlement, and loading can all contribute to this deterioration. The pipe's structural failure or breakage results from this deterioration. According to Rajani and Kleiner (2001), there are three types of breakage: circumferential breakage, longitudinal breaks, and bell split or joint breakage.

Circumferential breaks: As illustrated in Figure 5a, circumferential cracks or fractures often result from vertical loads in combination with uneven bedding. Such loading causes the pipe to act like a beam, exceeding its design limits. Small leaks that disrupt the soiled bedding, or soil movements and settlements, typically in clay soils, can cause this type of failure. The cracks can occur at the pipe's top, bottom, or around.

Longitudinal breaks: These are horizontal cracks or fractures that occur along the pipe's walls, as shown in Figure 5b. Overload, cylinder (hoop) stress from internal water pressure, and frost loads are the most common causes of such cracks (Rajani and Kleiner, 2001). These cracks typically begin with minor deformations that may extend horizontally along the pipe.

Bell splitting (or joint failure): occurs due to insufficient or deteriorated joint or ground movements.The red "line" depicts the insufficient joint or bell splitting(Figure 5c)

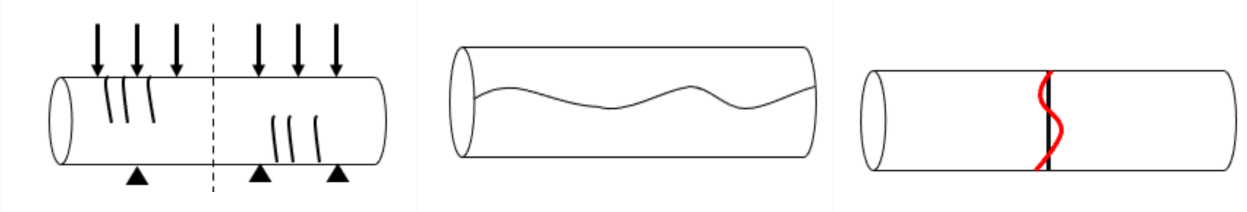

Figure 5: a.circumferential crack,b. longitudinal crack and c.joint failure (Rajani and Kleiner 2001).

Pipe failure is typically a gradual process of deterioration rather than an abrupt failure. Small cracks may form initially and then grow into larger fractures, accelerating deterioration when combined with infiltration, disturbed bedding conditions, and ground movements.Sewer structural failure can result in significant operational failures. When a sewer line fails, it can result in blockage, sewer inflow, infiltration, exfiltration, or even sewer overflow, which leads to service interruptions, environmental damage, and safety hazards. For example, if a sewer line ruptures, sewage can overflow into nearby bodies of water or onto streets, posing health risks to the public and causing environmental damage. Sewer backups can also occur in homes and businesses, resulting in costly repairs and health risks.(Rajani and Kleiner 2001)

4.2 Impact of sewer failure

Sewer impact failure can be widely varying. It has an impact on the functionality of the system as well as the impact on ecology. To understand the impact, this chapter discusses this in terms of sewer exfiltration and inflow and infiltration.

4.2.1 Exfiltration

Sewage exfiltration from both gravity sewers and pressure mains is a phenomenon that poses potential hazards to public health and the environment, as it can contaminate the soil and groundwater. Studies conducted in several US cities found that sewer water exfiltration ranged from approximately 25% to 45% (Selvakumar et al., 2004). Similarly, exfiltration ratios in Hue City, Vietnam, were as high as 65.6% during the dry season and 24.0% during the rainy season (Watanabe et al., 2019).

Sewer leaks can cause groundwater pollution and contamination bacteria, viruses, protozoa, and other microorganisms. Factors such as hydraulic head, substrate characteristics, and pollutant type and concentration can affect the transport of pollutants into groundwater. Faecal bacteria contamination poses the greatest health risk associated with sewage leakage. At the same time, high levels of organic carbon, nitrate, chloride, and sulphate exfiltrated through horizontal cracks or fractures were found to travel together as evidence of sewage pollution. At the same time, phosphate and boron are effective indicators of sewage contamination (Amick and Burgess, 2000).

A study conducted in Rastatt, Germany, showed that groundwater beneath the city was influenced by sewage leakage, resulting in elevated concentrations of boron, potassium, and sodium and increased electrical conductivity overall. Groundwater near broken sewers also contained sewage indicators, such as iodinated X-ray contrast media and microbiological parameters. Despite significant concentrations of pharmaceuticals in wastewater, no

contamination with pharmaceutical residues or gadolinium was found in groundwater (Held et al., 2006).

Exfiltration sewage can enter the distribution system through a broken water main or a hole that leaks water out under normal positive pressure conditions. Infiltration of sewage through a reduction of main water pressure mainly occurs due to backflow and surges (Amick and Burgess, 2000). In 1989, freezing temperatures caused a suspected cross-connection between sewage overflow and two major distribution system line breaks in Cabool, Missouri. This resulted in 243 diarrhoea cases, 32 hospitalisations, and four deaths from the E. coli strain.(Amick and Burgess, 2000)

Surface water pollution due to exfiltration impacts is common in areas with steep topographic conditions, where sewers are located near surface waters and at elevations higher than the surface water. (Selvakumar et al. 2004) Exfiltration can happen continuously and significantly all year, reducing the wastewater loads at the sewer outlet. However, this reduced sewer loading may be interpreted incorrectly as a positive outcome for plants. Much sewage may go to groundwater or surrounding water bodies (Watanabe et al., 2019).

4.2.2. Inflow & Infiltration

Infiltration is a physical factor that occurs unintentionally due to wastewater sewer system damage (Jenssen Sola et al., 2018). Infiltration typically occurs at faulty joints, pipes, connections, and manholes. Infiltration may occur if the system is damaged and the groundwater table exceeds the defective pipe. As a result, infiltration is affected by the state of the sewer system, hydrogeologic conditions, and potential sources of infiltration water.

The percentage of industrial and commercial (I/I) wastewater infiltration varies widely across different countries. Germany (Baden-Württemberg) has an I/I share of 35%; the Netherlands has an I/I share of 38%, while Norway (14 different cities) has a high share of 67%. Austria (32 WWTPs) has an I/I share ranging from 25-50%, Sweden has an I/I share of 50%, and the UK has an I/I share of 45%. Scotland (Edinburgh) has an I/I share of 60%. Combined sewer overflows (CSOs) are widespread worldwide, ranging from 35 to 65%, while Canada has the lowest I/I share of 8%. Finally, the Czech Republic has an I/I share of 45%, while the USA has an I/I share of 55-65% (Hey, Jönsson, and Mattsson 2016). Alenius, Clementson, and Gustafsson (2020) found that the share of infiltrated water in the sewer systems of the Swedish municipalities studied ranged from 20-60%. Stormwater and water from leaking underground pipes are all potential sources of infiltrated water (Staufer, Scheidegger, and Rieckermann, 2012). It can enter the sewer system through pipe connections that are either intentional or unintentional (Ohlin Saletti, 2020). Furthermore, I/I-water can infiltrate due to damaged pipes or other components.

The impact of infiltration and inflow (I&I) on wastewater treatment facilities can be measured in various ways, including the amount of pollutant load discharged, the toxicity of the wastewater, and the frequency of bypasses and overflows. However, in the case study of Hey et al. (2016) , wastewater dilution is used as a common indicator of the impact of urban runoff on I&I. Table 3 shows that most wastewater treatment plants (WWTPs) have an average dilution percentage of 200%. This means that the total volume of I&I is of the same order of magnitude as the volume of debited wastewater (domestic and industrial wastewater) annually. The degree of dilution, on the other hand, varies greatly over a year. (Hey et al. 2016)

Table 3. Percentage (%) dilution of incoming wastewater (Hey et al. 2016)

WWTP	Average	Median	90 percentile	99 percentile
Gryaab	282	234	479	760
Bromma	224	207	288	471
Henriksdal	182	166	240	399
Syvab	172	167	206	276
Käppala	186	170	257	412
Sjölunda	157	139	209	363
Gässlösa	226	198	330	515
Umeva	212	190	307	445
Göviken	211	188	275	578
Västerås	216	192	300	442
Kalmar	154	130	220	352
Sundet	179	168	230	379

The high dilution factor suggests that I&I has a significant impact on WWTP performance. Infiltration and inflow can overload the system and reduce treatment efficiency, resulting in the discharge of untreated wastewater into the environment. This can harm the receiving water body's water quality, potentially causing ecological damage and harm to human health. As a result, addressing the issue of I&I by implementing effective measures to reduce its volume and impact on wastewater treatment facilities is critical. Repair and maintenance of existing sewer infrastructure, implementing green infrastructure practices, and developing policies and regulations to control urban runoff are examples of such measures. Reduced I&I can improve the efficiency of wastewater treatment facilities, resulting in better water quality and a healthier environment. As shown in Table 3, water dilution provides insight into the additional flow that a wastewater treatment plant (WWTP) must handle. These indicators are not affected by the size of the WWTP, implying that all WWTPs, regardless of capacity, must handle similar amounts of extra flow.

To understand the impact of excessive flow on a wastewater treatment plant (WWTP), the relationship between flow per capita per day (l/p/d) and the WWTP's secondary (biological) treatment capacity must be examined. Table 4 shows that the majority of WWTPs have a secondary treatment capacity that is significantly greater than the median flow. Still, there is a significant margin at the 90th percentile of flow. The 90th percentile of flow for a few WWTPs is close to capacity, indicating that the treatment capacity exceeded approximately 10% of the flow events during the year study. The 99th percentile of flow at these two treatment plants and three other WWTPs is significantly higher than capacity. Furthermore, overflows upstream of the WWTP may have contributed to the low likelihood of exceeding secondary treatment capacity.

Table 4. Incoming Flow to Swedish WWTP (Hey et al. 2016)

WWTP	Debited (l/p/d)	Fow in WWTP					
		Average (l/p/d)	Median (l/p/d	90th percentile (l/p/d)	99th percentile (l/p/d)	Dilution factor 90th percentile	Dilution factor 99th percentile
Bromma	199	443	410	570	933	4.8	7.6
Henriksdal	198	361	329	475	791	2.9	4.7
Gryaab	204	575	478	977	1549	2.4	4.0
Syvab	242	417	404	499	669	2.1	2.8
Käppala	194	361	330	498	799	2.6	4.1
Sjölunda	254	398	354	532	921	2.1	3.6
Gässlösa	235	533	466	776	1212	3.3	5.2
Umeva	200	424	381	614	889	3.1	4.4
Göviken	200	421	376	550	1156	2.8	5.8
Västerås	200	431	384	601	883	3.0	4.4
Kalmar	200	279	263	353	517	1.8	2.6
Sundet	200	359	336	460	759	2.3	3.8

Excessive infiltration may also impact surface water quality by increasing the risk of sewer overflow (Liu and Prigiobbe, 2018). The imposed volumes can impact removal rates, leading to greater total pollutant loads in the effluent, which can endanger the aquatic system (Hey et al., 2016). Furthermore, subsidence can occur due to lower groundwater tables caused by infiltration (Bäckman, 1985). Basement flooding may occur when the sewer system's capacity is exceeded due to infiltration (Bäckman, 1985). Basement flooding usually accompanies heavy rains when backflow occurs into the house's pipe (Bäckman, 1985). Flooding caused by infiltration can also happen in other places, such as streets and roads (Saletti, 2022).

The release of combined sewer overflows (CSOs) can seriously affect public health and water quality. These overflows transport various pollutants like nutrients, microorganisms, particulates, and metals, which can degrade the quality of receiving waters and pose risks to human health . Consequently, they cause environmental pollution. Previous studies have demonstrated that these sewer overflows are major sources of water pollution in receiving water bodies.(Muttil, Nasrin, and Sharma, 2023)

Combined sewer overflows (CSOs) are widespread worldwide, with thousands of incidents occurring annually in the US, Europe, and elsewhere. Changing precipitation patterns due to climate change may lead to more frequent and severe CSO events, particularly in urban areas with combined sewers already vulnerable due to increasing urbanisation. While some areas may see a reduction in rainfall events, much of North America and northern Europe are expected to experience more rainfall and worsening wet extremes. Research predicts that CSO events will worsen in urban areas under climate change, with increasing urbanisation and

absent mitigation measures contributing to the frequency and volume of CSO discharges (A. Bizer and Kirchhoff).

Abbasi, Zeynolabedin, and Nabi Bidhendi (2021) evaluate the impacts of combined sewer overflows (CSOs) in a wastewater treatment plant (WWTP) in New York City during intense floods. The study uses multi-criteria decision-making (MCDM) to evaluate the impacts of CSOs on health, economic, social, and environmental factors. The results show that volume and depth are the most significant factors for the CSO impact assessment. The sensitivity analysis reveals that Total Suspended Solids (TSS), Biochemical Oxygen Demand (BOD), and dissolved oxygen impact CSO the most. The uncertainty analysis shows that evaluating the impacts of CSOs in different aspects can help improve the efficiency of flood planning and management during storms.

Organic pollutants, including faecal matter, can consume dissolved oxygen in the water, harming aquatic life. Toxic pollutants, such as ammonia, hydrogen, copper, phenol, cyanide, and other poisonous substances, can cause severe environmental damage. Excess nutrients in a water body can lead to eutrophication and sewage-associated bacterial pollutants can pose serious health hazards. (Daher et al., 2018)

4.2.1 Financial Burden

The increased volume of water necessitates more energy consumption in terms of pumping, more maintenance, and a shorter life span for the materials (Dirckx, Van Daele, and Hellinck, 2016). More water in the WWTP means more chemicals used in the treatment (Bäckman, 1985).

Stormwater inflow and groundwater infiltration account for nearly 50% of the flow at treatment plants with ageing infrastructure. According to SEH Water Resources, a single leak from a joint in a manhole or sewer pipe can infiltrate up to 7,200 gallons of water per day (Singer, 2021). The additional water in the systems affects the treatment plant's life expectancy. As a result, new ones must be built to replace sewer systems that have reached capacity due to increased demand, which consumes energy and labour and generates costs. Sediment and debris that enter the system with the I/I may cause blockage (USEPA, 1970 in Saletti 2022) and accelerate pipe ageing. Sand and soil entering the wastewater system can also cause the undermining of streets and roads (Karpf and Krebs, 2011).

Furthermore, infiltration can result in increased land taken for enlarging WWTPs and elevated construction efforts to build larger systems (Broadhead, Horn, and Lerner, 2015). It may also impact new urban developments if existing wastewater structures lack spare capacity (Dirckx, Van Daele, and Hellinck, 2016). It also incurs additional pumping costs (Kracht, Gresch, and Gujer, 2008). Infiltrat, finely suspended wastewater dilution results in less appropriate WWTP treatments in WWTPs (Bäckman, 1985; Parkinson et al., 2005). Communities often have to choose between making investment funds available to reduce I&I and limiting new residential or industrial growth; new developments can overload collection and treatment structures that are already overburdened, necessitating additional repairs. On the other hand, residential and institutional development opportunities are critical to community mobilisation, quality of life, and capturing additional tax revenue. Limiting either of these limits opportunity and may result in long-term financial difficulties.(Cossalter, Mckenzie, and Kubesh, 2021).

Basement flooding and sewer overflows can be caused by inflow and infiltration (I&I), resulting in property damage and compensation costs. Too much water entering the sewer system can

overwhelm it, resulting in basement backups and overflows in streets and waterways. These occurrences can cause significant property damage to homes and businesses and pose health risks to the general public.Repairing and compensating for property damage caused by basement flooding and sewer overflows can be substantial. Depending on the circumstances, it may fall on the shoulders of either society or the sewer authority. In some cases, homeowners may be required to obtain additional insurance to cover the costs of sewer backup damage. Alternatively, if it is discovered that the sewer system was not properly maintained or that there were design flaws in the system, in that case, the sewer authority may be held liable for compensating homeowners for their losses.(Mobini, 2021) Metropolitan St. Louis Sewer District (MSD) states in its policy outline that if the sewer line overflows due to heavy rain, the excess water may not be contained, resulting in a discharge into buildings. In such cases, MSD will reimburse up to $3,000 (approximate 30,000 SEK) for any damages incurred, with a $100 (1000 SEK) deductible. However, it is important to note that the cost of the damage may exceed this amount, so homeowners should seek additional coverage from their insurance companies. (Mobini, 2021)

Andersson et al. (2020) created a model that was used to simulate scenarios of changing input water to three Swedish wastewater treatment plants, which were then used to assess environmental impacts using life cycle assessment models. According to the study, increased flow peaks have a greater impact on the environment than infiltration. Reduced infiltration had a lower environmental impact per kilogram of nitrogen removed across all categories studied, whereas increased infiltration had the opposite effect. Lowering infiltration caused a 7% to 20% decrease in total flow, resulting in cost savings per kilogram of nitrogen removed during treatment. Because of the expected increase in pollutant concentrations in wastewater, future demands must be considered for lowering organic matter and nutrient concentrations in wastewater. Chemicals used in treatment processes account for a significant portion of wastewater treatment plant operating costs. However, if the rate of the I&I decreases, the overall costs will not rise because treating higher concentrations of pollutants is less expensive than treating large volumes of water. Improving the removal efficiency of some residual fractions in effluent wastewater, such as soluble nitrogen and phosphorus, is critical.

The cost of wastewater treatment is determined by several factors, including the type of water delivered to the treatment plant. According to a study conducted at Ryaverket, a wastewater treatment plant in Gothenburg, the cost per cubic metre flow of I/I water from 2011 to 2015 was 1.97 SEK/m3, which was higher than the average cost of total wastewater of 1.55 SEK/m3. However, the cost includes the revenue generated by district heating, biogas production, and sale. The Ryaverket plant can handle flows of up to 7 m3/s, but higher flows cause some treatment processes to be bypassed. Various factors, including the type of water delivered to the treatment plant, influence the cost of wastewater treatment(Nivert & Alenius, 2017).

The provision of sewer infrastructure is a capital-intensive process, with fixed costs accounting for up to 80% of total utility costs (Hukka and Katko 2015). However, estimating appropriate investment levels for wastewater infrastructure can be challenging due to several factors such as long asset life, time-consuming asset condition assessment, differences between accounting and real value, and the difficulty of calculating the costs of deferred investments (Tscheikner-Gratl et al., 2019). In addition, the combined investment requirement for urban water supply and drainage infrastructure is also set at 0.75% of the gross domestic product (Cashman and Ashley, 2008).

Austria requires a yearly reinvestment of €490 to €830 million for its sewer infrastructure (Neunteufel et al. 2012). Similarly, Berger et al. (2016) found that 20% of Germany's sewer

network requires short or mid-term rehabilitation, with an estimated capital need of €7 billion. However, an annual investment in sewer rehabilitation of approximately €4 billion offsets this capital need, representing a rehabilitation rate of 1.1%. In the Netherlands, 1% of the sewer network is affected yearly, and an annual budget of €800 million is expended on sewer restoration or replacement, which falls short of the anticipated need (Oosteroman and Hermans, 2013). France's annual investments during 2010-12 were at the Dutch level, resulting in a €1.4 billion deficit per year (Lesage 2013). Sweden's water and wastewater industries face significant future challenges that will necessitate significant investments to restore older pipe networks, water treatment plants, and wastewater treatment plants. Furthermore, due to the effects of climate change, municipalities must invest heavily in stormwater management (Svenskt Vatten, 2021).

Phosphorus recovery from wastewater has become a pressing issue due to its limited natural availability and increasing demand in the agriculture industry. To address this issue, wastewater treatment plants (WWTPs) can recover phosphorus by treating wastewater to a higher level, requiring more sophisticated technologies and higher operating costs. The Henriksdal WWTP aims to recover phosphorus at a rate of 27 tons per year. This necessitates purifying the water in the membrane bioreactor (MBR) to a much lower level of 0.10-0.12, as opposed to the previously stated requirement of 0.15 (SVOA 2023). Meeting this phosphorus recovery target is critical, and it necessitates controlling wastewater dilution and investing in plant expansion or rebuilding. Without these measures, the plant may struggle to meet future phosphorus requirements and may reach its maximum hydraulic capacity. This may result in inefficient operation, increased operational costs, and service disruptions (Pollert et al., 2005). Investing in plant expansion or rebuilding to meet future phosphorus requirements is thus critical for the WWTP's efficient and cost-effective operation. This investment will allow the plant to recover phosphorus more efficiently and expand its capacity, allowing it to handle incoming wastewater flows without compromising the quality of the treated water. This will provide a long-term and dependable solution for wastewater treatment and phosphorus recovery, avoiding the need for future costly expansions or upgrades (Baresel et al., 2017).

The current cost of treatment per cubic metre (m3) of wastewater in Henriksdal WWTP varies between about 1.04 and about 1.16 Swedish Krona (SEK). It was also discovered that the cost per kilogram (kg) of recovered nitrogen (N) ranged between 29 and 33 SEK/kg N separated. If the input water is reduced, the cost per treated m3 of wastewater rises (SVOA 2023). Minimising wastewater dilution and avoiding additional water to the treatment plant is critical for cost reduction and efficiency. If the additional water could be reduced from 44% to 34% of the inflow (corresponding to a reduction of approximately 74,000 m3/d), the daily cost reduction would be approximately SEK 24,000, considering the increased major functional factors related to the concentration of pollutants and reduction of total wastewater. Although there may be a cost increase of SEK 0.12/m3 that passes through the plant (due to the high concentration of pollutants requiring additional chemical use), a savings of SEK 0.32/m3 of additional water (decreased burden) that the treatment plant can avoid outweigh the increased cost.(SVOA 2023)

However, dilution, to some extent, has some benefits also. A decrease in infiltration would result in a higher density of sanitary sewage, substantially increasing the chemical cost of sulphide remediation per unit (Sun et al., 2015). Less infiltration in the system may decrease the frequency of self-cleaning velocities, resulting in sediment accumulation in the wastewater sewer system (Parkinson et al., 2005; Karpf and Krebs, 2011). Less infiltration may also result in higher pollutant concentrations in CSOs and SSOs if they occur. Increased pollutant concentrations in the wastewater sewer system due to decreased flows may also cause odour

and corrosion issues (Sun et al., 2015; Karpf and Krebs, 2011). According to Sun et al. (2015), the lower water level in pipes would increase methane concentrations in the wastewater sewer system. This implies that removing infiltration from the wastewater sewer system could increase greenhouse gas emissions. Cook, Samaras, and Van Briesen (2018) state that infiltration up to 30% of total dry weather flow is better for the system.

5.2.2 Case study on the impact of inflow and infiltration

Ohlin Saletti et al. (2023) conducted a study to determine the societal cost of infiltration and inflow to wastewater systems in the centre of Gothenburg, Sweden. The study focused on a densely populated region covering 310 hectares, with around 35,000 connected person equivalents, where the wastewater system is mostly combined, and there are various discharge points for CSOs. The study area was chosen due to water issues prevalent in the region, and it was included in an existing hydrological and hydraulic model called Future City Flow. The wastewater from the area is directed to the Rya WWTP, built in 1972 and serves a population of 800,000, with upgrades planned for completion in 2036.

Figure 6 shows the distribution of cost categories based on simulation results. The majority of the total cost comes from expenses related to WWTP and basement flooding events. The cost of WWTP primarily comprises investment costs, while the cost of restoring basement flooding events makes up most of the expenses.

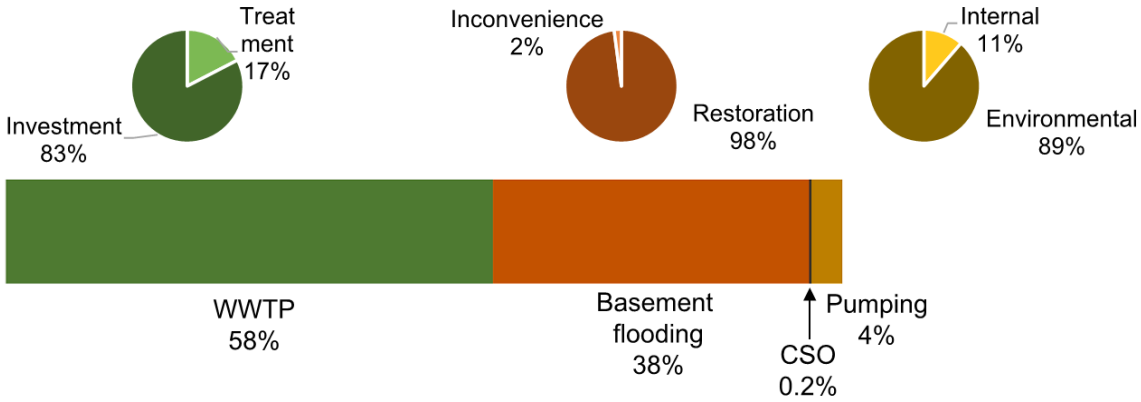

Fig. 6: The proportion of different categories based on medians of PV of cost categories.(Ohlin Saletti et al., 2023)

Figure 7 presents the total present value (PV) and the PV for various cost categories. The median of the total PV is approximately 687 million SEK, with the 10th percentile being 32% lower (470 million SEK) and the 90th percentile being 165% higher (1,819 million SEK). The mean of the medians of the PV for ten simulations with 100,000 iterations was 689 million SEK, with a standard deviation of 0.8 million SEK, which is 0.12% of the mean

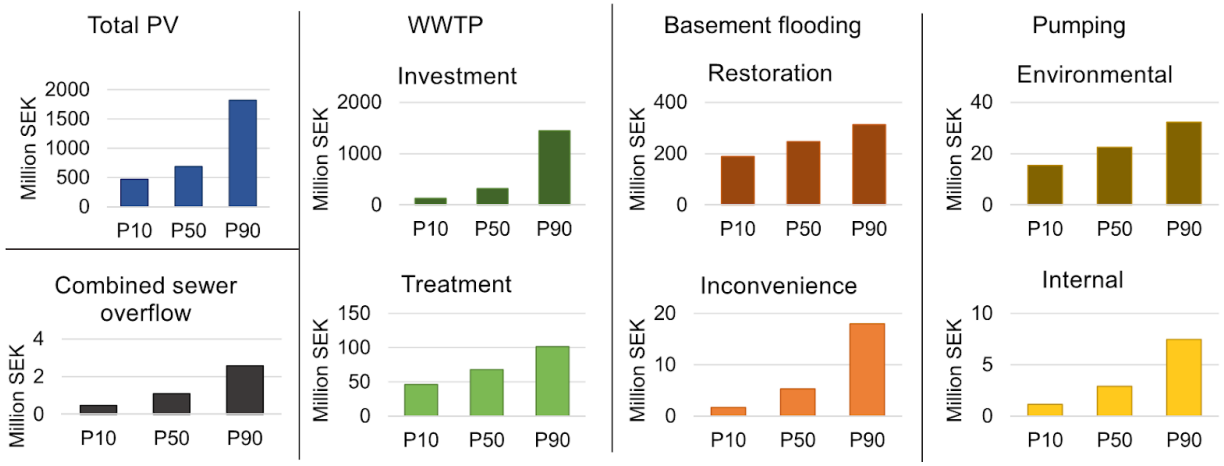

Fig. 7: PV of 10th, 50th, and 90th percentiles for the cost categories.(Ohlin Saletti et al., 2023)

The case study findings indicated that the major cost drivers associated with I/I-water were investments in the wastewater treatment plant and basement flooding events. The study showed that the cost of CSOs and pumping was negligible, which was an unexpected result. The study used a monetisation approach based on achieving the good status of recipients for inhabitants and was found to be approximately 300 SEK/kg released PO4 equivalent.

5. Proactive sewer pipe inspection approaches

Inspecting sewer pipes is critical for maintenance because it detects defects and blockages that can lead to system failure and environmental damage. Data on pipe conditions is collected using various methods, including sonar, robots, radar, and MFL. Proactive models attempt to predict the likelihood of failure before it becomes a major issue. These models collect data and make predictions using advanced equipment and techniques. Sonar uses sound waves to create images, robots navigate pipes to collect data, radar detects structural changes, and MFL detects defects and corrosion. Condition assessment models combine data from databases and records to prioritise intervention for deteriorated pipes. Degradation models establish the relationship between factors and pipeline conditions. Modelling sewer deterioration requires data with deterioration factors and observed pipeline conditions.

Sewer failure prediction models are mathematical models that forecast potential sewer system failures based on age, condition, blockages, and weather conditions. There are three types of models: deterioration models, blockage models, and CSO (Combined Sewer Overflow) models. Deterioration models predict sewer failure based on factors such as pipe material, age, soil type, and environmental conditions, determining a sewer system's remaining useful life. Blockage models forecast blockages and overflows based on variables such as pipe diameter, flow rate, and debris, identifying potential problem areas and recommending preventive maintenance. CSO models forecast combined sewer overflows by considering data such as rainfall intensity, runoff, and sewer system capacity, allowing for system optimisation and future planning.

The concept, data requirements, and calibration methods of models for estimating the future condition of sewer pipelines differ. Physical models establish a mathematical relationship between degradation factors and pipeline conditions, but they do not consider uncertainty. Through probability-based equations, statistical models incorporate uncertainties. Using inspection report knowledge, data-driven artificial intelligence models analyse computational interactions between deterioration factors and condition data. Each model has a distinct approach and set of characteristics (Scheidegger et al., 2011). However, as the study did not find any physical model with validated efficiency or precision, the physical model is opted out of the literature and discussion.

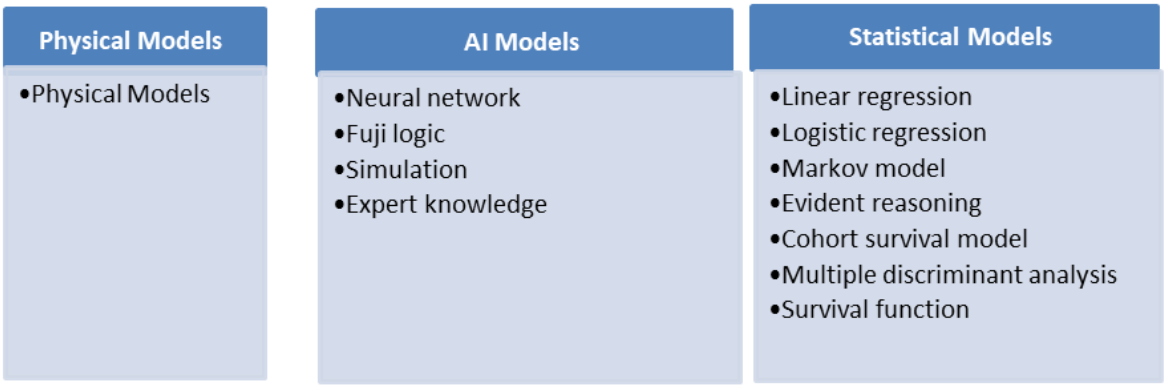

Figure 8: Sewer failure prediction models addressed in the literature review. (Scheidegger et al., 2011, Hawari et al., 2017).

5.1 Deterioration models

5.1.1 Artificial intelligence models

The goal of artificial intelligence (AI) models is to mimic human-like problem-solving and pattern recognition abilities. They include Artificial Neural Networks (ANN), rule-based fuzzy logic models, rule-based simulation models, and expert systems, among others. (Tran, Ng, and Perera, 2007). It has many branches as follows.-

Artificial Neural Networks (ANN) simulate the human nervous system by using interconnected artificial neurons. They learn through pattern recognition and can predict outcomes based on historical information(Salman and Salem, 2012) ANN models are effective in dealing with complex relationships and incomplete data. However, they require extensive datasets and can be challenging to interpret due to their "black box" nature.(Abiodun et al., 2018). Rule-based fuzzy logic models employ fuzzy if-then rules to deal with uncertainty and imprecision. These models capture relationships between variables and linguistic terms, allowing them to deal with qualitative and uncertain data. On the other hand, obtaining both accuracy and interpretability in fuzzy logic models is a trade-off that remains a personal challenge(Gacto, Alcalá, and Herrera, 2011). To estimate real-world behaviour, rule-based simulation models generate virtual outcomes. These models define systems as collections of entities with attributes and state transitions, allowing them to provide insights into the system's dynamics. The reliance on generating random probabilities and limited data points, on the other hand, can introduce uncertainty in condition ratings.(Chylek et al., 2013). Expert systems imitate domain experts' knowledge and reasoning. To solve problems and separate knowledge from inference, they use if-then rules. Within their domain, expert systems excel at efficient and accurate

problem-solving. (Pandya, 1999). However, they are limited to problems that can be solved, and their conservative nature can lead to errors in real-world situations (Eugenia et al., 2014).

AI-based models in literature

Hahn et al. (2002) proposed an expert system to assess the condition of the sewer system and highlight the need for repair. Consequences of failure included socioeconomic and reconstruction impact, installation history, pipe age, material, soil type, groundwater level, surface load, exfiltration, structural defect history, corrosion, wastewater type, soil properties, and many other factors considered as a knowledge base. The developed system was implemented in the Paris sewer system. The model accuracy was tested, providing 55% prediction similarity, 37% more conservative predictions, and 8% less conservative predictions. Furthermore, the authors concluded that by including more case studies, the accuracy of the predictions could be improved even further.

In a study by Mashford et al. (2011), a vector machine was used to predict the failure of pipes based on several variables, including pipe age, pipe diameter, road type, pipe inclination angle, pipe material, and soil type. The results showed that pipe age and diameter were significant predictors of failure, with a prediction accuracy of 91%.

Harvey and McBean (2014) present a data mining approach that utilises existing inspection records to identify the uninspected pipes in the network that are most likely structurally defective. The random forests algorithm is used to develop predictive models that classify the pipes as either in good or bad condition. In a case study application to the City of Guelph, Ontario, Canada, the random forests algorithm achieved a stratified test set false negative rate of 18%, a false positive rate of 27%, and an area under the ROC curve of 0.81, which is considered excellent. Moreover, by including condition information of pipes attached at either the upstream or downstream manholes of an individual pipe, the predictive power for bad pipes is enhanced, resulting in a reduction of the false negative rate to 11%, a reduction of the false positive rate to 25%, and an increase in the area under the ROC curve to 0.85.

Sousa, Matos, and Matias (2014) developed an ANN-based model along with two other models based on Support Vector Machines (SVMs) and Logistic Regression (LR) to assess sewer condition. Material and diameter of the pipe, no of sewer, total length, average age, average depth, average slope, and average length were considered model input. The models were tested using a case study of Costa do Estoril wastewater, and the ANN model performed the best compared to the others, with a precision of 78.5%. In comparison, the statistical model precision was 72.6%.

Alsaqqar, Khudair, and Jbbar (2017) used a neural network deterioration model (NNDM) to forecast the condition of sewer pipelines in Baghdad. Data from various municipalities were collected to develop the model, which included pipe condition, age, diameter, length, slope, depth, shape, function, type, and traffic intensity. With an efficiency of 87.3%, the model provided a high overall prediction. Zublin sewer pipelines in Baghdad were found to be in poor condition.

Liang et al. (2021) developed a failure prediction framework for pipe networks using a multi-hop Graph Neural Network (GNN). They collected data on 941,142 pipes connected by 947,183 joints from two large-scale pipe networks in the real world, including the number of failures, age, length, diameter, pipe material, coating, soil type, tree canopy, slope and shape of the pipes,

node degree, node rank, and node cluster. They used AUC, F1 score, precision, and recall to evaluate the model's performance. Their results showed that the MAG-LSTM model achieved a precision of 0.855 ± 0.018, F1 factor 0.452 ± 0.015, and recall of 0.661 ± 0.014. The model revealed that historical failures and sewer pipe characteristics such as diameter, VC material, and soil quality were significant factors in predicting sewer pipe failure.

5.1.2 Statistical models

A statistical model is a random variable X that denotes a quantity whose output is uncertain. The probabilistic character of historical information is used in statistical models to explain the model output as a random variable. Estimates in statistical analysis are "best guesses" based on the status of given historical data. According to Dasu and Johnson (2003), the parametric density function is used in statistical models to measure errors and determine probabilistic interactions among independent and dependent variables. The advantages of statistical models include predicting the ordinal data type and considering the probabilistic nature of the underlying deterioration process. In contrast, the disadvantages include statistical models' sensitivity to noisy data and methodologies for measuring errors (Giraldo-González and Rodríguez, 2020). Previous studies used various statistical models to predict the condition of sewer pipes, including linear regression, exponential regression, logistic regression, Markov chain, Semi-Markov chain, ordinal regression, and cohort survival models.

Linear regression models establish a relationship between two independent and dependent variables. They can forecast sewer pipe conditions by considering factors like material, age, length, slope, and environmental factors. (Rawlings, Dickey, and Pantula, 1998). However, linear regression models have limitations when dealing with categorical variables, as they make assumptions about constant distance and normally distributed errors, which may not hold in sewer deterioration.(Raghuvanshi, 2016). The relationship between multiple independent variables and a categorical dependent variable is investigated using logistic regression. It calculates the likelihood of an event occurring and is appropriate for both binary and multinomial outcomes. Building accurate logistic regression models requires much data on the factors influencing sewer deterioration.(Osborne 2015).

Evidential reasoning employs degrees of belief to deal with uncertainty and make sound decisions. It combines evidence from multiple sources to reach reliable conclusions. However, this approach has limitations in dealing with dependent factors and conflicts.(Hawari et al., 2018). Markov chain models forecast future events based on current values without considering past effects. (Pérez-Ocón and Torres-Castro, 2002). They reveal the chronological progression of sewer deterioration. However, determining transition probabilities and assuming time independence can be difficult, particularly with limited historical data.(Ching et al., 2013).

For pipes with similar characteristics, cohort survival models explain sewer deterioration. They assume cohorts survive for a set period of time in a given condition. However, difficulties arise due to selective data bias and underestimation of the worst condition states, resulting in overestimated survival rates and remaining service life.Duchesne et al., 2012).

The linear correlation between a categorical dependent variable and multiple predictor variables is investigated using multiple discriminant analyses. It is useful when dealing with multiple outcomes. To ensure accurate predictions, however, sufficient data, linearity, normality, and no multicollinearity between independent variables are required.(Tran, 2007 & Da et al., 2013). These models provide useful insights into sewer deterioration prediction, but they all

have limitations. Understanding these models can help you choose the best approach based on the available data and your needs.

Statistical Models in Literature

To study the decline of gravity pipelines in Australia, Tran (2007) used multiple discriminant analysis. The factors considered as predictors were diameter, age, depth, slope, location, tree roots, soil properties, and hydraulic condition. However, the model did not perform well as it could predict with less than 50% accuracy.

Chughtai and Zayed (2008) researched predicting sewer pipeline deterioration using multiple regression analysis. The study analysed various independent variables such as pipe material, depth, length, age, diameter, bedding, road type, and slope to develop the model. The best subset analysis was used to identify the most significant variables. The study also employed statistical tests such as the F-test, t-test, residual analysis, lack of fit test, and Durbin-Watson test to determine the significance of the variable. According to Dasu and Johnson (2003), the parametric density function of the concrete, asbestos, cement, and PVC pipes. The results demonstrated 72% to 88% accuracy in predicting pipeline deterioration. Based on their findings, the researchers recommended prioritising the inspection of pipes with steep bed slopes.

Salman and Salem (2012) used three statistical models, including ordinal regression, multinomial logistic regression, and binary logistic regression, to analyse the deterioration of wastewater collection lines. Five ordinal regression models were generated, but none met the odds assumptions. The developed multinomial logistic regression achieved only 52% accuracy, while binary logistic regression was the only model to predict sewer pipe condition with 66% accuracy. A confusion matrix and real data were used to validate the logistic regression models. The results indicated that pipe size, length, slope, age, material, and sewer type were significant factors in the model. This study also provided deterioration curves and equations better to understand the behaviour of individual pipes in a network.

Sousa, Matos, and Matias (2014) utilised a logistic regression model to evaluate the structural deterioration of sewer pipelines. They developed two models: a full model with all independent variables and a reduced model with only significant variables. Wald Test and likelihood-ratio test were employed to determine the significance of variables in the model. The logistic regression model was verified using a confusion matrix and showed an accuracy of 65%.

Daher (2015) applied evidential reasoning in conjunction with fuzzy set theory to assess the overall condition of pipelines by considering potential defects in various pipeline components. These defects were classified into three categories, namely structural, operational, and installation defects. The authors assigned weights to each defect family and category and to different pipeline components based on their relative significance in determining the overall pipeline condition. To aggregate the various defects in the pipeline components, a fuzzy-based evidential reasoning approach was utilised, allowing for the determination of the overall pipeline condition as well as the condition of each component in terms of its structural, operational, and installation aspects. The validation of the model in practice showed 40% to 50% precision.

Bakry et al. (2016) developed a prediction model for the condition of sewer pipes that had been previously rehabilitated using the CIPP method. The researchers utilised CCTV inspection reports from Quebec to gather data on various physical, operational, and environmental factors, which were then used to create the regression models. The coefficient of multiple determinations was used to validate the models, resulting in a range between 80% and 97%

accuracy. Additionally, mean absolute error and root mean square error were calculated to determine the accuracy of the models. By examining the effect of increasing age while changing dependent variables, linear deterioration curves were developed in this study.

Malek Mohammadi et al. (2019) conducted a study in which they aimed to predict the condition of sanitary sewer pipes in the City of Tampa, Florida, using a logistic regression model. To develop the model, the researchers included various independent variables, such as pipe age, material, diameter, depth, length, slope, water table, and soil type. To assess the significance of the variables, the researchers used statistical tests such as P-test, Wald test, and likelihood-ratio test. While multiple logistic regression could not predict all five condition states of the sewer pipes, the binary logistic model achieved 81% accuracy in predicting the condition rating of the sanitary sewer pipes. The researchers validated the model's performance using a confusion matrix. The findings revealed that the degradation of sewer pipes was largely influenced by factors such as pipe age, material, diameter, length, and water table.

A condition assessment model for sewer pipelines was created by Hawari et al. (2018), utilising fuzzy set theory (FST) and evidential reasoning (ER). Seventeen factors, including Pipe age, diameter, material, depth, length, bedding, slope, groundwater table, and physical, environmental, and operational factors, were identified as affecting the pipe deterioration of gravity sewers, and eighteen factors for pressurised sewers. FST was used to establish the thresholds for the effect values of each factor on the sewer pipeline condition. In contrast, ER was used to predict the condition by combining each factor's effect values and relative weights. The model was validated using data from inspection reports for 549 existing gravity sewer pipelines in Qatar, resulting in 84% accuracy.

Sempewo and Kyokaali (2019) experimented with assessing the comparative efficiency of predicting pipe failure events tested efficiency by statistical regression and Markov-based approaches.This study aims to fill this aim by comparing the performance of these models in predicting the condition of pipes in a developing country, using data from Kampala Water in Uganda. Input data for the model were - location, pipe diameter, length age, and historical data of pipe breaks. The results were expressed as grouping pipes as broken or good. The results were validated with historical failure data of the city. The results show that the Markov model (88.4% precision) outperforms the regression model (78.26%) in accurately predicting the condition of pipes with limited data. This approach could aid water utilities in developing water pipe renewal plans with limited budgets and data availability.

A Berlin, Germany, study used statistical and machine learning approaches to establish benchmarks for sewer condition prediction models. The goal was to provide metrics that assess model performance from the end user's perspective and boost confidence in using deterioration models for asset management strategies. The study examined a statistical model called GompitZ using data from 35,826 inspections. GompitZ is a statistical model based on the theories of survival analysis and Markov chains. Relevant covariates such as sewer material, sewage type, diameter, and depth were included in the model. The GompitZ model predicted sewer pipe conditions well, with a mean absolute error of 0.16 and a root mean square error of 0.21. The model worked well, especially when CCTV data was abundant. (Caradot, 2020).

5.2 Models for CSO Events

Kurth et al. (2008) developed an operational strategy to predict the hydraulic performance of combined sewer overflow (CSO) assets using an Artificial Neural Network (ANN) model. The methodology involved building a three-hidden-layer feed-forward multilayer perceptron (MLP)

using NeuroSolutions software to predict regular CSO performance in three-time steps. The raw data was pre-processed using Matlab and Excel, and the input data was normalised from -1 to 1. The ANN model used water level data recorded by telemetered Hawkeye data monitors relative to the weir height in the Masbrough Street CSO in the Masborough & Kimberworth catchment in Rotherham. The authors ensured that all important patterns were covered to overcome the limitation of forecasting beyond the range of data the ANN was trained and validated with. The limitation of the model was that it only predicted 15 minutes (3-time steps) into the future. The results showed that the MLP trained with backpropagation could learn the relationship between local rainfall and CSO response, with a Mean Squared Error (MSE) of 7.18 achieved during testing. The model's preliminary results suggested that the underlying relationship between local rainfall and water depth within the CSO structure can be captured successfully to predict regular CSO performance in three-time steps.

Mounce et al. (2014) predict combined sewer overflows chamber depth using artificial neural networks with rainfall radar data up to 75 minutes in advance.To better comprehend their efficiency, the UK water industry has installed many monitoring systems to collect data on these assets. This paper presents a study on using artificial neural networks (ANN) to predict the hydraulic performance of CSOs instead of traditional hydraulic models. The research involved training an ANN model with data from rain gauges and rainfall radar devices, which enabled the model to accurately forecast CSO depth with less than 5% error for predictions more than an hour in advance for unseen data.

5.3 Blockage prediction model

The CARE-S project began in 2002 and aimed to create a decision support system for sewer network rehabilitation that employs a multicriteria decision-making approach. The project includes software tools for assessing sewer conditions, determining optimal operating or rehabilitation methods, and prioritising projects. It focuses on preventing major failures and rehabilitating sewers efficiently. Level 1 predicts failure rates based on a statistical analysis of the network. In contrast, Level 2 assesses the state of individual pipes and calculates the risk of failure based on factors such as infiltration, exfiltration, blockage, and structural damage. CCTV inspection is recommended for assessing structural conditions, and failure-level guidelines have been proposed. To understand sewer blockage, the project developed an empirical factorial model that considered factors such as sewer type, pipe material, diameter, position, and manhole bending. Cross-collaboration among CityNet projects speeds up information exchange and project progress. In addition, the project created a method and software for assessing hydraulic performance by simulating 3D models and characterising failures such as breaks, missing sections, collapse, displacement of adjacent pipes, and root intrusion. The reduction in pipeline cross-sectional area is used to quantify root intrusion. (SÊgrov and Schilling, 2014)

The Google Flood Forecasting Initiative employs machine learning and hydrologic models to provide accurate and actionable flood forecasts for riverine areas. The system uses data such as precipitation, temperature, soil moisture, and river discharge to forecast flood conditions. These AI-based models aim to deliver more precise and reliable forecasts to assist governments, organisations, and individuals in flood preparation by overcoming the limitations of traditional models. Based on data availability and performance, Google has created two production architectures. For model calibration and validation, historical data is used. Different techniques are used in flood forecasting models, such as linear and Long Short-Term Memory (LSTM) models for hydrologic modelling and Thresholding and Manifold models for inundation modelling. These models have performed admirably in India and Bangladesh, achieving. (Nevo, 2020)

Okwori, Viklander, and Hedström (2021) investigated sewer blockage propensity using a linear regression model. Considered physical properties of the pipe network (PPN) included -pipe diameter, length, age, material, depth, self-cleaning capacity, CCTV grading, potential sagging, and several connections, while environmental properties included -population density including age range in the neighbourhood, risk of tree root intrusion and distance of nearby restaurants or food service. After the model was analysed, it found that material type, number of service connections, self-cleaning velocity, sagging pipes, root intrusion risk, closed-circuit television inspection grade, and distance to restaurants all demonstrated significant spatial heterogeneity and varying effects on blockage propensity. The model was validated with historical data from 3 municipalities whose names were not revealed. The model achieved a 60-80% accuracy in two municipalities and less than 50% for the third.

6. Results

6.1 Impact of sewer failure

This section summarises the key impact of sewer failure previously stated in the literature. The results are presented as bullet text quantitatively as the study mainly adopted qualitative literature analysis to understand how sewer failure affects the environment and economy and does not undertake any lab or modelling-based research.

Key environmental and economic impacts of Sewer exfiltration based on the literature analysis are summarised as follows-

Environmental Consequences

- contamination of soil and groundwater
- increased concentrations of boron, potassium, and sodium
- release of bacteria, viruses, and other microorganisms to environment
- faecal bacteria contamination poses health risk
- contamination of drinking water supplies
- surface water pollution by reducing wastewater loads

Economic Consequences

- economic burden on treatment and repair costs
- loss of nutrient recovery at WWTP

Similarly key impacts of sewer inflow and infiltration are presented below-

Environmental impact

- surface water contamination due to basement flooding and untreated sewer release
- higher pollutant loads in the effluent pose risks to aquatic systems and water quality.
- sewer overflows transport various pollutants, degrading the quality of

Economic impact

- increased maintenance and repair costs.
- increased energy consumption to pumping and operation
- overloading wastewater treatment facilities, reducing treatment efficiency.
- necessitates expanding treatment plant capacity to handle high flow conditions.

receiving waters and posing risks to human health.
- can harm aquatic life and cause severe environmental damage.
- release of untreated wastewater conflicts with wastewater directive
- additional cost required to treat excessively diluted wastewater
- increase chemical usage
- and additional cost to recover nutrients
- basement flooding can incur property damage and lead to financial compensation

Table 5 depicts the wastewater released to water bodies from WWTPs because of excessive dilution. Here cubic metre/day can not be generalised throughout the year; rather can be understood as the mentioned amount went untreated during that percentage of flow event.

Table 5: Wastewater release to water bodies without treatment (cubic metre/ day)

WWTP	Avoided any treatment			Avoided secondary treatment		
	Median flow	90th percentile flow	99th percentile flow	Median flow	90th percentile flow	99th percentile flow
Bromma	-	-	39827	167859	500413	881617
Henriksdal	-	-	143837	81405	132685	249027
Gryab	-	46313	427517	-	109735	357037
Syvab	-	1492	50862	49126	76716	126086
Käppala	-	-	-		39422	176349
Sjölunda	-	-	-	45945	97778	211055
Gässlösa	-	-	-	21412	47018	83031
Umeva	-	-	-	25702	47455	73131
Göviken	-	-	-	2301	11140	41925
Västerås	-	-	-	28238	56520	93274
Kalmar	-	-	2730	4836	9866	19030
Sundet	-	-	-	6447	14085	32503

6.2 Summary of the identified sewer prediction models

This subchapter summarises the sewer prediction models reviewed in the literature. To understand the comparative properties of the model, those are presented in a table highlighting their input parameters, output, and efficiency, along with the most critical parameters identified.

6.2.1 AI based deterioration models

In recent research, artificial intelligence was the most prevalent method for predicting sewer. Table 6 showcases the comparative properties of AI-based sewer prediction models studied in this thesis.

Table 6: AI models for sewer deterioration prediction

Author	Input Parameters	Output	Efficiency
Hahn et al. (2002)	installation history, pipe age, material, soil type, groundwater level, surface load, exfiltration, structural defect history, corrosion, wastewater type, soil properties, and many other factors	Criticality value for each pipe	55%
Mashford et al. (2011)	pipe age, pipe diameter, pipe length, road type, slope, soil type	failure prediction	91%
Harvey and McBean (2014)	pipe age, pipe diameter, and pipe type	pipe condition	76%
Sousa, Matos, and Matias, (2014)	age, material, diameter, length, depth, slope, no of sewer,	the structural condition of sewer pipelines	78.5%.
Alsaqqar, Khudair, and Jbbar (2017)	age, material, sewer type, shape, diameter, depth, length, slope, and traffic intensity.	condition of the sewer pipeline	87.3%.
Liang et al. (2021)	history of failures, age, length, diameter, pipe material, coating, soil type, tree canopy, slope and shape of the pipes, node degree, node rank, and node cluster.	the probability of failure in a pipe	85 %
Hawari et al. (2017)	Age, diameter, material, depth, length, bed type, street type, slope, groundwater table, operational, environmental, and physical factors	Condition rating	82%

2. 2.3 Statistical Deterioration Models

Statistical analysis was also widely used for sewer deterioration modelling in the studied literature. Table 7 presents the reviewed statistical models for sewer prediction.

Table 7: Statistical models in literature for sewer deterioration prediction

Author	Input Parameters	Output	Efficiency
Tran (2007)	diameter, age, depth, slope, location, roots of trees, soil properties and hydraulic condition	deterioration of gravity pipelines	50%
Chughtai and Zayed (2008)	pipe material, depth, length, age, diameter, material class, bedding factor, and street category	Condition prediction	72% to 88%.
Salman and Salem (2012)	Pipe age, material, diameter, length, slope and sewer type	deterioration of sewer collection lines	66%
Sousa, Matos, and Matias (2014)	Material, diameter, no of sewer, total and average, length, age-depth, slope	structural condition	72.6%
Bakry et al. (2016)	Age, depth, material, diameter, length, bedding, physical, environmental, and operational factors	Conditions state	80% to 98%
Daher (2015)	Defects in pipeline components	condition grade	40-50%
Hawari et al. (2018)	Pipe age, diameter, material, depth, length, bedding, slope, groundwater table, and physical, environmental and operational factors	Sewer pipeline condition assessment	84%
Mohammadi et al. (2019)	pipe age, diameter, length, slope, depth, material, soil type and water table	condition of sewer pipelines	81%
Sempewo and Kyokaali (2019)	location, pipe diameter, length, age, and historical data of pipe breaks	Pipe condition (broken or good)	88.4%
Caradot(2020)	sewer material, sewage type, diameter, and depth	Deterioration factor	84%

6.2.4 Summary of the CSO Models

CSO prediction models are different from deterioration models as they predict CSO events or CSO depth and volume to prepare for managing CSO events based on a different set of data. Table 8 presents the summary of the studied CSO models.

Table 8: CSO prediction models.

Author	Principle	Input Parameters	Output	Efficiency
Kurth et al. (2008)	AI	Rainfall and CSO history data	CSO prediction 15 min ahead	95%
Mounce et al. (2014)	AI	Radar data of rainfall and rain gauge data of flooding	CSO depth up to 75 min ahead	95%

6.2.5 Summary of the Blockage models

Blockage is sometimes a result of sewer deterioration. However, the blockage is also a big problem in the sewer system, so predicting blockage is an important step forward to face the challenge effectively. Table 9 summarises the blockage prediction model in the literature.

Table 9: Sewer blockage prediction model

Author	Principle	Input Parameter	Output	Efficiency
Okwori, Viklander, and Hedström (2021)	Statistical	Pipe age, diameter, length, material, depth, self-cleaning capacity, CCTV grading, potential sagging, population density, tree root intrusion and distance of nearby restaurants or food service	Blockage probability	60-80%

6.2.6 Frequently used parameters in the studied model's

Figure 9 summarises the data requirements (illustrated as input parameters) for condition assessment and deterioration models. These models are critical for infrastructure management and maintenance because they predict future structure performance and identify necessary repairs or replacements. The type of structure, modelling approach, and desired level of accuracy all influence data requirements. Understanding these data requirements is critical for effective infrastructure management and improving the safety and dependability of our built environment. This section considers validated models with at least 70% precision. Other factors in the figure refer to location, number of sewers, distance from nearest industries or restaurants, failure history, waste type, tree root intrusion, and other environmental and operational factors; some models include at least one or more of these other factors categories.

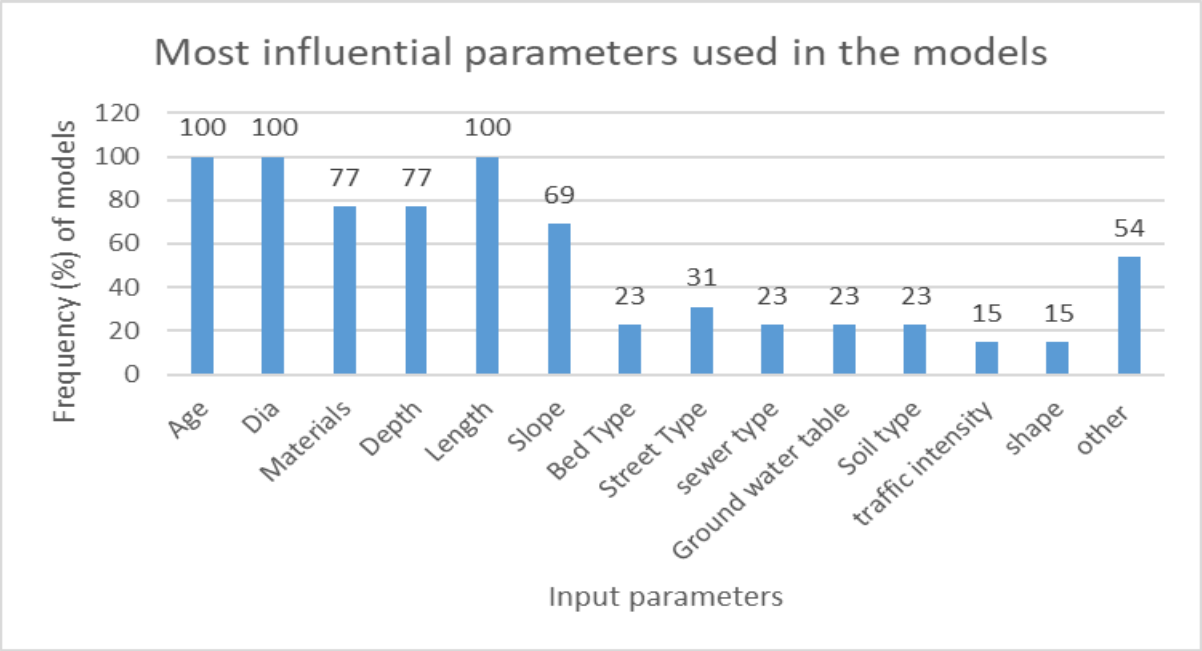

Figure 9: Most frequently used input parameters in the studied models.

Unlike the deterioration models, CSO models use different sets of data, mostly based on GIS and hydrological databases. Data requirements include rainfall data, flow rate, flooding history, etc.

7. Discussion and Conclusion

7.1 Problems associated with sewer failure

Sewer failure, in its various forms of exfiltration, blockage, overflow, inflow, and infiltration, can have serious consequences for the environment and the economy. These effects range from soil and groundwater contamination to increased energy consumption and maintenance requirements, as well as chemical usage and treatment costs. To mitigate these effects, it is critical to conduct sewer inspections on a regular basis.

Sewer exfiltration, a serious problem, can have various negative consequences. One major source of concern is soil and groundwater contamination, which poses serious health risks. Contamination with faeces is especially dangerous, but elevated levels of boron, potassium, sodium, and overall electrical conductivity can also occur. Furthermore, when there are broken water mains or leaks under normal positive pressure conditions, sewer exfiltration can contaminate drinking water supplies. Another consequence to be aware of is surface water pollution, which occurs when a significant amount of sewage enters groundwater or nearby bodies of water. Because it contaminates the soil and groundwater with bacteria, viruses, protozoa, and other microorganisms, this type of exfiltration has serious environmental and economic consequences. The health risk associated with faecal bacteria contamination is especially severe. Furthermore, sewer leaks can raise the concentrations of boron, potassium, and sodium in groundwater. Drinking water supplies can be contaminated by broken water mains or leaks under normal positive pressure conditions. Due to water volumes, research shows that sewer inflow and infiltration increase energy consumption and maintenance

requirements in wastewater treatment systems. Furthermore, the increased water volume necessitates using more chemicals in treatment, resulting in higher treatment costs. Moreover, increased infrastructure expansion and construction efforts are frequently required to accommodate the increased water volume, resulting in increased land use, construction efforts, and associated costs.

Infiltration dilutes wastewater, affecting treatment processes and potentially resulting in inadequate treatment and higher pollutant loads in the effluent, both of which can harm aquatic ecosystems. This conflicts with the guidelines of the wastewater directive discussed in Chapter 2. This can lead to legal consequences in the future. Dealing with this might necessitate financial investments to expand the plant's capacity. Besides, the communities must weigh the risks of inflow and infiltration against development opportunities that contribute to tax revenue and community mobilisation. Infiltration can also cause flooding, including basement flooding and infrastructure deterioration, exacerbating the strain on infrastructure. Moreover, combined sewer overflows induced by inflow and infiltration seriously affect public health, water quality, and the environment. Nutrients, microorganisms, particulates, and metals can all be transported, degrading the quality of receiving waters and endangering human health. Organic pollutants like faeces can deplete dissolved oxygen, risking aquatic life. Toxic pollutants can have serious environmental consequences, and abundant nutrients can contribute to eutrophication. Due to increased urbanisation and insufficient mitigation measures, climate change is expected to exacerbate combined sewer overflow (CSO) events in urban areas, resulting in more frequent and higher-volume discharges.

Because of the serious consequences of sewer failure, an effective and proactive sewer maintenance program is critical. It aids in the prevention of environmental issues such as soil and groundwater contamination, surface water pollution, and aquatic ecosystem damage. It also addresses economic implications by lowering energy consumption, maintenance needs, and treatment costs. Effective maintenance optimises resource utilisation, reduces the need for infrastructure expansion, and ensures environmental compliance. Communities can protect public health, preserve water quality, and reduce the economic burdens of sewer failure by investing in proactive sewer maintenance. Moreover, with predictive inspection, faulty pipes can be replaced or repaired well before a major failure occurs, offering the municipality significant environmental and economic benefits and less social disruption.

Sewer prediction models can significantly improve the effectiveness of a proactive sewer maintenance program. Planners can prioritise maintenance activities, allocate resources more effectively, and reduce the risk of emergency repairs and replacements risk by identifying potential problems early on. This reduces the likelihood of downtime and service disruptions, ensuring the sewer network operates at peak efficiency. By identifying potential issues early on, planners can also prevent them from worsening and negatively impacting system performance
Municipalities can improve their ability to protect public health, preserve water quality, and reduce the economic burdens associated with sewer failure by incorporating predictive capabilities into their maintenance programs.

7.2 State of the art

According to the literature, evaluation, and prediction of the sewer pipeline condition have gotten much attention in recent years. It has been a topic of interest for researchers and engineers. As a result, various physical, artificial intelligence, and statistical models for assessing their condition have been developed. As shown in Figure 9, these models typically include a variety of factors or variables, the most common of which are age, length, material,

depth, and diameter. These variables are widely available in most databases, making them easier to obtain and incorporate into models. Despite efforts to determine the impact of these factors on pipeline conditions, the correlation has been difficult due to differences in construction practices, quality and standards, environmental conditions, and data availability. Therefore, the results obtained from different studies cannot be easily compared.

Most studies have discovered that age and material influence pipeline conditions. Other factors, such as pipe size, depth, slope, and traffic, are deemed less important. However, there is a gap in assessing potential high-influence factors such as construction standards and groundwater table. More research is needed to determine the impact of these potential factors on pipeline conditions to close this gap. Efforts should also be made to standardise data collection methods, construction practices, and quality standards across studies to ensure comparable results. Researchers can develop more accurate models for a more efficient assessment of sewer pipelines' condition, which is critical for infrastructure maintenance and public health and safety.

It is critical to assess the condition of sewer pipelines for infrastructure maintenance and public safety. Sewer failure prediction models can aid in optimising rehabilitation and inspection policies and informing budgetary decisions for network maintenance. However, reliable models necessitate standardised data collection methods and complete and clear data, which can be difficult to obtain when the historical data of sewer development and maintenance is not well recorded. Besides, regular inspections and the use of emerging technologies are essential for accurate and complete data collection.

When deploying these models, it is critical to consider the end user's perspective and develop accurate and reliable models for sewer pipeline deterioration. End users must understand the modelling outcomes and know model uncertainties to make informed decisions. Developing a user-friendly, easy-to-perceive, and socially acceptable set of metrics is critical to increasing utility confidence in using deterioration models. The degree to which an individual or an organisation believes technology will improve their performance is perceived usefulness. In the case of sewer failure prediction models, the model's perceived usefulness is based on its ability to predict sewer failures accurately. A model which can accurately predict sewer failures would be useful because it would allow preventive measures to be taken to mitigate the impact of the failures. Artificial intelligence has been used to develop more robust and computationally efficient models for assessing sewer pipeline conditions. AI-based models such as artificial neural networks (ANN), simulation, and fuzzy-based models in some cases outperform statistical models in terms of computational efficiency. However, these models require large datasets, making their underlying mechanics difficult to understand.

Validation and determining the accuracy of predicted conditions is one of the most difficult aspects of developing reliable condition assessment models. Few case studies have attempted to validate the accuracy of their condition assessment models' prediction. The quality and quantity of inspection data calibrating sewer pipeline condition assessment models heavily influence their reliability. As a result, determining which modelling approach is the most reliable is difficult. Again, different validation methods are used to validate the accuracy of the models. Also the accuracy and precision is often a vague term as they often do not clarify the percentage of false positive and false negative. Hence comparing model precision with different validation methods might not be justified.

Furthermore, the sewer deterioration models should have easily perceivable practical implications for sewer network operators and managers. While the models can prioritise inspection and maintenance tasks, assist with strategic rehabilitation planning, and optimise

resources, resulting in more efficient and effective maintenance and rehabilitation programs. However, these models must be user-friendly, simple to understand, and socially acceptable to be widely accepted and used. Therefore, it is critical to continue developing deterioration models that accurately predict the condition of sewer pipelines and consider end-users perspectives. Benchmarking and developing user-friendly metrics can boost the confidence of utilities and decision-makers in using these models, resulting in better infrastructure maintenance and public safety. The Berlin case study demonstrates how various techniques such as logistic regression, multiple discrimination, and Markov chains can be used to determine the condition state of pipelines in a network of sewer deterioration models by comparing the performance of two models and establishing benchmark metrics. This framework can provide utilities with easy-to-understand metrics that persuade them of the value of using deterioration models to support asset management strategies.

Sewer pipelines are critical infrastructure components that transport wastewater but are prone to deterioration and blockages. Current models are designed to assess pipe conditions rather than predict blockages and Combined Sewer Overflow (CSO) events. Sewer backups can cause property damage and health risks, but there are few models for predicting them. Predicting bottlenecks can help prioritise maintenance activities, reduce costs, and improve public health. Similarly, CSOs during heavy rain events can cause water pollution and health risks, but few models can predict them accurately and well ahead. Most of the models can only predict the depth of CSO structures, and that too only less than one hour before the event happens. If a model can predict it earlier, providing adequate time to make necessary preparations could help the planners much more. The precision of the Google flood forecasting model can be an inspiration in this regard though that is not directly applicable in the context of sewer systems. Besides, the CARE-S project includes various tools for assessing sewer system conditions, selecting the best operational or rehabilitation method, and prioritising rehabilitation projects. To proactively manage and maintain sewer systems, the software package employs a multicriteria decision-making approach to rehabilitate the correct sewer at the correct time using the correct method at the lowest cost, thereby avoiding severe failures. The work packages for the project include assessing the structural and operational condition of pipes, understanding the occurrence of a sewer blockage, and developing methods and software to assist engineers in evaluating the hydraulic performance of sewer systems. Overall, continued research and development in sewer deterioration, blockage, and CSO modelling will improve sewer system understanding and management by addressing issues such as deterioration, blockages, and public health risks.

7.3 Conclusion

Based on the literature, the study concludes sewer failure can have serious environmental and economic consequences. Multiple Sewer exfiltration can pollute soil and groundwater, posing serious health risks. Sewer overflow can harm public health, water quality, and the environment. Inflow and infiltration can significantly impact many aspects of wastewater management and infrastructure, resulting in increased energy consumption, maintenance needs, chemical usage, and treatment costs. Sewer pipeline deterioration and blockages can result in costly repairs, environmental damage, and public health risks.

Sewer prediction models can be a valuable tool for sewer system operators to prevent or mitigate sewer failure's impact. These models can assist in identifying areas of potential failure and contamination, prioritising maintenance and repair efforts, optimising sewer system operation, and reducing the economic impact of sewer system failure. The study highlighted the key data requirements for predictive models in sewer pipe inspection, emphasising pipe age,

material, diameter, depth, and length as the primary input parameters used by existing model developers.

Predicting sewer blockages and CSO which can help prioritise maintenance activities and reduce the risk of hazards, got less attention. Although developing reliable sewer pipeline condition assessment models remains difficult because of intensive data requirements and demand for higher precision, recent studies have yielded promising results. Validation techniques for determining prediction accuracy are available. Still, more research is needed to develop reliable models that accurately predict blockages and CSOs and determine the best modelling approaches and validation techniques.These findings can serve as valuable guidance for future efforts to improve sewer pipe inspection practices and inform decision-making in this field.

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Appendix

Appendix 1: AI models for sewer failure prediction with no validation

Author	Input Parameters	Output
Najafi and Kulandaivel (2005)	age, diameter, length, material, depth, slope, and effluent type	condition rating of pipelines
Khan, Zayed, and Moselhi, (2010)	pipe age, length, depth, diameter, material, and bedding material	structural condition of a sewer pipeline
Jiang et al. (2016)	corrosion data from the lab, H_2S concentration	corrosion
Tade (2018)	material age, depth, shape, size, length, slope, location, use, seismic zone, construction period, debris, collapse history, groundwater level, soil type, presence of H_2S, and proximity to ground installation	condition of sewer pipe
Rajani, Kleiner, and Sadiq (2006)	Pipe defect data from an existing database	pipe condition rating
Kleiner, Rajani, and Wang (2007)	pipe material, size, age, soil type, climate, cathodic protection, pressure zone changes	future condition of pipe
Anbari, Tabesh, and Roozbahani (2017)	age, material, diameter, and depth of the sewer, traffic volume, groundwater level, and the number and type of trees around the pipe	a risk value for each pipe
Ruwanpura, Ariaratnam and El-assay, (2004)	Pipe age, material, and length.	Condition rating
Li et al. (2019)	Corrosion data from the lab, H2S concentration	corrosion of concrete sewer pipelines
Elmasry, Tarek Zayed, and Hawari (2016)	CCTV inspection reports	condition states of pipes
Tagherouit, Bennis, and Bengassem (2011).	Hydraulic condition, internal condition, surrounding condition, and site vulnerability	structural performance index for each pipe

Appendix 2: Statistical deterioration model with not validation

Author	Input Parameters	Output
Ariaratnam, El-Assaly and Yang (2001)	age, diameter, material, waste type, and average depth	probability of sewer pipes to be in a certain state
Koo and Ariaratnam 2006)	wastewater collection database, pipe age, cumulative flow, and maximum velocity	Deterioration subclass
Ana et al. (2009)	sewer age, diameter, material, depth, length, slope and sewer type, traffic intensity, installation year	Deterioration value
Bai et al. (2008)	Cement lining condition and degree of internal corrosion	Pipe condition assessment
Micevski, Kuczera, and Coombes (2002)	diameter, construction material, soil type, bedding, and exposure classification	Structural condition of pipes
Sinha and McKim (2007)	-	Condition rating
Le Gat (2008)	diameter, sewer type and installation period	Condition prediction
Scheidegger et al. (2011)	Sewer age	probabilities of the change in condition
Baur and Herz (2002)	age and pipe shape, material, pipe size, pipe slope, sewer function, and soil type	condition of network
Laakso et al. (2019)	inspection results, pipe attributes, network data, and data on pipe environment	pipe condition rating
Alsaqqar et al. (2017)	pipe condition, age, diameter, length, slope, depth, shape, function, type, and traffic intensity	Condition rating of individual pipe

Appendix 3: Physical models for sewer failure prediction with to no validation

Author	Input Parameters	Output	Efficiency
König (2005)	Soil aggressiveness, pipe cement quality, and soil moisture.	External corrosion of concrete pipes	-

Appendix4: CSO prediction models with no validation

Author	Principle	Input Parameters	Output
Zhang, Lindholm, and Ratnaweera (2018)	ANN & IOT	Rainfall and flooding data from sensors	CSO events
Rosin et al. (2021)	ANN	Rainfall history and forecasting data	CSO depth