Application of a hybrid fuzzy-based algorithm to investigate the environmental impact of sewer overflow

ABSTRACT

Purpose: This study underscores the critical importance of well-functioning sewer systems in achieving smart and sustainable urban drainage within cities. It specifically targets the pressing issue of sewer overflows (SO), widely recognized for their detrimental impact on the environment and public health. The primary purpose of this research is to bridge significant research gaps by investigating the root causes of SO incidents and comprehending their broader ecological consequences.

Design/Methodology/Approach: To fill research gaps, the study introduces the Multi-Phase Causal Inference Fuzzy-Based Framework (MCIF). MCIF integrates the fuzzy Delphi technique, fuzzy DEMATEL method, fuzzy TOPSIS technique, and expert interviews. Drawing on expertise from developed countries, MCIF systematically identifies and prioritizes SO causes, explores causal interrelationships, prioritizes environmental impacts, and compiles mitigation strategies.

Findings: The study's findings are multifaceted and substantially contribute to addressing SO challenges. Utilizing the MCIF, the research effectively identifies and prioritizes causal factors behind SO incidents, highlighting their relative significance. Additionally, it unravels intricate causal relationships among key factors such as blockages, flow velocity, infiltration and inflow, under-designed pipe diameter, and pipe deformation, holes, or collapse, providing a profound insight into the intricate web of influences leading to SO.

Originality: This study introduces originality by presenting the innovative MCIF tailored for SO mitigation. The combination of fuzzy techniques, expert input, and holistic analysis enriches the existing knowledge. These findings pave the way for informed decision-making and proactive measures to achieve sustainable urban drainage systems.

Keywords: Sewer overflow; Sewer pipelines; Fuzzy sets theory; Artificial intelligence; Environmental concerns.

1. INTRODUCTION

Sewer overflow (SO) is currently one of the most important environmental concerns, potentially threatening infrastructures, the environment, and people's health (Montserrat *et al.*, 2015). In this regard, there are two types of SO: (1) Combined Sewer Overflow (CSO) and (2) Sanitary Sewer Overflow (SSO). CSO occurs when excessive rainfall flows through the sewer system. It occurs when the rainfall inflow surpasses the flow capacity of the network. This causes the pipes to get a surcharge and the combined medium (storm and wastewater) to overflow from manholes. On the other hand, SSO is regarded as untreated wastewater released directly into the environment from the network (Ogidan and Giacomoni, 2015a), which occurs due to sewer pipeline defects (such as pipe collapse, weak design, blockage, or excessive flow of pipe capacity) (Getuli *et al.*, 2021; Ogidan and Giacomoni, 2017). According to the Environmental Protection Agency (EPA) in the United States, between 23,000 and 75,000 SSO cases are annually discovered across this country, and 11.4-37.9 million cubic meters of untreated wastewater are annually released into the environment (Itaquy *et al.*, 2017a).

It is highly important to regulate SO properly, and any failure in this process can lead to serious risks to society and the environment (Ryu *et al.*, 2017). Once heavy rainfall overpowers the capacity of the stormwater/wastewater system, it may lead to SO, urban runoff pollution, and localized flooding (Tao *et al.*, 2020). In this case, the target regions would be at high risk because of the rapid increase in pollution loads emitted from SO (Zhang *et al.*, 2018). In old cities, SO becomes more critical due to the decrepitude of constructed facilities, leading to destructive impacts on people's health, aquatic life, environment, infrastructures, etc. (Lund *et al.*, 2020). What adds more complexity to realizing a smart and sustainable drainage system is that it has been linked to rapid population growth and urban development, urging the need for well-performed sewer systems within cities (Al-Mhdawi *et al.*, 2024; Quijano *et al.*, 2017).

Throughout the body of relevant knowledge, it can be observed that many researchers have focused on improving the functions of sewer networks and reducing the magnitude of SO (Mohandes *et al.*, 2022). In these studies, many different models have been proposed, ranging from pure simulations to those designed based on artificial intelligence (AI) (Bonamente *et al.*, 2020; Casadio *et al.*, 2013; Chen *et al.*, 2003; Duchesne *et al.*, 2001; Even *et al.*, 2004; Habibi and Seo, 2018; Itaquy *et al.*, 2017b; Sharior *et al.*, 2019). With that in mind, various studies have been undertaken on the deterioration of sewer pipelines to reduce the SO rate using different techniques based on AI, statistical data, and probabilistic algorithms. For instance, Najafi and Kulandaivel (2005) and Tran *et al.* (2006) used a neural network model to predict the deterioration of sewer pipelines. In another study, Harvey and McBean (2014) utilized random forests to predict the condition of constructed pipelines.

Moreover, Yin *et al.* (2020) proposed a novel neural network model for predicting individual sewer pipe conditions. In this regard, some studies have developed advanced types of neural networks (Haurum *et al.*, 2022; Wang *et al.*, 2021). Syachrani *et al.* (2013) and Mashford *et al.* (2011) utilized decision trees and support vector machines, respectively, to anticipate the related failure of such pipelines. In the case of the utilization of statistical-based methods, Gedam et al. (2016) proposed linear regression for the prediction of sewer deterioration, while Kabir et al. (2018) and Chughtai and Zayed (2007) employed logistic and multiple regression to model the related failure of sewer pipelines. Kineber *et al.* (2022) and Mohandes *et al.* (2022) quantified the importance of critical factors for selecting stormwater pipelines and uncovered the importance of causes of SO, respectively. This extensive literature review critically examines the challenges in predicting sewer pipeline conditions using CCTV inspection reports and proposes an innovative AI-based model, integrating unsupervised regression and Weibull analysis (Salihu *et al.*, 2023a). The findings provide essential guidance for decision-makers in prioritizing maintenance actions, particularly in the context of sustainable urban drainage systems. The review also synthesizes four common evaluation standards for drainage pipes, establishing a comprehensive system of influencing factors and reviewing the progress of physical, statistical, and AI models in predicting deterioration and breakage (Zeng *et al.*, 2023). Addressing concerns about sewer pipe degradation, the study underscores the need for structured inspection plans integrating various data sources. The proposed methodology evaluates statistical and machine learning models, with ensemble models offering high accuracy but limited long-term inference and Logistic Regression providing slightly lower accuracy but consistent degradation curves and high explainability (El Morer *et al.*, 2023).

Furthermore, the paper introduces an intelligent method for detecting and segmenting damages in aging sewer pipes, utilizing a fine-tuned fully convolutional network (FCN) algorithm with impressive evaluation metrics. The study also presents a data-driven approach for assessing the condition of reinforced concrete sanitary sewer pipelines (RCSSPs), leveraging LiDAR inspection data to probabilistically evaluate pipe wall erosion and estimate remaining service life (Ebrahimi *et al.*, 2023; Goulding and Rahimian, 2012; Seyedzadeh *et al.*, 2017). Comparative analysis validates the proposed algorithm using closed-circuit television (CCTV) images and Monte Carlo Simulation (MCS), offering an automated framework for non-destructive inspections.

Additionally, there have been loads of studies dealing with sewer deterioration through different probabilistic-based approaches, including Bayesian (Ana *et al.*, 2009; Balekelayi and Tesfamariam, 2019; Salman, 2010), Markov chain (Dirksen and Clemens, 2008; Lubini and Fuamba, 2011; Micevski *et al.*, 2002), cohort survival method (Baur and Herz, 2002), and cox model (El-Housni *et al.*, 2018). In addition, numerous researchers have attempted to model SO through different techniques. For instance, Rosin *et al.* (2021) and Zhao *et al.* (2017) used ANN and advanced regression techniques to predict the sewer discharge of constructed pipelines. The literature also contains many studies that have applied the Genetic Algorithm (GA) to reduce the rate of sanitary overflows (Itaquy *et al.*, 2017b; Ogidan and Giacomoni, 2015b; Rathnayake and Tanyimboh, 2015; Wu *et al.*, 2022). Likewise, the Monte Carlo simulation has extensively been used to calculate the probability of overflow within the sewer systems (Kumar *et al.*, 2018; Sriwastava *et al.*, 2018; Szeląg *et al.*, 2021; Tondera, 2019). In addition, many researchers have focused on using the Storm Water Management Model (SWMM) simulation platform to model the run-off from SO. For instance, an urban drainage model was developed to quantify adverse dissolved oxygen conditions associated with SO (Riechel *et al.*, 2016). In another research, Riechel *et al.* (2020) used SWMM to curb the acute oxygen depressions of overflow discharged into the receiving river. In China, K. Chen *et al.* (2021) examined the pollution emitted from overflows of an interception sewer system using SWMM. This study introduces temporal fragility models for aging concrete sewer pipes, addressing corrosion and truck loads with Bayesian Additive Regression Trees (BART) (Zamanian and Shafieezadeh, 2023). Findings highlight critical serviceability and collapse factors, aiding quantitative risk assessment for underground wastewater systems. The research evaluates the visual inspection method for sewer and stormwater pipelines, exposing uncertainties. Reclassifying condition classes based on identical video footage quantifies and assesses uncertainty's impact on deterioration model outcomes, significantly influencing decisions for pipeline rehabilitation and replacement strategies (Fugledalen *et al.*, 2023). Utilizing a Markov chain model with historical CCTV data, the study estimates Hume pipe deterioration in the City. Sub-catchment EM experiences accelerated deterioration, with projected main defects and serious failures expected within 35 and 100 years, respectively. Larger pipes (600 mm) deteriorate approximately 12 years faster than smaller pipes (450 mm), and life expectancy estimates range from 34 to 60 years based on a 40% main defects generation assumption (Jun *et al.*, 2023).

In addition to modeling-based approaches, different types of laboratory and field experiments have been undertaken to study the impact of such phenomenon on the environment (Ahmed *et al.*, 2020; Al Aukidy and Verlicchi, 2017; Calderón *et al.*, 2017; Cao *et al.*, 2019). Likewise, intending to achieve more lucid and reliable findings, some researchers have used hybrid methods (based on the integration of modeling- and experimental-based approaches) to investigate how overflow affects the environment (Leirens *et al.*, 2010; Masseroni *et al.*, 2018; Su *et al.*, 2020; Zhao *et al.*, 2017).

Innovatively addressing the challenge of sewer overflow, Bourahla and Bourahla (2023) integrate the Internet of Things (IoT) and eXplainable Artificial Intelligence (XAI) to create a real-time control system. By leveraging historical data for AI-based prediction models and real-time data for monitoring, their approach diagnoses sewer systems to detect abnormalities. Ghazouli and Khatabi (2022) shed light on the detrimental effects of urbanization and climate change on combined sewer overflows (CSOs) and propose a Model Predictive Control (MPC) system powered by neural networks and genetic algorithms to mitigate CSO impacts. Meanwhile, Mounce *et al.* (2014) explore the potential of artificial neural networks (ANNs) to predict CSO depth, offering a promising alternative to traditional hydraulic models and crucial insights for future sewer system management.

Based on the study of Omrany *et al.* (2022) lists energy conservation, production, and storage as main themes, as well as emerging ones such as electric vehicles, zero-emission neighbourhoods, and smart buildings. Omrany *et al.* (2023) list seven research themes for using BIM in high-rise building early design: optimising energy efficiency, collaborative design, life-cycle assessment, net-zero energy design, smart technology integration, cost analysis, and structural design. According to Omrany *et al.* (2021), the main factors affecting home life-cycle energy assessment (LCEA) outcomes are system boundary definition, calculation methodologies, geographical context, and interpretation. The study proposes a conceptual framework to standardise LCEA processes and decrease variability. Rodrigo *et al.* (2024) identified AI, IoT, and BIM as crucial technologies for circular construction waste management and resource efficiency. The report outlines the benefits and drawbacks of using these technologies in construction. Omrany *et al.* (2023) evaluate 195 City Information Modelling (CIM) articles and identify nine implementation domains, including natural disaster management and urban building energy modelling. They also identify eight difficulties, including data quality and integration, and give CIM development recommendations for urban planners, policymakers, and scientists. Al-Obaidi *et al.* (2022) reviewed IoT applications for energy-efficient buildings and cities, finding built environment professionals' knowledge and application gaps. The study concluded that a lack of awareness of IoT technologies and procedures hinders their application and suggests ways to improve energy efficiency through IoT integration. In a hybrid systematic review of 843 IoT-enabled smart cities (IESC) articles, Omrany *et al.* (2024) identified four study areas: data analysis, network and communication management, security and privacy management, and data collection. The study identified seven challenges—energy consumption, privacy, interoperability, ethical problems, scalability, and adaptability—and suggested ways to improve IoT integration in urban design for future smart cities.

Past studies on sewer overflow (SO) management show that there is an opportunity to enhance it by integrating recent advancements in digital tools and fuzzy-based algorithms, particularly in connection to machine learning (ML) and artificial intelligence (AI) applications. Recent research has shown promising results in leveraging digital tools, such as the Internet of Things (IoT), Internet of Drones (IoD), and Internet of Vehicles (IoV), along with fuzzy-based algorithms, to optimize SO design, development, and operation/management while minimizing environmental impacts (Heidari *et al.*, 2022). By leveraging IoT, IoD, and IoV technologies, cities can collect real-time data on sewer system conditions and flow patterns, enabling proactive detection and mitigation of SO events (Gul *et al.*, 2023). Moreover, integrating AI, ML, and deep learning (DL) approaches holds promise for managing automated activities in smart cities, including SO management (Sun *et al.*, 2023). These technologies analyze vast amounts of data from IoT devices and drones to predict and prevent SO incidents, enhancing overall system resilience and efficiency.

Furthermore, recent advancements in smart city technologies, such as smart traffic management, smart power and energy management, city surveillance, smart buildings, and patient healthcare monitoring, highlight the potential for integrating SO management into broader urban management frameworks (Montoya-Coronado *et al.*, 2024). By leveraging cloud computing, edge computing, and fog computing platforms, cities can process and analyze data in real-time, enabling more effective decision-making and resource allocation for SO prevention and mitigation. Additionally, hybrid models that combine various technologies and approaches offer new opportunities for improving SO management strategies in urban environments.

In view of the prevailing literature mentioned above, there is a dearth of studies investigating cause-and-effect relationships between these causes and their consequent impacts on many environmental aspects. Thus, this study aims to tackle the following research questions:

(1) Considering the inherent uncertainties within the complex environmental setting, how can we effectively prioritize the causes contributing to sewer overflow (SO) occurrences? Given the intricate and uncertain nature of urban drainage systems, this question addresses the challenge of determining the relative importance of various factors leading to SO incidents. The research aims to devise a methodology or framework capable of systematically evaluating and prioritizing these factors, clarifying their significance in the context of SO occurrence.

(2) How can we unveil the complex cause-and-effect relationships among the critical factors contributing to SO incidents? This research question delves into the intricacy of understanding the interconnections and dependencies among key factors like blockages, flow dynamics, and structural issues in sewer systems. The goal is to develop a comprehensive approach, potentially utilizing advanced analytical techniques or frameworks, to unravel multifaceted causal relationships and provide insights into the dynamics leading to SO occurrences.

(3) What are the specific environmental aspects that deteriorate due to sewer overflow incidents, and how can these aspects be systematically prioritized? This question seeks to identify and prioritize the environmental impacts associated with SOs, considering factors such as damage to infrastructure, groundwater contamination, and consequences on surface ecosystems. The research aims to develop a methodology for systematically assessing and ranking these environmental deteriorations, providing a clear understanding of their relative significance and guiding effective mitigation efforts.

(4) What practical and feasible strategies can be implemented to prevent the occurrence of sewer overflow phenomena? This question focuses on developing practical and implementable strategies to mitigate and prevent SO incidents. The research explores a range of preventive measures, potentially incorporating engineering solutions, policy interventions, and community engagement approaches. By addressing the root causes identified in the study, the research aims to contribute to developing proactive strategies that can effectively reduce the occurrence of SOs and enhance the resilience of urban drainage systems.

To prudently answer all the above-noted research questions, this study developed a multi-phase research framework called Multi-Phase Causal Inferences Fuzzy-based framework (MCIF), which is based on integrating several fuzzy-based algorithms. This distinctive framework contributes substantially to sewer overflow (SO) research, offering a systematic and comprehensive methodology for identifying, prioritizing, and understanding the root causes of

SO incidents. By employing the MCIF, the research provides a novel perspective on addressing the crucial issue of SOs within urban drainage systems.

The MCIF employs advanced fuzzy-based techniques to effectively address the complexities and uncertainties inherent in analyzing environmental data related to SO incidents. This integration enhances the overall robustness and comprehensiveness of the framework, enabling a detailed examination of the factors contributing to SO occurrences and their environmental impacts. The key aspects of this integration are outlined as follows. Firstly, it effectively handles uncertainty and ambiguity. Environmental data, especially in urban drainage systems, often contains high levels of uncertainty and ambiguity. Traditional analytical methods may struggle to accommodate these uncertainties, leading to less reliable results. Fuzzy logic, however, is well-suited to manage such complexities. Secondly, the framework incorporates expert knowledge. Fuzzy systems can integrate expert opinions and qualitative data, which are often subjective and ambiguous. This enhances the framework's ability to include a wider range of information sources in the analysis.

Thirdly, by accommodating uncertainty, the MCIF framework provides more reliable and nuanced insights, supporting better decision-making processes for prioritizing factors and implementing mitigation strategies. Fourthly, the fuzzy-based approach within the MCIF framework systematically evaluates and prioritizes various factors contributing to SO incidents. This systematic prioritization is achieved through the use of Multi-Criteria Decision Making (MCDM) techniques to evaluate and rank the importance of different factors based on multiple criteria. Weighted aggregation is also utilized, where the weights represent the relative importance of each criterion, ensuring that the prioritization process reflects the complex interplay of different factors and their impacts on SO occurrences. Furthermore, the framework offers dynamic causal analysis. Fuzzy logic allows for the dynamic analysis of causal relationships, accommodating changes in environmental conditions and system parameters over time. This provides a more accurate depiction of the evolving nature of SO incidents. Finally, based on the prioritized impacts, the framework proposes practical and feasible mitigation strategies. These strategies incorporate engineering solutions, policy interventions, and community engagement approaches.

A notable strength of the study lies in its ability to efficiently pinpoint and prioritize the causal factors behind SO incidents. Through the application of MCIF, the research illuminates the relative importance of various factors, including blockages, flow velocity, infiltration and inflow, and structural issues in sewer systems. This thorough identification process is crucial for comprehending the intricate dynamics leading to SOs and forming a robust foundation for developing targeted mitigation strategies.

The study identifies causes and unveils complex causal relationships among key factors contributing to SO incidents. The research provides profound insights into the intricate web of influences leading to SO by examining the interplay between blockages, flow dynamics, and structural integrity. This deep understanding of causal interrelationships is a crucial contribution that addresses significant research gaps, advancing knowledge about the mechanisms behind SO incidents.

Furthermore, the study goes beyond academic inquiry by compiling practical mitigation strategies. The emphasis on actionable insights for decision-makers and urban planners sets the research apart, offering a valuable resource for implementing measures to address identified root causes and prevent future SO incidents. The study's practical applicability and focus on mitigation contribute to its potential impact on improving the current conditions of SOs in cities.

In enriching existing knowledge, the study introduces a novel framework and combines fuzzy techniques and expert input to provide a holistic analysis of SO incidents. This comprehensive approach contributes to a more nuanced understanding of SOs, effectively bridging significant gaps in the field. The study's findings pave the way for informed decision-making and proactive measures, aligning with the broader goal of achieving sustainable urban drainage systems and making a substantial contribution to advancing knowledge in the field.

2. RESEARCH METHODOLOGY

In this section, the detailed steps involved in the development of the Modified Cause and Impact Framework (MCIF) are elaborated, focusing on its application in minimizing the Environmental Impact (EI) of Sewer Overflow (SO) in cities and the built environment. Given the widespread utilization of Fuzzy Sets Theory (FST) within MCIF, a brief explanation of FST is provided before elaborating on the methods adopted. Fig 1 illustrates the developed MCIF, depicting several phases as follows:

Phase A. The utilization of FDT aims to identify all the underlying causes leading to SO and determine the critical ones.

Phase B. The FDEMATEL method is utilized to uncover the causal relationships among the critical causes leading to SO.

Phase C. The overall importance index is created based on combining the outputs from Phases A and B.

Phase D. Using the FTOPSIS technique to identify and rank the aspects of the environment deteriorated by SO occurrence.

Phase E. Conducting several interviews to provide a detailed list of measures to be taken to prevent the occurrence of SO or improve the conditions when SO occurs.

Phase F. The validation of the results was elicited from the interviews and focus group discussions.

Furthermore, this study paves the way for integration into AI applications, particularly for smart cities and environmental management. By leveraging advanced AI techniques such as machine ML algorithms, deep learning, and natural language processing (NLP), the MCIF framework can be automated and optimized for real-time decision-making. ML algorithms can analyze vast amounts of historical data on sewer systems, environmental conditions, and previous overflow events to identify patterns and correlations. By training predictive models on this data, the MCIF framework can forecast the likelihood of future overflow incidents based on various contributing factors such as rainfall intensity, sewage system capacity, and urban development.

Deep learning techniques, particularly neural networks, can further enhance the accuracy of predictive models by extracting complex relationships and non-linear dependencies within the data. Deep learning algorithms can automatically learn and adapt to changing environmental conditions, improving the framework's ability to anticipate and prevent sewer overflow events. NLP techniques can analyze unstructured data sources such as maintenance reports, sensor readings, and public feedback regarding sewer systems. By extracting insights from textual data, the MCIF framework can incorporate qualitative information into its analysis, providing a more comprehensive understanding of the factors influencing sewer overflow incidents. By integrating these advanced AI techniques, the MCIF framework can be optimized for real-time decision-making in managing sewer systems. Automated algorithms can continuously monitor relevant data streams, detect anomalies or potential risk factors, and recommend adaptive interventions to prevent or mitigate sewer overflow incidents. This proactive approach enables municipalities and utility operators to respond swiftly to emerging challenges, minimizing environmental impact and enhancing the resilience of urban infrastructure.

This study holds significant promise for the industry, particularly in enhancing sewer condition assessment practices employing CCTV applications. Platforms such as Pipe Insights were developed by AECOM (Kaddoura, K., & Atherton, 2021), and Sewer AI developed Pioneer. Sullivan & Kumar (2021) showcase the fusion of advanced AI capabilities with sewer infrastructure management. These platforms leverage sophisticated AI algorithms to scrutinize CCTV-captured footage of sewer pipelines. These algorithms adeptly discern heightened water levels, blockages, and structural defects within the pipelines by harnessing cutting-edge computer vision and machine learning techniques. These discernible indicators serve as crucial harbingers in gauging the potential for sewer overflow scenarios. These platforms facilitate early identification of at-risk areas through automated detection processes, empowering proactive maintenance and intervention measures.

Furthermore, identified indicators of potential overflow are seamlessly integrated into criticality assessment frameworks for prioritization modeling. AI algorithms meticulously assign risk scores to different pipeline segments based on the severity of identified issues, enabling asset managers to optimize maintenance activities with precision. This data-driven approach not only streamlines resource allocation but also mitigates the likelihood of sewer overflow incidents in high-risk areas, thus bolstering overall system resilience and operational efficiency.

This integration of AI technologies enhances the MCIF framework's efficacy and enables adaptive and responsive solutions tailored to dynamic urban environments. By harnessing the power of AI, cities can achieve greater sustainability, resilience, and efficiency in managing environmental challenges such as sewer overflow. Furthermore, the insights gained from this study contribute to the ongoing discourse on the intersection of AI, environmental management, and sustainable urban development, facilitating interdisciplinary collaboration and innovation in addressing complex societal issues.

This study is poised to bolster forthcoming R&D initiatives targeting the integration of AI/ML applications for the early detection of significant environmental challenges, such as sewer overflow. By pinpointing the primary causes of sewer overflow, researchers can hone their focus and data collection efforts on factors pertinent to these causes. This targeted approach enables the judicious construction of models, ensuring cost-effectiveness without compromising reliability.

2.1 Phase A: Fuzzy Delphi Technique (FDT)

Delphi is an extensively-used method generally aimed at eliciting, refining, and drawing upon several experts' collective opinions regarding a certain topic (Mahdiyar *et al.*, 2020a; Tabatabaee *et al.*, 2019). This method is expected to decrease the negative effects of group interactions and provide equal opportunities for all participants to share when making the required decisions (Zhang and Mohandes, 2020). The major drawback of the conventional Delphi method was the low convergence of experts' opinions and the inefficiency of the method's execution process. The reason was that iterative investigations were required to achieve consistency in the experts' opinions.

Additionally, this method is largely based on verbal expressions of the participants' opinions (Mohandes *et al.*, 2020). The challenge is that verbal expression has many limitations in reflecting completely the real thinking styles of human beings and showing their mental latencies. As a result, an FST was designed in such a way to effectively address the problems related to ambiguity, subjectivity, and imprecision of human beings' judgments, which was capable of quantifying the linguistic facets of existing data and the preferences for individual or group decision-making sessions (Durdyev *et al.*, 2022). FST is indeed an extended version of the conventional set theory, in which the elements of a set possess membership grades that range from 0 (indicating non-membership) to 1 (indicating a full membership) (Tabatabaee *et al.*, 2021) (detailed explanation about fuzzy sets are straddled in appendix A).

With the above background in mind, the combined Fuzzy Delphi Technique (FDT) is employed to identify the underlying causes of SO and determine the critical ones. To this end, the steps straddled were followed (Sadeghi *et al.*, 2020). The developed surveys were sent to all the selected respondents twice a month, and 104 responses were received. The profiles of the respondents involved in completing the FDT-based survey are illustrated in Fig. 2.

Step 1. *Identification of the causes contributing to the occurrence of SO using a comprehensive literature review.* Initially, the research team investigated relevant literature to identify the related causes. This resulted in several causes mentioned standalone and fragmented in some studies, including blockages (Wang *et al.*, 2012), flow velocity (McCarthy *et al.*, 2011), corrosion (Emmons and Emmons, 2017), infiltration and inflow (Akimana, 2016), and cracks (Strifling, 2003).

Step 2. *Finalizing the list of causes through interviewing the participating experts.* To compile a detailed list of causes leading to SO, several face-to-face and online interviews with four qualified experts were undertaken (Ali and Kidd, 2015; Mohandes *et al.*, 2024). More specifically, one of the experts was an academic with the title of professorship who had more than 20 years of experience in infrastructure asset management, while the other three were senior engineers with more than 15 years of relevant working experience. The list of causes obtained from the literature was provided to the selected experts, who were then requested to add any other factors that had been missed. Once all the interviews were completed, a detailed list of causes leading to SO was obtained, including twelve sub-causes under three main ones.

Step 3. *Designing and distributing the FDT-based questionnaire survey.* Once a detailed list of relevant causes was provided, an FDT-based survey was designed to uncover the importance of the identified items. To this end, there was a need to achieve a reflective sample size that could reveal reliable results. To prudently tackle this issue, two selection criteria were considered as follows: (1) the respondents must have at least a degree relative to the area of civil and environmental engineering, and (2) the respondents must have relative working experiences in dealing with sewer networks in a developing country setting. This led to the selection of 138 qualified respondents for contributing to the study using the employed FDT from different developed nations, for instance, Canada (CAN), the United States (US), the United Kingdom (UK), Australia (AUS), and Hong Kong (HK). Once the sample size was selected, the designed FDT-based survey was built up in Google Docs and sent to the selected respondents. In doing so, they were asked to rate the importance of identified causes using the linguistic variables shown in Fig. A1 (see Appendix B).

Step 4. *Checking the consensus of the collected responses.* After collecting the responses provided by the qualified respondents, there was a need to check whether the answers were of reliability or not. Two indices were considered to do this (Singh and Kumar, 2024; Tabatabaee *et al.*, 2022a; Tinarwo *et al.*, 2023). First, the standard deviation to mean ratio for each cause provided by all the experts was calculated (denoted as ϖ); if the calculated ϖ for each cause was less than 30%, then a good level of consensus among the pool of respondents had been reached. Otherwise, the corresponding cause(s) must be highlighted and sent to the respective experts for reevaluation. In addition, the Cronbach reliability test (α) was considered in this study; the calculated α for all the responses provided by all the respondents for each cause should be more than 0.7. Otherwise, the respective respondent must reevaluate the provided answer(s). The mentioned process is repeated until the specified consensus has been reached.

Notably, to check the reliability of the answers provided by the respondents, the corresponding linguistic variable given to a cause was replaced by a raw score, based on which the ϖ and α were calculated. For instance, for the case of α calculation, “no influence”, “very low influence”, “low influence”, “high influence”, and “very high influence” were respectively replaced by 1, 2, 3, 4, and 5, based on which the α for each expert was calculated.

Step 5. *Fuzzification of the collected responses*. Once the consensus of the provided responses was reached, the variables given to each cause were transferred to the corresponding fuzzy sets that included three values. In doing so, the variables mentioned in Fig. 2 were used; for instance, if the importance of a factor is low, then its importance can be shown within the range of *(0.00, 0.25, 0.5)*.

Step 6. *Defuzzification of the collected responses*. The collected responses need to be aggregated to obtain a reflective crisp value that represents the importance of identified causes. To this end, the following procedures were followed. Considering that there were n experts involved in the study, the importance of the cause j from the perspectives of the respondent i was $\tilde{A} = (l, m, u)$, for $i = 1,2, \dots, n$ and $j = 1,2, \dots, m$. Based on the mentioned components, the following equations were obtained for the aggregation of all the responses:

$$l_j = \{min(l_{ij})\} \quad (2)$$

$$m_j = \frac{\sum_{i=1}^{n} m_{ij}}{n} \quad (3)$$

$$u_j = \{max(u_{ij})\} \quad (4)$$

$$\tilde{A}_j = (l_j, m_j, u_j) \quad (5)$$

where l_j, m_j, and u_j are respectively the minimum, the mean, and the maximum of the values assigned by the experts. On the other hand, $\tilde{A}_j$ Indicates the aggregated fuzzy-based value collected from all the respondents involved in the study. Afterward, the aggregated value for each cause was defuzzified using the following equation (Hafezalkotob and Hafezalkotob, 2017a):

$$\theta_j = \frac{\tilde{A}_j}{6} = \frac{l_j + 4 \times m_j + u_j}{6} \quad (6)$$

where θ_j denotes the importance weight of the cause j in the form of a crisp value.

Step 7. *Setting a threshold value.* To distinguish the critical causes from the less important ones, coming up with an appropriate threshold value is vital; thus, the following equation was used (Tabatabaee *et al.*, 2022b):

$$\rho = \frac{\sum_{j=1}^{C} \theta_j}{C}, \qquad for\ C = 1,2,\dots,n \tag{7}$$

where ρ indicates the required threshold value, C denotes the number of causes identified in the study.

Step 8. *Retaining the critical causes.* Based on the calculated threshold value, the following two rules were considered:

- If $\theta_j \geq \rho$, then the respective cause was critical, and accordingly, it was retained for further consideration.

If $\theta_j < \rho$, then the respective cause was a non-critical one; it was thus excluded for further analyses.

2.2 Phase B: Fuzzy DEMATEL (FDEMATEL) Method

Between 1972 and 1976, the Battelle Memorial Institute of Geneva developed DEMATEL for the Science and Human Affairs Program in a way that is well applicable to investigating more complicated and challenging problems such as hunger, racism, environmental hazards, energy issues, etc. (Rajabpour *et al.*, 2022). This method has been recently applied to various domains, e.g., urban planning and design, corporate planning and decision-making, geographic, and environmental evaluations, and global problem cluster analyses (Yazdi *et al.*, 2020).

The DEMATEL method has the capacity to transform complicated systems into well-organized cause-effect relationships (Mao *et al.*, 2020). On the other hand, as language may be ambiguous and uncertain, the results may suffer from a low level of precision (Tabatabaee *et al.*, 2019). Fuzzy numbers (due to their nature) can be applied to quantify the expert semantics, and FST and DEMATEL can be applied to obtain results of higher precision and correctness (Xu *et al.*, 2020). Accordingly, this study employs the Fuzzy DEMATEL method to unravel the causal relationships among the factors contributing to SO (Acuña-Carvajal *et al.*, 2019a). In this regard, the steps involved in the employed FDEMATEL method are straddled:

Step 1. *Distribution of the designed FDEMATEL-based survey.* A reflective and prudent sample size was needed at the first stage to handle an MCDM-based technique. To tackle MCDM-based problems, the involved experts must be competent enough (Sadeghi, *et al.*, 2020). To do this, among the respondents participating in the FDT step, those with more qualified profiles (regarding their relevant experience and education degrees) were shortlisted. Then, the selected respondents were contacted twice to fill out the designed FDEMATEL-based survey, leading to the collection of forty-four responses. Notably, all the shortlisted experts had more than 5 years of relevant experience and held at least a bachelor's degree at the moment of data collection in the relative area. In the designed survey, the experts were asked to determine the influence of the identified causes and critical sub-causes on each other using the linguistic variables stipulated in Table B1 (see Appendix B) (Acuña-Carvajal *et al.*, 2019b).

Step 2. *Checking the reliability of the responses provided by qualified experts.* To confirm the reliability of the filled-out surveys, the Cronbach reliability test α was taken into account, as suggested by (Jang and Kim, 2021). To this end, the variables assigned by the experts were replaced with raw numbers; only if the calculated α had crossed 0.7, the provided responses would have been considered reliable.

Step 3. *Obtaining the initial direct relation matrix.* Once the reliability of the responses was assured, then the filled-out surveys were fuzzified; a particular linguistic scale assigned by a respondent (for a pairwise comparison carried out between two causes) was transformed to a triangular fuzzy number, as can be seen from the values mentioned in Table 1. This led to the obtainment of the following matrix, considering the evaluations made by k experts:

$$Y^k = \begin{bmatrix} 0 & \cdots & Y_{1n}^k \\ \vdots & \ddots & \vdots \\ Y_{n1}^k & \cdots & 0 \end{bmatrix}, for\ k = 1,2,\dots,p \tag{8}$$

$$Y_{ij}^k = (l_{ij}^k, m_{ij}^k, u_{ij}^k) \tag{9}$$

where Y^k is the initial direct relation matrix (including the pairwise comparisons made by the kth expert, which are in the form of fuzzy numbers), and Y_{ij}^k indicates the influence of cause i on cause j through a pairwise comparison made by the kth expert. It is notable that each Y^k the matrix consists of three matrixes, each of which contains its values, namely l, m, u.

Step 4. *Obtaining the normalized direct-relation fuzzy matrix.* Based on the initial direct relation matrix obtained at the previous step, the corresponding normalized matrix was attained as follows:

$$g_j^k = \sum_{j=1}^{n} Y_{ij}^k = \left(\sum_{j=1}^{n} l_{ij}^k, \sum_{j=1}^{n} m_{ij}^k, \sum_{j=1}^{n} u_{ij}^k\right) \tag{10}$$

$$\sigma_k = max\ g_j^k \tag{11}$$

$$\lambda^K = \frac{Y^k}{\sigma_k} \tag{12}$$

where g_j^k, σ_k, and λ^K are the summation of the initial direct relation matrix, the normalized factor for the kth expert, and the normalized fuzzy matrix related to the kth expert, respectively.

Step 5. *Attaining the aggregated direct relations matrix.* Given the normalized fuzzy direct relation matrix λ^K, the aggregation of the responses provided by all the experts involved in the study was achieved using the following equations:

$$\tilde{X}_{ij} = \frac{\sum_{k=1}^{p} \tilde{\lambda}_{ij}^{k}}{p} \tag{13}$$

$$\tilde{X} = [\lambda_l, \lambda_m, \lambda_u] \tag{14}$$

where $\tilde{X}$ is the aggregated matrix, in which the aggregated lower bounds, the aggregated most likely values, and the aggregated upper bounds are respectively denoted as $\lambda_l, \lambda_m, \lambda_u$. Notably, each $\tilde{X}_{ij}$ is comprised of three matrices; one for lower bounds, one for the most likely values , and one for the upper bounds.

Step 6. *Obtaining the fuzzy matrix of the total relations.* Using Eqs. (15-17), the total relations matrix was attained. This matrix characterizes the total direct and indirect causal relationships between each pair of objectives:

$$\tilde{T} = \lim_{r \to \infty} (\tilde{X}^1 + \tilde{X}^2 + \cdots + \tilde{X}^r) \tag{15}$$

$$\tilde{T} = X \times (I - X)^{-1} \tag{16}$$

$$\tilde{T} = \begin{bmatrix} \tilde{T}_{11} & \cdots & \tilde{T}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{T}_{n1} & \cdots & \tilde{T}_{nn} \end{bmatrix} \tag{17}$$

where $\tilde{T}$ is the fuzzy matrix of total relations, while I is the identity matrix. Notably, $\tilde{X}^r$ is related to the normalized fuzzy matrix for rth expert, while $\tilde{X}$ is the aggregated matrix for all the experts involved in the study.

It is noteworthy that each value of the matrix $\tilde{T}$ is corresponding to a fuzzy triangular number, as can be observed in Eqs. (18-21). In other words, three matrixes of the total relations were achieved: one for the minimum values, one for the most likely values, and the last one for the maximum values.

$$\tilde{T}_{ij} = (l''_{ij}, m''_{ij}, u''_{ij}) \tag{18}$$

$$\left[l''_{ij}\right] = \lambda_{l_{ij}} \times (I_{l_{ij}} - \lambda_{l_{ij}}) \tag{19}$$

$$\left[m''_{ij}\right] = \lambda_{m_{ij}} \times (I_{m_{ij}} - \lambda_{m_{ij}}) \tag{20}$$

$$\left[u''_{ij}\right] = \lambda_{u_{ij}} \times (I_{u_{ij}} - \lambda_{u_{ij}}) \tag{21}$$

Step 7. *Obtaining the defuzzified matrices*. Through the following equations, the fuzzy matrices of the total relations were defuzzified:

$$DEF_{ij} = (1/3) \times (\tilde{T}_{ij}) = \frac{(l''_{ij} + m''_{ij} + u''_{ij})}{3} \tag{22}$$

$$DEF = \begin{bmatrix} \widetilde{DEF}_{11} & \cdots & \widetilde{DEF}_{1n} \\ \vdots & \ddots & \vdots \\ \widetilde{DEF}_{n1} & \cdots & \widetilde{DEF}_{nn} \end{bmatrix} \tag{23}$$

Step 8. *Constructing causal diagrams.* With the use of the resulting F matrix, summation was computed on columns "D" and rows "R", as expressed in Eqs. (24) and (25). The value (D + R) stands for the strength of both input and output ratios and shows the "central role level" of each target. On the other hand, the value (D - R) stands for the "type of influence".

$$D_i = \sum_{j=1}^{n} DEF_{ij} \tag{24}$$

$$R_j = \sum_{i=1}^{n} DEF_{ij} \tag{25}$$

Step 9. *Determination of the criticality of analyzed causes.* To determine the cause-and-effect relationships among the identified critical causes, the following two rules were followed (see Fig. A2):

- If the cause is placed in ZONE 1, then it is a cause dispatching the influence on the whole system, and accordingly, it needs to be controlled by the concerned decision-makers towards minimizing the magnitude of SO.
- If the cause is placed in ZONE 2, then it is an effect cause being influenced by the other causes, and accordingly, it needs less attention compared to those placed in ZONE 1.

2.3 Phase C: Overall Score Index

To think about a reflective value for the identified critical sub-causes, there is a need to combine the outputs produced from FDT and FDEMATEL, which will act as inputs to the employed FTOPSIS technique at the next stage. To do this, the following equations (1-4) were considered in order (Durdyev, Mohandes, Tokbolat, et al., 2022; Hafezalkotob and Hafezalkotob, 2017):

$$\phi_i = \sqrt{(D_i + R_j)^2 + (D_i - R_j)^2} \tag{1}$$

$$\phi = \frac{\phi_i}{\sum_{i=1}^{n} \phi_i} \tag{2}$$

$$\kappa_{SC} = \phi_C \times \phi_{SC} \tag{3}$$

$$\Omega = \theta_j \times \kappa_{SC} \tag{4}$$

where ϕ_i, ϕ, κ_{SC}, and Ω denote the relative weights of causes and sub-causes, the normalized weights of causes and sub-causes, the global weights of sub-causes, and the overall score of sub-causes, respectively.

2.4 Phase D: Fuzzy TOPSIS (FTOPSIS) Method

In 1981, the TOPSIS method was pioneered by Tzeng and Huang (Tzeng and Huang, 2011) to rank different alternatives that exist in a Multi-Criteria Decision-Making (MCDM) problem (Mohsin *et al.*, 2019). TOPSIS is used extensively since it ranks the alternatives rapidly, handles conflicting conditions within a complicated context through compromise, and is capable of placing the judgment data without any lengthy computation (Taylan *et al.*, 2014). For that reason, the current paper makes use of FTOPSIS proposed by Nilashi *et al.* (2019), to obtain a precise ranking system for the aspects of the environment impacted by SO. To this end, there is a need for sequentially taking the steps straddled:

Step 1. *Providing a list of environmental aspects that SO can impact.* These aspects were extracted from the literature (Owolabi *et al.*, 2022a) and also from the senior experts' opinions. It was concluded that SO deteriorates the environment in five ways: air (damages to the air caused by evaporation of pathogens and viruses), soil (damages to the soil slope around the sewer pipeline), business (financial losses that result from the blocked crossings and closure of malls/groceries), structure (damages to the adjacent infrastructure and the sewer pipelines), and water (damages to the quality of ground water).

Step 2. *Building an FTOPSIS-based questionnaire.* The critical sub-causes identified at the first step were embedded in the questionnaire against the determined five aspects of the designed survey. After that, each expert was required to assess the impact of the determined critical causes on each of the five defined aspects. To do this, the linguistic variables presented in Table B2 (see Appendix B) were used (Kutlu and Ekmekçioğlu, 2012). The respondents were asked to answer the following question: "To what extent a particular sub-cause of SO can negatively impact (deteriorate) the conditions of the environment that is under investigation?"

Step 3. Distributing the FTOPSIS-based survey to predefined experts. When the questionnaires were provided, they were distributed to qualified experts to have them filled out. Notably, the 44 respondents participating in filing out the FDEMATEL-based survey were also involved at this stage.

Step 4. Building the following Environmental Matrix (EM) after the collection of the FTOPSIS-based questionnaire:

$$\text{EM} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{nn} \end{bmatrix}, \ for\ i = 1,2,\dots,m, and\ j = 1,2,\dots,n. \tag{26}$$

where a_{ij} stands for the evaluation of the causes with regards to each environmental aspect determined in this research with the use of the linguistic scales presented in Table 2, and m and n signify the number of the relevant causes and aspects, respectively.

Step 5. Checking the consistency of the collected responses after obtaining EM. As recommended by Kozarević and Puška (2018), Cronbach α should be considered in assessing the reliability of the collected responses (the related threshold for α should be at least 0.7).

Step 6. Aggregating the obtained matrix with the use of the following equation:

$$\tilde{a}_{agg_{(ij)}} = \frac{1}{h} \times [\tilde{a}_{ij1} + \tilde{a}_{ij2} + \cdots + \tilde{a}_{ijh}] \tag{27}$$

where $\tilde{a}_{ij1}$ stands for the evaluation attained from the previous step (where the fuzzy scales assigned to the cause i with respect to the environmental aspect j accomplished by the number h expert, for $i = 1,2,\dots,5$, $j = 1,2,\dots,5$, and $k = 1,2,\dots,46$, in this study).

Step 7. Normalizing the matrix consisting of the evaluations, as follows (which is demonstrated as $\tilde{T} = [\tilde{T}_{ij}]_{m*n}$):

$$\tilde{T}_{ij} = \left[\left(\frac{l_{ij}}{u_j^+}\right); \frac{m_{ij}}{u_j^+}; \left(\frac{u_{ij}}{u_j^+}\right)\right], \quad i = 1,2,\dots,5, \tag{28}$$

where,

$u_j^+ = \underset{i}{\mathrm{Max}}\ u_{ij}^+$.

Step 8. Determining the weighted normalized decision matrix after achieving the normalized fuzzy decision matrix, as follows (shown as $\tilde{Y} = [\tilde{y}_{ij}]_{m*n}$):

$$\tilde{y}_{ij} = \tilde{T}_{ij} \times W_j \tag{29}$$

Step 9. Calculating the Fuzzy Negative Ideal (FNIS, A^-) together with the Fuzzy Positive Ideal Solution (FPIS, A^+), as follow:

$$A^+ = \{\tilde{y}_1^+, y_2^+, \dots, \tilde{y}_m^+\}, \qquad for\ j = 1, \dots,5 \tag{30}$$

$$A^- = \{\tilde{y}_1^-, \tilde{y}_2^-, \dots, \tilde{y}_m^-\}, \qquad for\ j = 1, \dots,5 \tag{31}$$

where,

$\tilde{y}_j^+ = (1,1,1)$ and $\tilde{y}_j^- = (0,0,0)$.

Step 10. Calculating the distances of the aspects from $\tilde{y}_j^+$ and $\tilde{y}_j^-$ with the help of the equations presented below:

$$D_i^+ = \sum_{j=1}^{5} d(\tilde{y}_{ij}, \tilde{y}_j^+) \tag{32}$$

$$D_i^- = \sum_{j=1}^{5} d(\tilde{y}_{ij}, \tilde{y}_j^-) \tag{33}$$

$$D(\tilde{x}, \tilde{z}) = \sqrt{\frac{1}{3}[(l_x - l_z)^2 + (m_x - m_z)^2 + (u_x - u_z)^2]} \tag{34}$$

Step 11. Obtaining the closeness coefficient for all the identified aspects using the following equation:

$$\Delta = \frac{D_i^-}{D_i^+ + D_i^-} \tag{35}$$

Step 12. Ranking all the identified environmental aspects based on the calculated Δ. Remember that higher weights of the relative aspects indicate that it deteriorated more by the SO occurrence.

2.5 Phase E: Interviewing the senior experts

- Once the critical causal factors and the environmental aspects deteriorated by SO had been obtained and analyzed, then the relative experts involved in the study for determining feasible strategies for controlling SO were interviewed. In doing so, the interviews were undertaken either face-to-face or online using a structured-based approach; the selected experts were asked to propose any strategies or solutions to mitigate the magnitude of SO, either from the perspectives of management or engineering. It is noteworthy that the following questions were asked form the experts:

    a. Can you propose management strategies to control and mitigate sewer overflows effectively?
    b. From an engineering standpoint, what solutions do you suggest for minimizing the magnitude of sewer overflow incidents?
    c. Are there innovative technologies or approaches that you believe could be implemented to address sewer overflow challenges?
    d. What are the policy- and regulations-related solutions that could be taken into account?

Once all the interviews had been undertaken, a detailed list of fruitful strategies and control measures for minimizing the impact of SO on the environment was garnered.

2.6 Phase F: Validation

To check the extent to which the results produced from the proposed model in this study are reflective, several interviews with qualified experts were carried out, as suggested by (Dolphin *et al.*, 2021). To this purpose, seven qualified experts (whose profiles were in line with the predefined criteria) were shortlisted. Notably, the selected experts were experienced specialists having rich experience in managing and maintaining different tasks in relation to sewer networks in Hong Kong for more than ten years. To this end, they were first asked to rate the importance of the twelve identified sub-causes towards the SO through the Likert scale, followed by determining the most influential sub-causes among the identified ones. Subsequently, they were required to determine if SO occurs and to what extent the considered environmental aspects would be deteriorated (using the Likert scale within the range of 1 to 5).

3. RESULTS, VALIDATION, and DISCUSSION

3.1 Results

In this sub-section, for the sake of brevity, only the gist of the results is reported. Table B3 tabulates the main causes and the corresponding sub-causes of the sewer networks' characteristics and offers a comprehensive categorization of the primary causes (C1, C2, C3) of sewer system challenges, each accompanied by specific sub-causes (SC1 to SC12). For a detailed understanding of these causes and sub-causes, readers are directed to Appendix B, where comprehensive explanations and definitions are provided. These insights are crucial for unraveling the intricacies of issues plaguing sewer systems, encompassing issues like inadequate pipeline design, diverse blockage factors, hydraulic conditions affecting flow rates, defective lining and connections, pipe corrosion and abrasion, physical damage including deformations, and topographical influences, ground movement, infiltration, inflow concerns, as well as damage inflicted by third parties. This knowledge forms the basis for a more profound analysis of sewer system vulnerabilities, guiding the formulation of effective strategies for maintenance and mitigation and ultimately ensuring the sustainability and optimal functionality of urban drainage systems Which contribute to SO occurrence. These results of FDT are reflected in Table 1. In addition, the results produced from the employment of the FDEMATEL technique are shown in Fig. 3, whereas the rankings obtained from the employment of the FTOPSIS technique are reflected in Fig. A3. Table B4 outlines a diverse array of strategies, coded as STG1 to STG25, aimed at effectively tackling sewer overflows (SO). The strategies for minimizing EI and optimizing SO design and operation encompass a multifaceted approach. This includes infrastructure enhancements, public education campaigns targeting littering and improper disposal, routine maintenance practices, the adoption of advanced monitoring technologies, and the implementation of risk management programs. These measures are crucial for improving overall system efficiency, reducing the risk of SO incidents, and promoting sustainable urban development.

A comprehensive framework, illustrated in the provided Table B4, serves as a valuable tool for decision-makers and practitioners involved in SO management. It outlines the interconnected nature of these strategies, emphasizing their implications for SO design and operation. By prioritizing environmental impact mitigation and resilience enhancement, this framework aids in the implementation of holistic solutions to mitigate SO incidents and foster resilient urban infrastructure systems. For a detailed understanding of the implementation and rationale behind each strategy, readers are encouraged to refer to Appendix B, where in-depth explanations are provided.

3.2 Reliability and Validation

Reliability and validation are essential elements of good research since they allow for the verification of study outcomes (Mahdiyar *et al.*, 2020b). Considering this, an investigation into the aforementioned matters was undertaken in this study, and several statistical-based indices were taken into account. Four main types of validation that apply to the area of construction engineering and management were considered, namely face, construct, internal, and external validation (Mohandes, 2020).

Given the methods used within the body of the framework proposed, three main indices were checked to confirm the reliability of the results produced in this research. First, as mentioned earlier, α and $SDMR$ were calculated to check the consensus of the results produced using FDT; the values of the aforesaid indices were 0.8633 and <30% for all the causes, respectively. To check the consistency of the responses provided by experts using the FDEMATEL technique, the Cronbach reliability test α was considered. It was observed that the corresponding results were of sound consistency since the related index for each group was way above the specified threshold value (the aggregated α obtained from all the experts equals 0.7865). Similarly, the aggregated α for checking the reliability of the results obtained from the FTOPSIS method was 0.8638, illustrating the fact that the corresponding results are reliable.

For validation purposes, this study considers all four validation types existing in the concerned area. Regarding the face and construct validities, due to respectively the involvement of the experts through the whole stages of the research and conducting a pilot test on the designed survey (to check whether the objectives specified for the study were attainable through the proposed framework), the outcomes were found valid enough. In addition, because of the senior experts involved in the identification of the causes and sub-causes contributing to SO (in addition to the literature review), this study is of good internal validation. On top of all that, as mentioned in the methodology section, this study held interviews with several experts (who were not involved in the main round of the study) so as to check the external validation of the study. Accordingly, Fig. A4 shows that the results produced from the validation part of the study are congruent with those of the main round. To take the critical sub-causes as examples, SC1, SC6, SC7, and SC11 were found to play the most important roles in SO occurrence in both cases (see Fig. A4(a)). These findings are in line with the main results.

The only difference between the results obtained from the main findings (which are based on the developed framework) and those of validation is the ranking of SC12; it was ranked in the 8th spot based on the aggregation of the experts' responses involved at the validation stage. This is partly linked to the fact that the streets are congested in Hong Kong, and there are numerous utilities buried underground, including water supplies, sewer networks, electricity cables, gas pipes, and telecommunication lines. Therefore, it is very likely that the entitled contractors damage a utility unintentionally during the repair/replacement of the others. Nonetheless, as can be seen in Figs. A4 (b) and (c), based on the viewpoints of the experts taking part in the validation stage, SC1 and structure were respectively, the most influencing sub-causes and the most impacted aspect of the environment by SO. These findings were in line with the corresponding outcomes derived from the employment of the proposed MCIF in this research.

3.3 DISCUSSION

Regarding the importance of the sub-causes contributing to the magnitude of SO, it can be seen that blockages, flow velocity, infiltration and inflow, under design pipe diameter, deformation, holes, or collapse of pipe are the most critical ones (see Table 1). In this regard, the blockage is ranked at the top of the list, with an importance weight of 0.7500. The importance of blockage to SO occurrence lies in the fact that it is one of the most probable types of operational defects occurring in sewer pipelines in either the combined or separate systems (Ossola *et al.*, 2023). In the separate sewer systems, blockage leads to the occurrence of SO in two ways: (1) the wastewater flowing through the sewer pipelines cannot pass through the clogged pipelines and, consequently, it backs up through the 'overflow relief gully', and overflow occurs near residential complexes or even in residential houses (known as flood basement); and (2) if the blockage exists in the pipelines near a manhole, then the wastewater discharges into the street, posing threats to more groups of people. Notably, in the case of combined sewer systems, the surcharge and backups caused by blocked pipelines increase storm drains, which have the potential to flood the nearby streets.

Another critical factor contributing to SO is flow velocity, which was ranked second. Based on the manning equation, the velocity is positively related to the hydraulic radius and slope (Cheng and Nguyen, 2011). If the slope increases with a constant hydraulic radius and also if the hydraulic radius increases for the same slope, in both conditions, the velocity will increase. In this regard, as the flow depth increases, the hydraulic radius increases, too, especially for irregular sewer pipeline shapes. Therefore, and based on the manning equation, the velocity will increase given the same slope. The increased flow velocity leads to SO in the following ways. First, the increased abrasion between the flow medium and the pipe increases surface damage defects (including missing walls), mainly at the invert level. Over time and due to the continued abrasion impact, the invert level of the pipe is washed out, increasing the hydraulic radius (wetted area and perimeter will partially increase), which will increase the flow velocity further. Thus, wastewater flow inside the pipelines is discharged from the manholes into the streets (Kaddoura and Zayed, 2018). Second, the abrasion caused by an increase in the flow medium causes the pipelines to have cracks, fractures, and holes. In this way, the ingress of soil (the embankment soil encapsulating the sewer pipelines), together with the root intrusion, penetrates the sewer system, causing sewer blockages to end up in backs and overflow.

Additionally, the increased flow and its velocity in the system result in irregularities and increased roughness along with the interior of the pipe, increasing the potential for deposits to be attached to the pipe interior, including encrustation, ragging, and grease. In the long run, the amount of these deposits is increased, decreasing the cross-section of the pipe (Bahnsen *et al.*, 2023). As the hydraulics is impacted, backups and sewer overflow are caused. More importantly, fast-flowing sewage hampers an appropriate and safe maintenance practice (either for checking the system or the use of inspection technologies for repairing the defected sewer pipelines) (Ebrahimi *et al.*, 2023). As a result of flawed maintenance practices, the pipelines are exposed to different types of defects, thereby causing the occurrence of SO in the sewer system.

In separate sewer systems, the major driver in the increased flow depth is infiltration and inflow. While inflow is defined as the medium other than sanitary that enters the system from sources (including drains and storm, maintenance hole/covers, or defective manhole structures), infiltration is the medium other than sanitary that enters the system from the ground through defective pipelines and sanitary services. Note that the defects include cracks, joint defects, fractures, roots, holes, and breaks. In light of this, inflow causes an increase in the velocity and volume of the flow, leading to abrasion of the pipelines, which, in turn, culminates in overflow and backflows in the system caused by blockages. In the same way, the deposits, sediments, and roots infiltrated into the system induce the clogged pipelines gradually.

The under-design pipe diameter is another critical contributor to the occurrence of SO due to several reasons. To begin with, in the case of steeped topography, when pipelines are constructed with an inappropriate diameter (i.e., small-sized pipelines), the velocity of flow inside the pipes increases drastically. This sudden increase in the flow velocity results in sewer overflow in the system, as mentioned earlier (due to abrasion and cavities, which lead to the blockage of pipelines). In addition, inappropriate change in pipe diameter between the inlet pipes (i.e., the pipes reaching a manhole) and outlet ones (i.e., the pipes coming out of a manhole) leads to a sudden increase in the flow velocity of an outlet pipeline.

Flexible pipelines (which include ductile, plastic, or corrugated steel) are prone to deformation, which causes the blockage of the pipelines. Another reason for SO is the deformation, holes, or collapse of the pipe. This factor ends up in SO in the following ways. First, due to the excessive external dead and live loads imposed on the sewer systems, constructed pipelines are prone to buckling (Kuliczkowska, 2016). As a result, they deform gradually, which leads to the blockages that cause the occurrence of SO. Notably, the aforesaid phenomenon is clearer in the case of flexible pipelines as compared to those of other types of materials. Additionally, the abrasion caused by increased flow medium raises the severity of existing defects; thus, the deterioration mode of rigid pipelines begins with slight deformation due to excessive external loadings.

Regarding the influence of critical causes and sub-causes on one another, it is observed that physical- and environmental-related factors play the most important role in SO occurrence within the sewer systems (see Fig. 3 (a)). On the one hand, the substandard structure of constructed sewer pipelines affects the appropriate functioning of the sewer system, causing different operational defects (e.g., cracks, fractures, and deformation) in the sewer system, which lead to the occurrence of SO. One interesting observation was that although the physical factor does not directly impact the environmental factor toward SO occurrence within the system, it dispatches a high level of influence to the operational factor through which the environmental factor is affected.

On the other hand, the most influential sub-cause among the determined critical ones is under-design pipe diameter (see Fig. 3 (b)). It can be seen that if the diameter of sewer pipelines is not appropriately and prudently designed, then the resultant impact on all the other factors is unavoidable, thereby causing the occurrence of overflow. In other words, all the other sub-causes are induced by the inappropriate design of sewer pipelines; thus, the concerned parties need to pay special attention to such matters, reducing the rate/volume of blockages, deformations, flow velocity, infiltration, and inflow. Contrary to this, it is witnessed that all of the other sub-causes impact flow velocity.

On the other hand, as flow and its velocity in sewer pipelines increase, the internal material will be subject to expedited structural and operational degradation. Velocity causes irregularities and increased roughness in sewer pipelines due to abrasion caused by the wastewater medium, resulting in severe surface damage, defects, and weakening of the overall material strength. Untreated sewer pipelines experiencing structural defects will further experience damage, and consequences will include fractures, breaks, holes, and collapses (Ma *et al.*, 2023). Broken pieces and collapsed pipes increase the host pipeline's fallen pieces, reducing the internal area and capacity of pipelines. Holes and fractures can also provide room for roots to intrude inside the pipelines, decreasing their operational performance. The amalgamated impacts of these operational and structural defects, resulting from the increased flow velocity, will result in wastewater exfiltration, discharge of wastewater into streets, and sewer backups into people's houses (mainly basements) (Pitiriciu and Tansel, 2021).

The impact of SOs on the environment transcends immediate structural damage, influencing both urban and natural ecosystems in diverse ways (see Fig. A3). SOs compromise the structural integrity of sewer pipelines, causing simultaneous hydraulic and structural failures. This dual impact not only poses a substantial threat to public health and safety but also places significant financial strains on municipalities, requiring urgent repairs or replacements of damaged infrastructure. The collateral damage on streets is particularly evident, especially in poorly paved areas where the accumulation of overflow disrupts the ground, necessitating substantial resources for remediation and reconstruction efforts, as highlighted by (Mutzner *et al.*, 2019). Moreover, the repercussions extend to groundwater quality. The exfiltrated flow, carrying toxicants and bacteria, permeates the ground, gradually contaminating groundwater. This becomes critical in agricultural regions where reliance on soil is high. The polluted groundwater not only alters soil composition but also introduces pollutants into the food chain supporting local populations, as emphasized by (Schertzinger *et al.*, 2019). The intricate relationship between SOs and environmental degradation underscores the pressing need for comprehensive mitigation strategies. Sustainable urban drainage systems are indispensable not only for safeguarding infrastructure and public health but also for preserving ecosystem integrity and ensuring the quality of essential resources like groundwater. As urbanization continues to expand, addressing these environmental consequences becomes paramount for cultivating resilient and ecologically sustainable communities.

Feasible strategies for effective sewer system management, derived from the analysis of factors contributing to SO, encompass a range of practical measures. These include the implementation of advanced monitoring and early warning systems (Fong *et al.*, 2023), regular inspection and maintenance protocols, and sustainable urban design practices, integrating input from urban planners, engineers, and environmental experts. Targeted programs to reduce inflow and infiltration (Ma *et al.*, 2024), public awareness initiatives, and optimized sewer system designs contribute to SO prevention. These strategies align with the need for a holistic and proactive approach to sewer system resilience. Moreover, the integration of green infrastructure (Owolabi *et al.*, 2022b) and ongoing investment in research and technology, including innovative solutions such as smart sewer technologies (Guo *et al.*, 2009), further enhance the overall efficiency and resilience of sewer systems. The combined adoption of these strategies is essential for addressing the multifaceted challenges associated with SO.

(1) The developed MCIF offers a systematic and unique method for identifying and prioritizing root causes of sewer overflows (SOs). Beyond simple identification, the research employs MCIF to unveil intricate causal relationships among key factors, providing profound insights into the complex interactions influencing SO incidents. Additionally, the study extends beyond identification by crafting practical mitigation strategies and delivering actionable insights for decision-makers and urban planners to tackle SO incidents effectively. With its emphasis on practical applicability, sustainability, and advancing existing knowledge, this research significantly contributes to the field by fostering a comprehensive understanding of factors and mechanisms involved in sewer overflows. Ultimately, the study informs decision-making and advocates for proactive measures toward achieving sustainable urban drainage systems. In a nutshell, this study offers the following contributions to the body of relevant literature: Through the employed Fuzzy Delphi Technique (FDT), all the underlying causes leading to sewer overflow were identified, and accordingly, the critical ones were highlighted.

(2) Using the employed Fuzzy Decision-making trial and evaluation laboratory (FDEMATEL) algorithm, the causal relationships existing among the critical causes were uncovered.
(3) The employed Fuzzy Technique for Order of Preference by Similarity to the Ideal Solution (FTOPSIS) algorithm determined and prioritized the environmentally deteriorated aspects resulting from the sewer overflow.
(4) Several feasible measures were suggested to reduce and control the deleterious impacts of sewer overflow.

Using current ICT, Ullah *et al.* (2020) explore AI, machine learning, and DRL for controlling urbanization, energy use, and living standards in smart cities. They discuss applications in intelligent transportation, cybersecurity, smart grids, UAVs, and smart healthcare, while highlighting research issues and future directions. Li *et al.* (2024) prioritize sewage sediment cleaning using knowledge-based and data-driven approaches. Kumar *et al.* (2024) use hybrid machine learning methods to project the particle Froude number in sewer pipes, finding these methods outperform single approaches. Jyothi *et al.* (2024) introduce an AI-based Data Management System (AI-DMS) for smart cities, utilizing PCA to categorize data and enhance privacy while optimizing data quality, processing efficiency, and sensitivity model accuracy. Ha *et al.* (2024) use deep learning to detect sewer network flaws, reducing the need for manual inspections with EfficientDet-D0 and addressing annotation issues. Veselov *et al.* (2021) discuss how AI and machine learning improve smart city applications across various domains, aiming to boost resident quality of life and city efficiency. El Morer *et al.* (2024) analyze sewer pipe inspection using statistical and machine learning techniques, noting that while ensemble models are accurate, logistic regression better balances accuracy, predictability, and explainability. Salihu *et al.* (2023) advocate for advanced AI techniques, including Weibull analysis and unsupervised multilinear regression, to improve sewer system degradation predictions. Yao (2024), examines AI's role in smart city traffic control, safety, and energy optimization, addressing challenges like data privacy and infrastructure needs. Goodarzi & Vazirian (2024). demonstrate that Support Vector Machines (SVM) can predict and localize sewer pipe failures with 84% accuracy, highlighting the effect of manhole proximity. Jagatheesaperumal *et al.* (2024). present a comprehensive vehicle safety framework using AIoT, incorporating various sensors and Li-Fi technology to enhance urban transportation safety. Seng (2024) applies deep CNNs and machine learning to identify and predict sewer defects, with two-stage CNN models and LightGBM-based techniques showing notable performance.

The outcomes of SO in cities are profound, affecting urban infrastructure, public health, and environmental quality. Cities experiencing frequent SO events face significant financial burdens due to the need for urgent repairs and infrastructure replacements. These events cause substantial damage to streets and public spaces, particularly in areas with inadequate paving, leading to costly and disruptive remediation efforts (Cheshmehzangi *et al.*, 2021). Additionally, SO compromises urban water quality by contaminating groundwater with toxicants and bacteria, posing severe public health risks and potentially affecting local food supplies through polluted irrigation water (Mora *et al.*, 2022). These challenges underscore the necessity for cities to implement comprehensive strategies, including advanced monitoring systems, regular maintenance, and sustainable urban planning, to mitigate the impacts of SO and enhance the resilience of urban sewer systems (Shamsuddin, 2020).

3.4 Implication

The study on SO has significant implications for the real world, particularly for urban areas and their inhabitants. It provides actionable insights for cities implementing proactive maintenance strategies to mitigate SO risks. By identifying blockages as a primary cause, the research emphasizes the need for regular sewer system inspections and cleanings, which are practical steps lead to substantial benefits for city residents. These measures prevent system failures and ensure uninterrupted service, reducing inconveniences and health hazards.

Moreover, the study's recommendations on sewer system design, such as optimal pipeline sizing, play a vital role in improving the reliability and efficiency of these systems. Such improvements directly affect the daily lives of city dwellers by minimizing potential disruptions and guaranteeing consistent access to essential services.

Theoretically, the research enhances our understanding of the mechanisms behind SO, aiding in developing more precise predictive models and simulations. This theoretical advancement informs better decision-making regarding infrastructure investments and management strategies for cities. By incorporating physical and environmental factors into theoretical frameworks, researchers can create more effective risk assessment and management strategies, thereby increasing the resilience of urban infrastructure against SO incidents.

Furthermore, the study advances the societal-practical implications and contributions of the proposed study-development by showcasing how improved sewer system management can lead to enhanced urban resilience and quality of life. The research's impact is far-reaching, extending beyond academic contributions to effecting positive change in urban living conditions. It informs maintenance strategies and advances theoretical models for managing sewer systems, ultimately leading to safer, more reliable, healthier environments for city residents. The study stands as a testament to the importance of scientific research in addressing and resolving practical challenges faced by cities and their inhabitants.

4. CONCLUSIONS

In this study, a novel ensemble fuzzy-based framework was developed to investigate the causal factors contributing to SO and the environment's deteriorated aspects caused by such occurrences. To this end, several fuzzy-based algorithms were used within the body of the proposed framework, including FDT, FDEMATEL, and FTOPSIS. Based on the responses of the qualified experts with rich experience in dealing with sewer networks through a step-by-step application of the proposed framework, the following contributions and the corresponding conclusions were drawn:

(1) The potential causal factors and their sub-causes were identified, and also the critical ones contributing to SO were uncovered; twelve sub-causes under the umbrella of three main causes were identified, of which five items were seen to be the most important causal factors, which were blockages, flow velocity, infiltration and inflow, under design pipe diameter, and the deformation, holes, or collapse of the pipe.

(2) The most influential causal factors and their related sub-factors were unraveled, while the physical factor was found the most impactful one among the others. Under design, pipe diameter, blockages, deformations, holes, or collapse of pipes exerted the highest level of influence on the whole system.

(3) The impact of SO on different aspects of the environment was unraveled; it was observed that the structures of the constructed facility as well as groundwater quality, are the most deteriorated aspects of the environment caused by SO.

(4) Twenty-five effective strategies were compiled, ranging from engineering improvements to the system and managerial/regulatory enhancements.

The findings obtained from this study, which are also validated by the involvement of qualified experts, provide a solid foundation for both the researchers and the concerned practitioners to design a smart and sustainable urban drainage system for future generations, which could result in the improvement of the environment resulting from a reduction in the magnitude of SO.

This study has certain limitations, such as the reliance on expert opinions, which, though enriched with practical experience, introduces subjectivity into the analysis. Additionally, the specificity of sewer systems may vary across regions, potentially impacting the generalizability of the identified strategies. Future research endeavors could address these limitations by expanding the dataset to encompass a broader range of geographical locations and integrating real-time data to enhance the model's predictive capabilities. Furthermore, the integration of socio-economic factors and community perspectives could offer a more comprehensive understanding of SO dynamics. Despite these constraints, the findings from this study establish a robust foundation for advancing research in urban drainage systems, guiding the development of sustainable strategies to mitigate SO and improve environmental outcomes in cities and the built environment.

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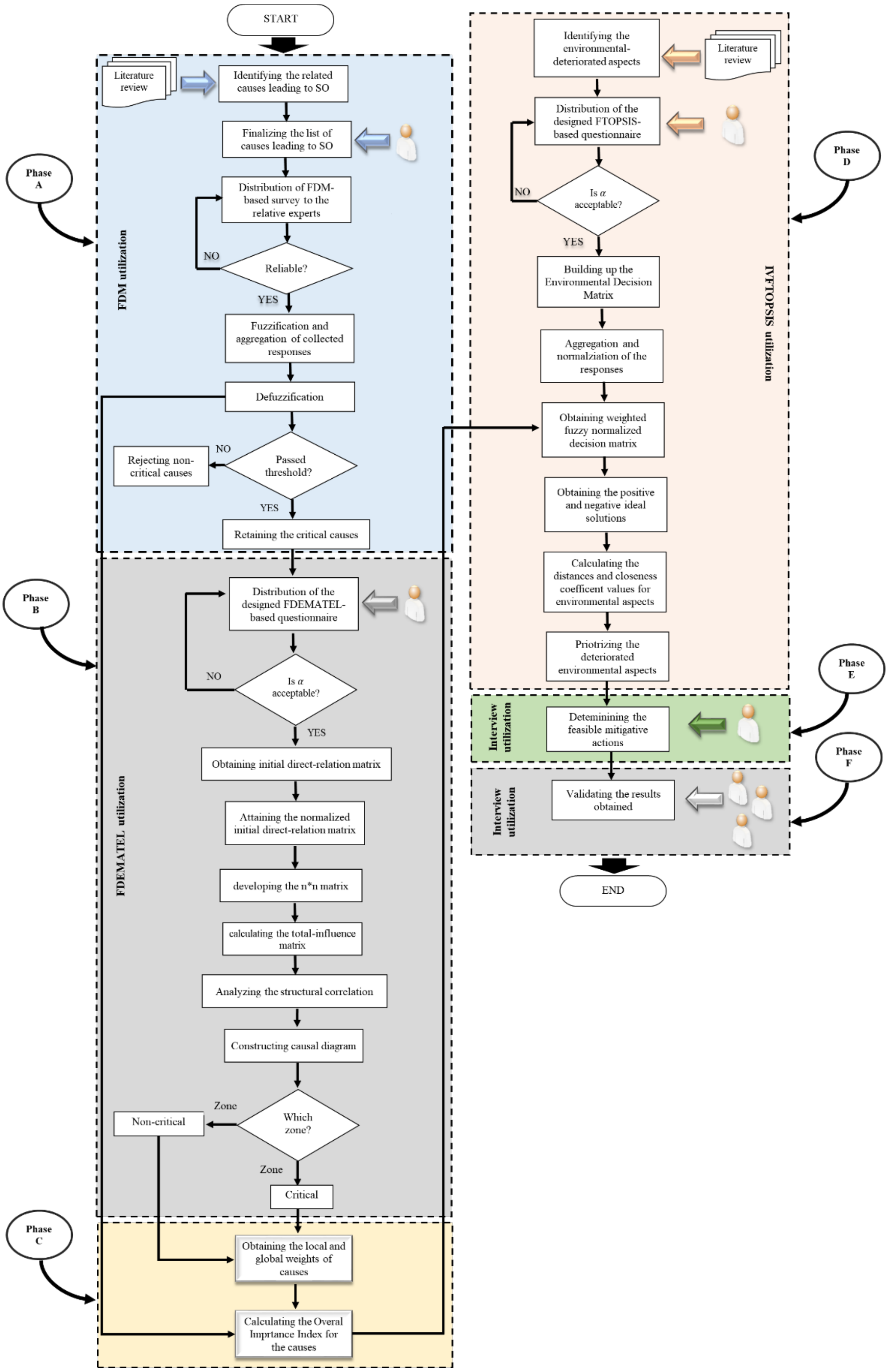

Fig. 1. The framework of the developed MCIF

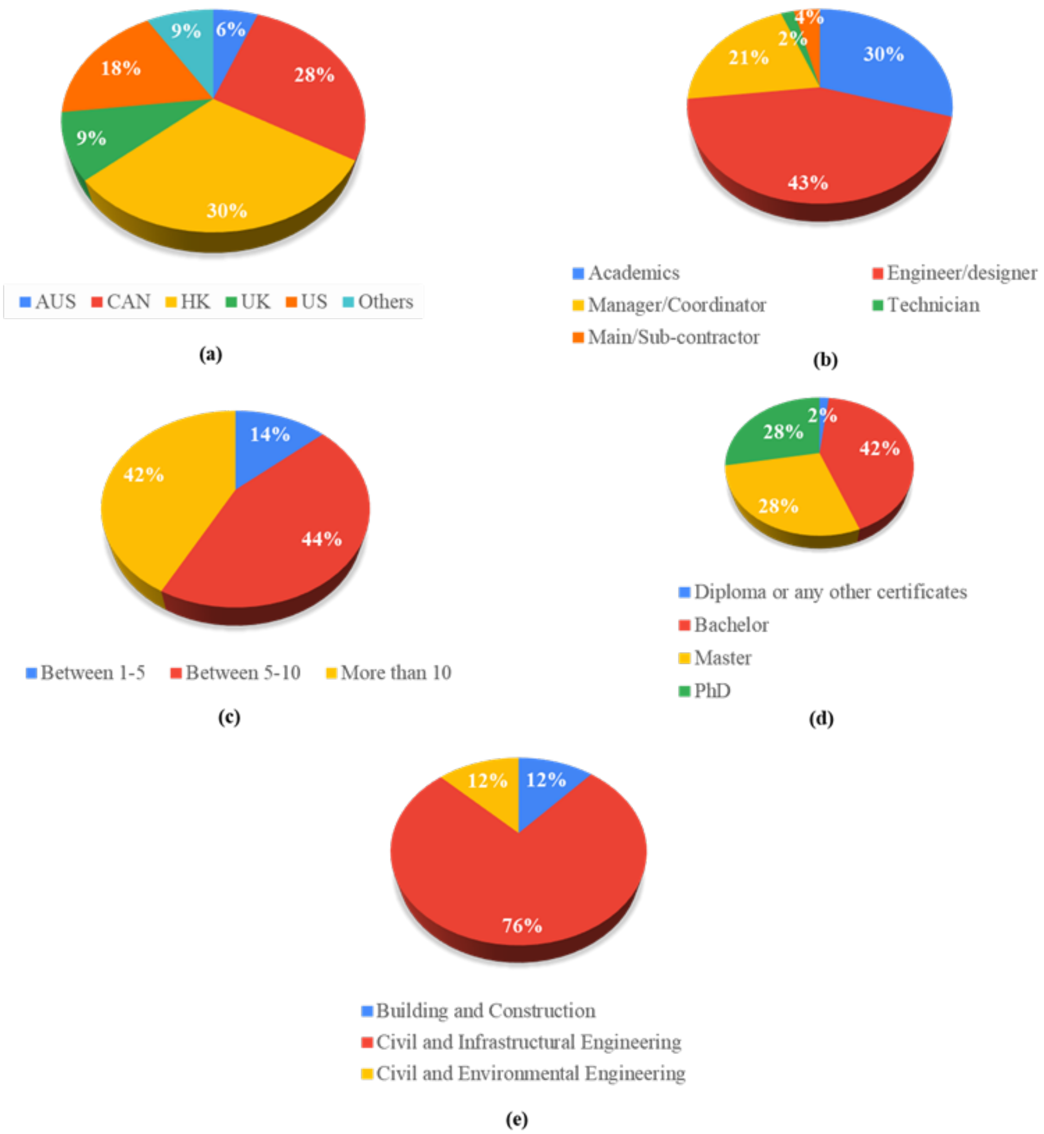

Fig. 2. Breakdown of respondents' profiles in terms of: (a) country, (b) education, (c) years of experience, (d) qualification, and (e) major.

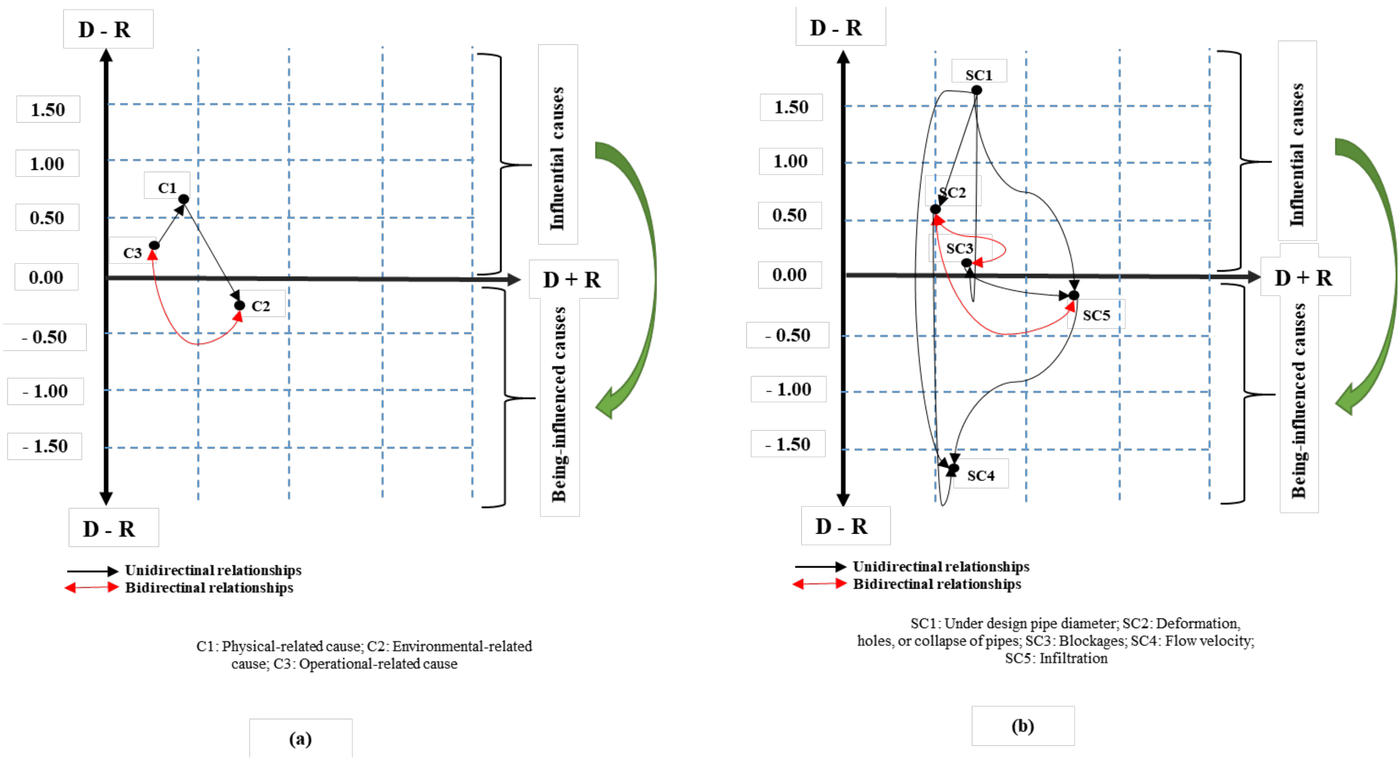

Fig. 3. Results of FDEMATEL: (a) causal diagram for the main causes, and (b) causal diagram for sub-causes

Table 1. Results of FDT

Main Causes	**Sub-Causes**	$\tilde{A}_j$			θ_j	**Critical/Non-critical**	**SDMR (%)**	**Rank**
		Min	Average	Max				
Physical	Pipe Diameter	0.25	0.6322	1	0.6298	**Critical**	13	4
	Pipe Gradient	0	0.5817	1	0.5545	Non-critical	11	6
Operational	Blockages	0.25	0.8125	1	0.7500	**Critical**	7	1
	Flow Velocity	0.25	0.7476	1	0.7067	**Critical**	8	2
	Defective Lining	0	0.4495	1	0.4663	Non-critical	23	9
	Defective Connection	0	0.5601	1	0.5401	Non-critical	15	8
	Corrosion & Abrasion	0	0.4255	1	0.4503	Non-critical	18	10
	Deformation, holes or collapse of pipe	0.25	0.6082	1	0.6138	**Critical**	16	5
Environmental	Land Topography	0	0.5721	1	0.5481	Non-critical	14	7
	Ground Movement	0	0.3389	0.75	0.3510	Non-critical	16	12
	Infiltration and Inflow	0	0.7284	1	0.6522	**Critical**	9	3
	Third party damage	0	0.3702	1	0.4135	Non-critical	28	11
ρ								**0.5564**
α								**0.8633**

Appendix: A

Fuzzy Sets Theory

The fuzzy sets theory (FST) was proposed by Zadeh to model the vagueness of cognitive processes in human beings (Mohandes and Zhang, 2021; Zadeh, 1988). Principally, FST was established on the idea that elements possess a degree of membership in a definite interval, i.e., [0,1] (Mohandes, Sadeghi, *et al.*, 2020). The FST comes in a variety of forms, including Triangular Fuzzy Number (TFN), trapezoidal fuzzy number, Pythagorean sets, and so forth (Mohandes and Zhang, 2019). Each TFN has linear representations on its right and left sides, and its membership function could be expressed as a relation presented in Eq. (1) as follows (Durdyev *et al.*, 2022):

$$\mu(x|\tilde{A}) = \begin{cases} 0, & x < l \text{ or } x > u, \\ \dfrac{x-l}{m-l}, & l \le x \le m, \\ \dfrac{u-x}{u-m}, & m \le x \le u \end{cases} \tag{1}$$

where $m, l, and\ u$ stand for the most likely value, the lower bounds, and the upper bounds of the fuzzy number $\tilde{A}$, respectively. For the sake of brevity, the readers can refer to (Seresht and Fayek, 2019) for grasping an in-depth understanding of the basic operations of two fuzzy sets. Notably, with a view to enhancing the reproducibility of this research, TFN has widely been used within the body of the proposed framework.

Appendix: B

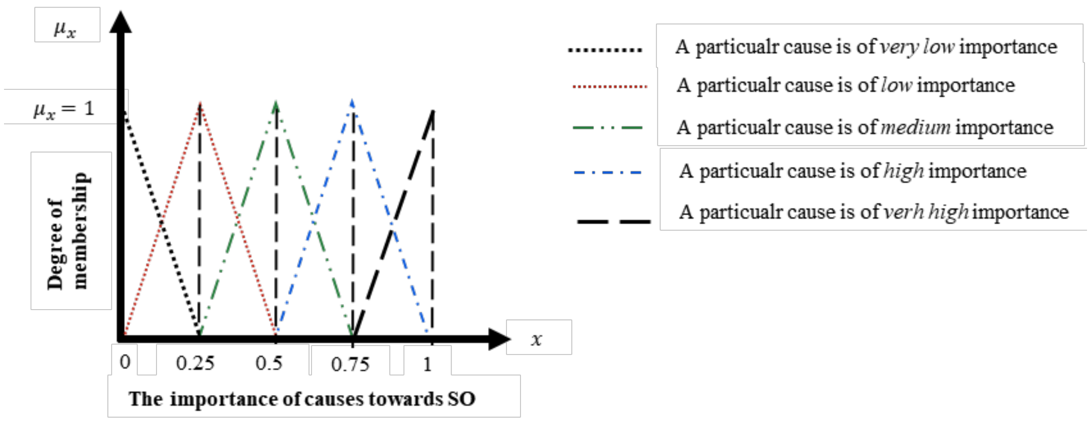

Fig. A1. Linguistic variables and their corresponding values

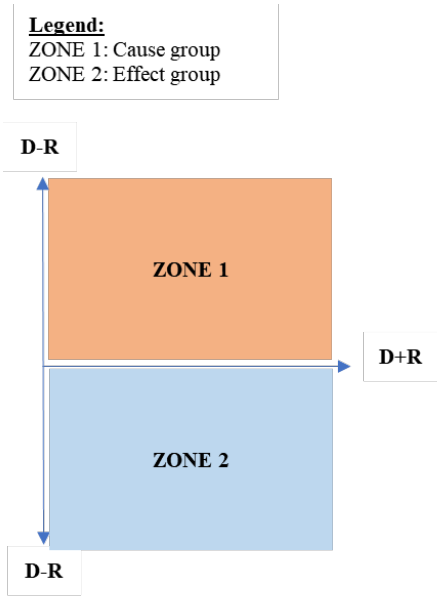

Fig. A2. Zones of causal diagrams

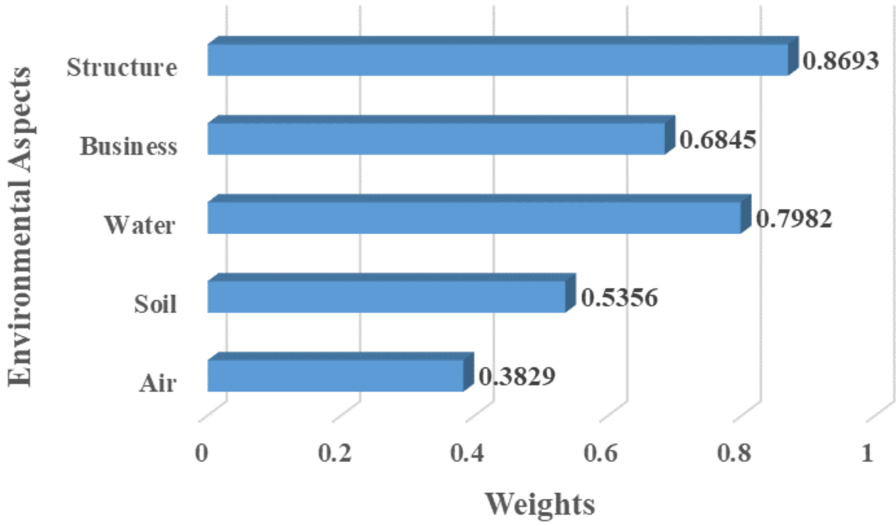

Fig. A3. Weights and rankings of the environmental aspects impacted by SO

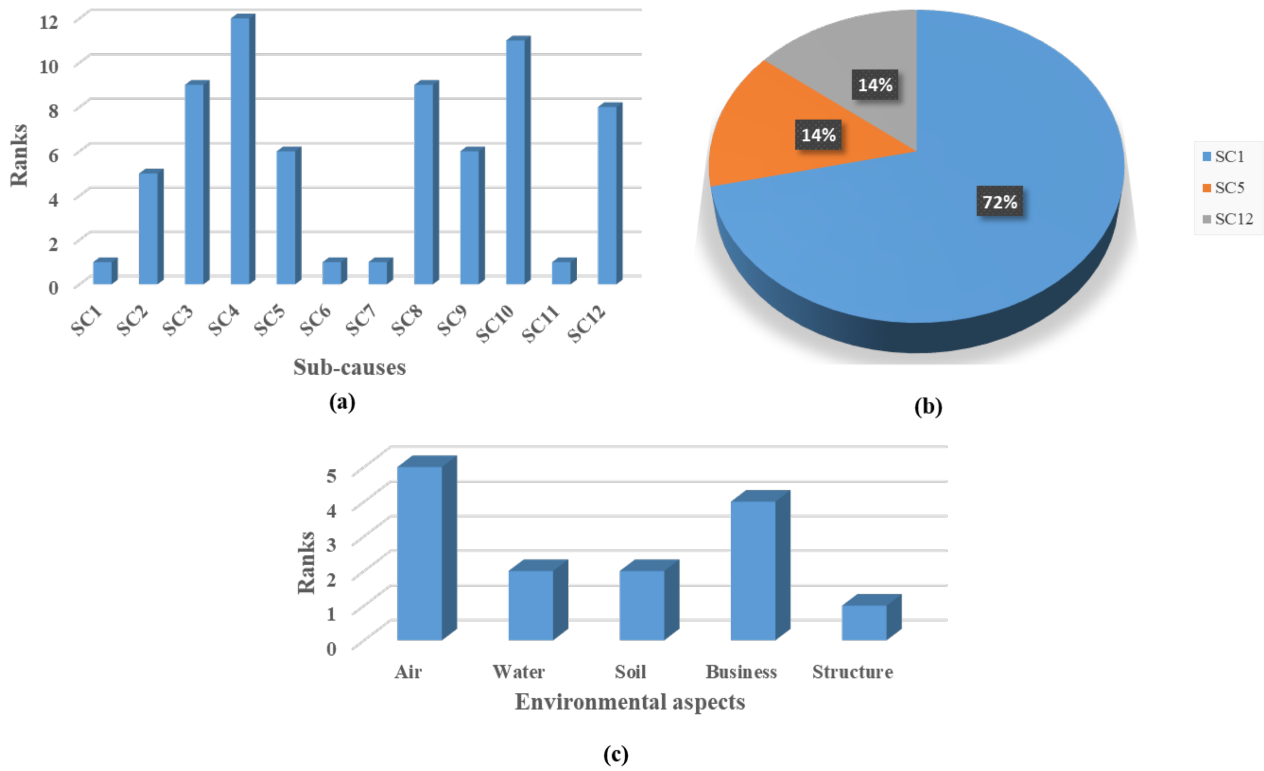

Fig. A4. Results of validation: (a) rankings of sub-causes, (b) most influential sub-causes, and (c) rankings of deteriorated environmental aspects

Table B1. Linguistic variables and the corresponding values used for the FDEMATEL technique

Linguistic variables	**Numbers**		
	l	***m***	***u***
There is *NO* relationship between the two factors	0	0	0
One factor has a *Very Low Influence* on the other one	0	0	0.25
One factor has a *Low Influence* on the other one	0	0.25	0.5
One factor has a *High Influence* on the other one	0.25	0.5	0.75
One factor has a *Very High Influence* on the other one	0.5	0.75	1.00

Table B2. Linguistic variables used for the FTOPSIS method

Linguistic variables	**Numbers**		
	l	***m***	***u***
A particular factor is *Very Low Important* to deteriorate a specific aspect of the environment that is under investigation	0	0	1
A particular factor is *Low Important* to deteriorate a specific aspect of the environment that is under investigation	0	1	3

A particular factor is *Medium Low Important* to deteriorate a specific aspect of the environment that is under investigation	1	3	5
A particular factor is *Medium Important* to deteriorate a specific aspect of the environment that is under investigation	3	5	7
A particular factor is *Medium High Important* to deteriorate a specific aspect of the environment that is under investigation	5	7	9
A particular factor is *Highly Important* to deteriorate a specific aspect of the environment that is under investigation	7	9	10
A particular factor is *Very Highly Important* to deteriorate a specific aspect of the environment that is under investigation	9	10	10

Table B3. The list of identified causes and sub-causes together with their definitions

Main causes	**Sub-causes**	**Definitions**
Physical (C1)	Pipe Diameter (SC1)	Under design diameter/substandard design of the pipelines to be installed.
	Pipe Gradient (SC2)	Substandard/inadequate distance between sections of pipe (in terms of the ratio of pipe length and the amount of fall).
Operational (C2)	Blockages (SC3)	Blockages occur due to the following reasons: sediment, grease, deposits, and other materials that are built up or intruded in the pipes; broken manhole covers or damaged manhole walls; vandalism; improper maintenance strategies; soil intrusion; movable/slid deposit; and root intrusion.
	Flow Velocity/Hydraulic Condition (SC4)	Under continuous rain and during heavy storm events, the flow slows down sharply to an estimated 0.03 m/s and backs up from the treatment plant, leading to an increase in the volume of stormwater discharged into the sewer exceeding the sewer capacity.
	Defective Lining (SC5)	The installed lining is defective such as having a missing section or distance with the pipe wall or any other sort of lining failure
	Defective Connection (SC6)	The connection is intruding into the pipe length blocking the flow, or the connection is damaged or blocked
	Corrosion & Abrasion of pipes (SC7)	Pipeline corrosion is the oxidization and electrochemical breakdown of the structure of a pipe used to convey any substance. (e.g., the attack of Hydrogen Sulfide on the concrete structure of a pipeline), while abrasion is the result of the inner surface of the pipe wall being eroded or degraded by the flow in the pipe
	Deformation, holes, or collapse of pipe (SC8)	It occurs due to the following reasons: a noticeable change in the original cross-section of the pipe (whether horizontally or vertically); when there is a noticeable hole in the pipe wall; and when 50% of more of the cross-section is broken in which the pipe completely damaged and cannot be used
Environmental (C3)	Land Topography (SC9)	Undulating topography may lead to easy flooding due to marginal changes in storm water flows
	Ground Movement (SC10)	Ground movement due to the removal of mine dumps destroyed the continuity of sewers, leading to the longitudinal and circumferential displacement of pipes
	Infiltration and inflow (SC11)	Inflow occurs when storm medium flows into manholes or so, while infiltration occurs when the groundwater flows into defective sewers

	Third-party damage (SC12)	Damages caused by the third party (e.g., contractor use heavy machinery or directional drilling) to the pipelines

Table B4. List of the measures to tackle SO

Code	Strategy
STG1	Increasing the capacity of the pumping stations
STG2	Promoting social culture so that people reduce littering (e.g., providing public education to reduce flushing of non-flushable items in toilets and promote techniques to properly dispose of fat, oil, and grease (FOG), for instance, through TV commercials, news articles, and cartoons (for kids))
STG3	Regular cleaning of the streets to be ensured that unwanted objects do not penetrate the manhole during raining
STG4	Designing pipes with a large factor of hydraulic and structural safety
STG5	Constant monitoring of the sewer pipelines conditions
STG6	Optimizing the operational schedule of the system
STG7	The correct and pragmatic design of the sewage system (e.g., with considering climate change)
STG8	Design year range
STG9	Proper cleaning of the system and regular inspection
STG10	Proper hydraulic modeling and mitigation actions based on results
STG11	Adhering strictly to recommendations of different environmental agencies (e.g., EPA, Natural England, and European Environment Agency)
STG12	Install separate sewer systems
STG13	Designing new technologies for self-cleansing of sewer pipelines
STG14	Regular maintenance of defective sewer pipes
STG15	Introducing the respective parties with regulations/laws to avoid sewer overflow and its negative impact (such as the introduction of incentives, if its occurrence is reduced)
STG16	Finding the critical points or nodes where the sewer is more likely to overflow to promote infrastructural strategies (such as tanks or natural buffers)
STG17	Quick response to report the overflow incidents
STG18	Providing/developing an online system to report sewer overflow incidents
STG19	Management of storm network including all stakeholders within the region to provide inputs, including O&M team
STG20	Early detection of overflow using real-time and flow monitoring sensors (e.g., Installing an electronic alarm sensor (with 4G data transmission function) below cover of the manhole to monitor the water level of sewage water and send an alarm signal to the control room).
STG21	Applying sewer bypass pumping and urgent repairs
STG22	The use of cloud-based systems where O&M team can access sewer pipeline information from mobile applications
STG23	Maintaining records of historical overflow incidents to study causes and eliminate them during design stages
STG24	Initiating basement flooding protection programs to prevent the public from backup incidents (this way, the sewer system's levels of service would increase as complaints decrease)
STG25	Developing risk management programs that prioritize segments for inspection/repairs and providing emergency repairs as an activity for those pipes that are in critical structural and hydraulic conditions.