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Methodologies for damage information modeling in bridge management systems

Ana Carolina Pereira Martins
Doctor Scientiae

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Thesis submitted to the Civil Engineering Graduate Program of the Universidade Federal de Viçosa in partial fulfillment of the requirements for the degree of *Doctor Scientiae*.

Adviser: Jose M. Franco de Carvalho

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ABSTRACT

MARTINS, Ana Carolina Pereira, D.Sc., Universidade Federal de Viçosa, March, 2025. **Methodologies for damage information modeling in bridge management systems**. Adviser: Jose Maria Franco de Carvalho. Co-advisers: Diogo Silva de Oliveira, Jose Carlos Lopes Ribeiro and Kleos Magalhaes Lenz Cesar Junior.

Efficient bridge maintenance management ensures their safety and extends their useful life. However, the large amount of data generated during the inspection and maintenance of these structures represents a significant challenge for decision-making. This thesis presents innovative methodologies for modeling damage information in Bridge Management Systems (BMS), focusing on inspection data integration, parametric damage modeling, preliminary estimation of maintenance services, and immersive technologies to improve damage documentation and analysis. The results showed that damage information modeling (DIM) can significantly improve the accuracy and efficiency of bridge maintenance management, enabling greater interoperability between systems and improving data traceability and communication. The use of parametric models contributes to the standardization of information and the preliminary forecasting of maintenance services, while the adoption of immersive technologies has proved viable for optimizing the inspection and documentation of damage in the field. The conclusions reinforce the importance of integrating BIM, DIM, and MR to modernize infrastructure management processes, proposing future directions to expand the application of the methodologies developed and incorporate new emerging technologies.

Keywords: Bridge maintenance management; Damage information modeling (DIM); Building information modeling (BIM); Mixed reality (MR); Bridge inspection; Parameterization

RESUMO

MARTINS, Ana Carolina Pereira, D.Sc., Universidade Federal de Viçosa, março de 2025. **Metodologias para modelagem de informações sobre danos em sistemas de gerenciamento de pontes**. Orientador: Jose Maria Franco de Carvalho. Coorientadores: Diogo Silva de Oliveira, Jose Carlos Lopes Ribeiro e Kleos Magalhaes Lenz Cesar Junior.

A gestão eficiente da manutenção de pontes é essencial para garantir a segurança e prolongar a vida útil dessas obras de arte especiais. No entanto, a grande quantidade de dados gerados durante a inspeção e manutenção dessas estruturas representa um desafio significativo para a tomada de decisão. Esta tese apresenta metodologias inovadoras para a modelagem de informações sobre danos em Sistemas de Gerenciamento de Pontes, com foco na integração de dados de inspeção, modelagem paramétrica de danos, estimativa preliminar de serviços de manutenção e uso de tecnologias imersivas para aprimorar a documentação e análise de danos. Os resultados obtidos demonstram que a modelagem de informações sobre danos pode melhorar significativamente a precisão e eficiência da gestão de manutenção de pontes, permitindo maior interoperabilidade entre sistemas e melhorando a rastreabilidade e comunicação dos dados. O uso de modelos paramétricos contribui para a padronização das informações e para a previsão preliminar de serviços de manutenção, enquanto a adoção de tecnologias imersivas se mostrou viável para otimizar a inspeção e documentação de danos em campo. As conclusões reforçam a importância da integração entre modelagem da informação da construção, modelagem da informação do dano e realidade mista para modernizar os processos de gerenciamento de infraestrutura, propondo direções futuras para expandir a aplicação das metodologias desenvolvidas e incorporar novas tecnologias emergentes.

Palavras-chave: Gestão da manutenção de pontes; Modelagem de informações sobre danos; Modelagem da informação da construção; Realidade mista; Inspeção de pontes; Parametrização.

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CHAPTER I

General introduction

Abstract

This chapter presents a general introduction to the work, including the general and specific objectives. The way this work is structured is also presented, with comments about its specificities, in order to facilitate its reading and understanding.

1. Introduction

Bridges are critical in modern infrastructure, enabling connectivity, mobility, and economic development. Throughout their lifecycle, bridges undergo numerous processes, including inspection, maintenance, and repair, which are essential to ensure their safety and extend their service life (KASIREDDY; AKINCI, 2015). Inspections are vital for assessing the condition of deteriorated structures, identifying existing damage types, and determining the extent and location of potential problems (AL-SHALABI; TURKAN; LAFLAMME, 2015; BOLAR; TESFAMARIAM; SADIQ, 2013; PANAH; KIOUMARSI, 2021; XU; TURKAN, 2019). The bridge inspector is responsible for monitoring and assessing the condition of these structures, and one of his main tasks is to identify damage and potential problem areas (BIANCHI et al., 2023).

Bridge maintenance management encompasses a systematic process to ensure that structures remain operational and safe over time (COSTIN et al., 2018; GUI et al., 2021; YANG et al., 2022). It involves collecting information through inspections, diagnosing damage via technical assessments, planning interventions based on condition reports, and implementing maintenance strategies, such as repair, rehabilitation, and reconstruction (GUI et al., 2021; REN; DING; LI, 2019; WU et al., 2021; YIN et al., 2011). A well-planned maintenance strategy addresses the structural need, optimizes operational processes, reduces the frequency of interventions, and mitigates complexity (BENÍTEZ et al., 2020).

The lifecycle of a bridge generates vast amounts of data, which must be efficiently managed to support informed decision-making. It highlights the importance of digital bridge models for integrating and centralizing information (ARTUS; KOCH, 2022; NGUYEN et al., 2022). Building Information Modeling (BIM) offers an innovative solution by enabling the creation of digital twins that represent structures' physical and functional characteristics. Acting as an information repository throughout the lifecycle, BIM provides significant benefits, including enhanced data visualization, collaboration, and efficiency in transportation infrastructure management (CHONG et al., 2016; COSTIN et al., 2018).

Through parametric modeling and the Industry Foundation Classes (IFC) schema, BIM facilitates the standardization, sharing, and interoperability of data across stakeholders. IFC, an open data standard developed by BuildingSMART, enables the structuring of geometric and semantic data, while the BIM Collaboration Format (BCF) allows efficient communication of issues related to the model, ensuring transparency and collaboration throughout the project lifecycle (BUILDINGSMART, 2021; ISO, 2018; VAN BERLO; KRIJNEN, 2014).

Given the growing concerns about the safety of aging and deteriorated structures, condition assessment has become a key research focus. Immersive visualization technologies, such as Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR), when combined with BIM, offer unprecedented opportunities for digitization and automation in information management. These technologies promote better documentation and interpretation of data in three-dimensional (3D) environments, enhancing decision-making processes (CATBAS et al., 2022; KARAASLAN; BAGCI; CATBAS, 2019; SADHU et al., 2023).

Damage Information Modeling (DIM) further complements BIM by providing a structured and parameterized approach to documenting damage data. DIM incorporates semantic and geometric data, including attributes such as width, length, orientation, position, and material descriptions, ensuring that damage information is precise and standardized for use across various Bridge Management System (BMS) operations (ARTUS; KOCH, 2022; XU et al., 2022). This standardization reduces information loss, enhances efficiency, and supports cost-effective maintenance strategies (HÜTHWOHL et al., 2018).

This study was conducted to provide a comprehensive approach to bridge damage management, covering all stages of the process, from identifying and recording damage during inspections to standardizing and modeling data for integration into the BIM environment. By focusing on structured information application in maintenance decision-making, this research presents innovative methodologies to improve the efficiency, accuracy, and bridge management systems reliability.

The relevance of this work lies in its contribution to the modernization of bridge management and maintenance processes, tackling critical challenges through advanced digital solutions. The integration of BIM and DIM, combined with the use of immersive technologies such as mixed reality, highlights the potential to significantly transform the way structural information is collected, analyzed, and used. This approach promotes greater efficiency, precision, and sustainability in maintenance processes, reinforcing the role of technological innovation in the infrastructure sector.

2. Objectives

This research's general objective was to develop methodologies for damage information modeling in bridge management systems, focusing on integrating inspection data, damage reports, proposed maintenance services, and associated costs.

Therefore, the following specific objectives have been proposed:

- Conduct a comprehensive literature review on the latest technologies and methodologies applied to bridge management, focusing on Damage Information Modeling (DIM) and Building Information Modeling (BIM).
- Develop a parametric model for the preliminary estimation of widening and strengthening services on old reinforced concrete bridges, considering unit costs and factors that influence cost variation in the different parts of the structure (infrastructure, mesostructure, and superstructure).
- Develop a methodology for associating damage parameters with maintenance interventions using parametric models associating geometric and semantic characteristics.
- Explore and validate immersive technologies, such as Mixed Reality (MR), to improve the inspection process and documentation of bridge damage.
- Investigate the limitations and opportunities of the proposed methodology, considering aspects such as interoperability, process automation, accuracy, and applicability in different contexts.

3. Thesis structure

This work has been structured in six chapters, with one chapter containing the general introduction, four chapters being presented in the form of articles and one chapter of final conclusions.

Chapter I presents a general introduction that contextualizes the research, its objectives, and its relevance into context. This chapter also describes the structure of the work, offering an integrated view of the topics covered in subsequent chapters. Chapter II discusses the main trends and challenges identified in the literature, including topics such as bridge inspection, structural monitoring, damage detection, information modeling, and decision processes. In addition, the chapter addresses recent advances in the application of BIM and DIM in bridge management.

Chapter III delves into the analysis of unit costs and the estimation of maintenance services, covering specific parameters for infrastructure, mesostructure, and superstructure. This chapter also analyzes the history of Brazilian bridge design standards and the use of reference cost systems, such as SICRO. Chapter IV presents a methodology for parametric damage modeling, focusing on the association with maintenance interventions, the calculation of adjustment coefficients, and the analysis of errors applied to the preliminary cost estimation process.

Chapter V explores the use of immersive technologies based on a case study carried out on the Coimbra I Viaduct. This chapter details how MR and BIM integration can improve the inspection, documentation, and damage measurement processes, demonstrating the feasibility and benefits of these approaches in practical scenarios. Finally, Chapter VI presents the work's general conclusions, outlining the main contributions of the research, and suggests directions for future studies, emphasizing the expansion of the methodological scope and the integration of emerging technologies.

All bibliographic references are presented at the end of each chapter, so that there is no specific section at the end of this work. It is important to emphasize that the subjects of the chapters are complementary, so that they share some bibliographic references and present elements with similar contents in their introductions.

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CHAPTER II

Detecting, monitoring and modeling damage within the decision-making process in the context of managing bridges: a review

Abstract

The expansion of transportation infrastructure and the aging and deterioration of its constituent elements make bridge maintenance management programs more expensive and complex. In this context, a bridge management system (BMS) has become a fundamental tool for managing and controlling the entire process involving the structures, from design, construction, operation, and maintenance. Information regarding bridges, inspection, and damage detection should be standardized and digitized for stakeholder access. The provided bibliometric analysis demonstrates that inspection, structural health monitoring (SHM), deterioration, damage detection, and decision-making are trending topics. These topics guided a comprehensive literature review bringing advances and discussing assessment quality, the ability to detect damage, and the most accurate and cost-effective intervention. Finally, the challenges and limitations of these topics are identified, and possible solutions to overcome these limitations are discussed.

Keywords: bridge management system (BMS); building information modeling (BIM); damage information modeling (DIM); damage detection; inspection; maintenance management; structural health monitoring (SHM).

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1. Introduction

Bridges are fundamental components of the transportation system, economic vitality, and personal mobility, facilitating access between different areas through the transposition of barriers (Kendall et al., 2008; Marzouk & Hisham, 2012; Wan et al., 2019). The growing and aging of the transportation infrastructure put pressure on developing more efficient technologies and tools to assess and manage these structures over their lifetime (Abudayyeh & Al-Battaineh, 2003; Boddupalli et al., 2019; Costin et al., 2018; Sedek & Serwa, 2016). Due to the nature of loads and the environmental conditions in which they are inserted, the bridge elements are subject to rapid deterioration, requiring intervention actions of maintenance, rehabilitation, or replacement (Frangopol & Soliman, 2015; J. Mohammadi et al., 1995; Xie et al., 2018).

Since various factors affect a bridge's performance, safety, maintenance, and cost, the intervention process chosen to rehabilitate or replace some elements is a difficult task (Benítez et al., 2020; J. Mohammadi et al., 1995). Besides an efficient and well-developed design, for a structure to perform satisfactorily throughout its service life, it is necessary to consider other durability analyses and parameters, such as the geometry of the designed elements, the materials used in the construction, traffic volume analysis, and environmental analysis (Pipinato, 2016).

Considering the difficulties encountered in the application of available bridge management methodologies, where decisions are made at a single level, in many countries, agencies responsible for infrastructure networks have made significant efforts to develop bridge management systems (BMS) that assess the structure's condition at the overall network level during its life cycle and provide information on the efficiency of resource allocation and management policy setting (Jeong et al., 2017; Pipinato, 2016; Shepard, 2005). BMS is used in data collection, inspection process, condition assessment, maintenance planning, repair or replacement, optimizing financial resources, and increasing user safety (Alonso Medina & León González, 2022; Hurt & Schrock, 2016; Marzouk & Hisham, 2012; Shepard, 2005).

Building Information Modeling (BIM) is an efficient tool for digitally representing a structure's physical and functional characteristics, comprising life cycle information, and costs throughout the design, management, monitoring, and repair. It is a methodology and technology usually used to create a digital twin (DT) of a physical asset, such as a building or infrastructure. In this context, DT technology emerges, combining the real and digital worlds, such as a digital replica model of a physical object (Hosamo & Hosamo, 2022; Nguyen, Kang, et al., 2022). BIM also supports integration with the Internet of Things (IoT), sensors, 3D scanning, machine learning, big data, and artificial intelligence (AI) to provide real-time data and collaboration, making it an essential tool for optimizing efficiency and decision-making (Chong et al., 2016; Costin et al., 2018). In addition, Fanning et al. (2015) demonstrated the economic benefits of using BIM in bridge construction, potentially reducing costs by approximately 5-9% with reduced waste, increased efficiency, and sustainability of projects throughout the life cycle.

BIM-based standardization through parametric modeling offers possibilities for improving the quality and efficiency of facility management operations to create, share, exchange, and manage information among all stakeholders, facilitating integration, interoperability, and collaboration (Chen & Wang, 2009; Isikdag et al., 2008). The IFC (Industry Foundation Classes) schema represents the BIM database. This data model is an open standard developed by BuildingSMART and is widely used for data exchange (ISO, 2018). IFC is an object-oriented data architecture that allows the structuring of geometric data and project information in a standardized way (buildingSMART, 2023). Until version 4, the IFC was focused on buildings, but an extension project was initiated with the growing international demand for a data schema for infrastructure (Byun et al., 2021).

This study provides a comprehensive and updated review of techniques and technologies of monitoring, damage detection, damage information modeling (DIM), and decision-making processes within a BMS. This paper's novelty is a literature review that covers all the issues surrounding the aging and deterioration of the enormous number of bridges worldwide and the high cost associated with maintenance, reinforcement, and rehabilitation of these structures. It emphasizes the role of inspection and structural health monitoring (SHM) in the timely detection of failures and damage, assisting in decision-making on maintenance and repair actions. Finally, the challenges and limitations of these topics are identified and discussed, with the proposition of possible solutions to overcome these limitations.

This paper is organized as follows. First, Section 2 covers the technical background: 2.1 Bridge Maintenance Management, and 2.2 Building Information Modeling (BIM) in a Bridge Management System (BMS). Section 3 presents the method applied in the literature review. Section 4 addresses the scientific interest and trends in bridge management. Section 5 incorporates the literature review and remarks about some specific themes: 5.1 Monitoring, 5.1.1 Inspection, 5.1.2 Structural health monitoring (SHM), 5.2 Deterioration and damage, 5.2.1 Damage detection, 5.2.2 Damage information modeling (DIM), 5.3 Decision-making process, and 5.4 Challenges and limitations. Section 6 summarizes the concluding remarks of the study.

2. Background

2.1 Bridge Maintenance Management

Bridge maintenance management plays a vital role in extending the service life and ensuring the safe operation of structures (Costin et al., 2018; Gui et al., 2021; J. Yang et al., 2022). A well-planned maintenance strategy should focus on enhancing the operational process, reducing the frequency of maintenance actions, addressing complexity, and streamlining the skills required for maintenance (Benítez et al., 2020). The maintenance management system comprises several key components (Figure 1), including information collection through inspections and monitoring, damage identification through technical assessments, maintenance decision-making based on inspection reports, and the actual implementation of maintenance through repair, rehabilitation, and reconstruction (Gui et al., 2021; Ren et al., 2019; Wu et al., 2021; Yin et al., 2011).

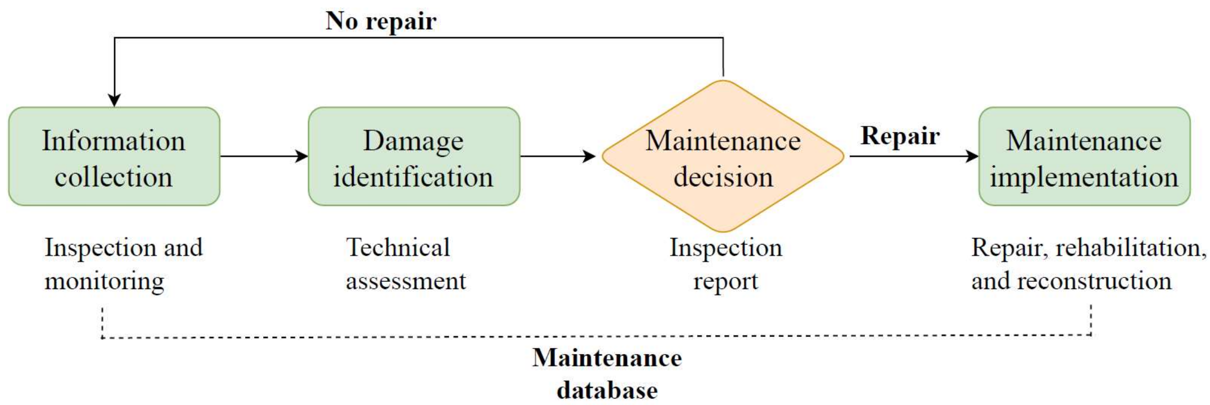

Figure 1. Bridge maintenance information and decision structure.

Maintenance operations can be classified into three main groups (Figure 2): preventive, predictive, and corrective, and they aim to ensure the structure's integrity, preserving it from deterioration. Preventive maintenance consists of periodic actions carried out in advance to avoid system failures and keep the structure performing above a minimum performance level (Frangopol & Kim, 2011; P. Helene, 2005; Sánchez-Silva et al., 2016; Xie et al., 2018). Preventive and routine maintenance represent actions necessary to preserve the structural and operational efficiency of the bridge, including activities that maintain the serviceability of the structure before it reaches a level of deterioration that requires corrective maintenance (Benítez et al., 2020; PennDOT, 2012; Rashidi, 2013). In general, routine actions do not change the bridge's condition and include cleaning the drainage, minor repairs to the road surface and deck joints, and removing debris (NYSDOT, 2008; Rashidi, 2013).

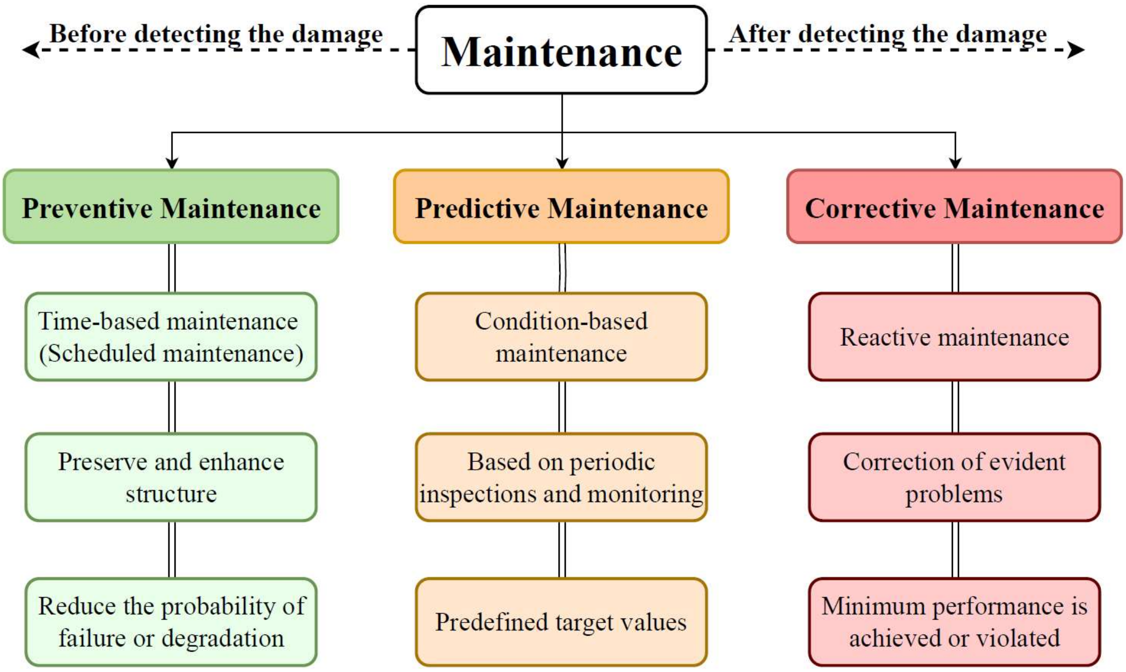

Figure 2. Main types of maintenance and their characteristics.

Essential or predictive maintenance is associated with performance-based monitoring and is promptly executed when specific indicators reach predefined target values, with particular emphasis on those related to the structural condition (Flores-Colen & De Brito, 2010; Frangopol & Kim, 2011; Xie et al., 2018). However, this can be highly debatable in practice, as the optimal solution often requires striking a balance among different indicators, even when pushing some of them to extremes (e.g., long-term costs).

Both preventive and predictive maintenance tend to focus on the technical condition of bridges (Gui et al., 2021). Intervention actions carried out when the minimum performance limit is achieved or exceeded are called corrective or reactive maintenance (Akcamete et al., 2010; Benítez et al., 2020; Sánchez-Silva et al., 2016). Much of the maintenance work is reactive, and this practice is ineffective since corrective maintenance tasks can cost three to four times more than the same repair activity performed planned (Akcamete et al., 2010; Flores-Colen & De Brito, 2010).

Proper maintenance planning can optimize costs during repair interventions in the bridge life cycle (Nili et al., 2021). The selection of the start time and time interval of preventive maintenance will influence both life cycle cost and the environmental impact of existing bridges

(Xie et al., 2018). The extent of servicing also plays a relevant role in defining an optimal maintenance program, as it sets the costs and influences the availability of services (Sánchez-Silva et al., 2016).

Many bridges have been built over the past decades around the world, especially after the Second World War, in the late 1940s. These structures were not designed for nowadays traffic following outdated standards, and need to be rehabilitated after a certain period of operation to ensure their safety and serviceability (J. Mohammadi et al., 1995; Rashidi et al., 2020; Xie et al., 2018). Over its entire life cycle, a bridge consumes between 0.4 and 2.0% of its construction cost per year in operation, inspection, maintenance, and demolition actions, corresponding to up to 80% of the construction cost (Artus & Koch, 2020).

The average age of the 617,000 bridges in the United States is 44 years, with 42% being at least 50 years old (ASCE, 2021). The annual budget of approximately $14.4 billion is spent on the maintenance of existing bridges, and this budget needs to be increased to $22.7 billion annually or by 58% to improve the condition of the structures since 7.5 % of the country's bridges are considered structurally deficient (ASCE, 2021).

Japan has approximately 730,000 road bridges and 11,000 road tunnels across the country. It is estimated that about 39% of bridges and 27% of tunnels will be over 50 years old in 2023 (MLIT, 2019). China has also experienced increased demand for the maintenance and management of its bridges due to infrastructure development and expansion (Wan et al., 2019). There are more than 800,000 highway bridges in China, and more than 1/3 of these bridges have structural failures in various degrees of damage, requiring safety monitoring, health diagnosis, and reinforcement maintenance (L. Zhang et al., 2018).

In Brazil, different agencies at the Federal, State, and Municipal levels of government (public sector) manage bridges. The main bridge management system in Brazil is the SGO - Sistema de Gerenciamento de Obras de Arte Especiais, developed by the DNIT – Departamento Nacional de Infraestruturae Transportes. Around 137,000 bridges are estimated to exist in Brazil (Fausto Da Silva & Almeida De Melo, 2021). The DNIT oversees the design, construction, operation, maintenance, repair, rehabilitation, and replacement of more than 8,000 bridges, tunnels, viaducts, walkways, and containment structures across the entire Brazilian road network (DNIT, 2020). In 2016, DNIT implemented the PROARTE – Programa de Manutenção e Reabilitação de Estruturas, which promotes and manages maintenance and rehabilitation services for these structures. So far, DNIT has invested more than BRL 97 million in maintenance work on 505 existing infrastructures (DNIT, 2020).

2.2 Building Information Modeling (BIM) in a Bridge Management System (BMS)

BMS is an integrated bridge computer system designed to coordinate and control the entire process involving the bridge structure by providing decision support during the design, construction, operation, and maintenance phases. This system aims to ensure that limited resources are used reasonably to provide services to users in the best possible way and maintain operational bridges (Hurt & Schrock, 2016; Wan et al., 2019; Yin et al., 2011).

Implementing a BMS based on periodic bridge inspections aims to identify bridges requiring intervention actions such as maintenance, repair, or rehabilitation (Alonso Medina et al., 2022; Alonso Medina & León González, 2022). From the information collected during the inspections, a database can be used to help understand the deterioration process of bridges under certain conditions to assist in planning maintenance actions and repair works (Alonso Medina et al., 2022; Alonso Medina & León González, 2022; Frangopol et al., 2017). Decisions on tasks related to maintenance plans are usually made based on various historical data and documents accumulated throughout the construction life cycle. However, most of this data is in written media of different natures and data structures, complicating the interaction between the different infrastructure components (Chen & Wang, 2009; Motamedi et al., 2014).

Planned maintenance using BIM provides a centralized system that can enhance the visualization and information retrieval to quality maintenance and structure performance, and reduce ongoing life cycle costs (Byun et al., 2021; Chan et al., 2016; Chong et al., 2014, 2016). BIM application studies of the maintenance phase have been conducted in parallel with the design/build stages. Using BIM through a stakeholder collaboration platform aims to facilitate the development of high-complexity construction and maintenance projects (Ghaffarianhoseini et al., 2017; Wan et al., 2019). Implementing BIM in bridge maintenance management requires linking the information to a 3D model, and each information must be appropriately distributed according to the information system (Byun et al., 2021). Topics on BIM application studies for bridge maintenance include safety diagnostics, schedule management, visualization of historical information, maintenance decision-making, and efficient asset management (Byun et al., 2021).

The information workflow in a BMS encompasses all structured and unstructured bridge data from the design, construction, operation, and maintenance phases. This data must be standardized and digitized through BIM for access by those interested in the bridge management process. Various researchers have made efforts to define standardized data delivery protocols for information management with BIM workflows (Bose et al., 2021; K. Kim et al., 2018; Li et al., 2023; Moretti et al., 2020; Patacas et al., 2020; Schwabe et al., 2018; Thabet et al., 2016; Tsay et al., 2022).

The COBie (Construction Operations Building Information Exchange) is an international standard published by the US Army Corps of Engineers in 2007 (East, 2007), which originated from the concept of Computer Aided Facility Management (CAFM) (Schwabe et al., 2018; Tsay et al., 2022). This specification describes processes and information requirements that simplify transferring specific data from the design and construction phases to the operation and maintenance of facilities. COBie proposes that data, documented on paper or in extensive electronic form, be collected and stored incrementally and systematically in digital format from the start of the project, allowing for a more efficient transition from the construction phase to the facility management phase, saving time and resources (Pärn & Edwards, 2017; Schwabe et al., 2018).

Moretti et al. (2020) and Patacas et al. (2020) focused on the open standards of BIM and created a framework for data integration. Moretti et al. (2020) developed an openBIM methodology to support asset management applications with limited availability of as-built information. For this purpose, they used an IFC entity for processing the geometric and semantic information of existing and newly created objects, supporting real-time data integration. As stated by Patacas et al. (2020), there is a challenge in effectively addressing the three capabilities of information management and maintenance management, as follows: 1) disseminating models and information, specifically Asset Information Models (AIM), sourced from multiple locations; 2) ensuring the validation of these information models against predefined requirements; and 3) utilizing the gathered information for effective facilities management, encompassing operational and maintenance activities. Thus, they developed a prototype Common Data Environment (CDE) based on using open standards and existing technologies to address these three issues.

Studies conducted by Kim et al. (2018) propose an innovative approach to efficiently manage BIM-based Facility Management (FM) information. The key idea was to establish a connection between IFC elements and FM. This connection was facilitated through the use of Semantic Web technology. Li et al. (2023) develop and demonstrate the utility of a BMS that utilizes BIM for managing bridge defects and maintenance. For standardization and unification of damage data during inspection, bridge defect information was classified and digitally coded according to the IFD (International Framework for Dictionaries) standard and used to create a database. The IFD standard was used to codify and transform the BIM data into a unified form for interactivity.

Poor management of structures has consistently been attributed to a lack of coordination and information during the maintenance process. Chong et al. (2014) studied improving maintenance quality and performance by integrating BIM and facilities management. The results revealed that BIM creates a collaborative and effective vision within the facilities management platform, improving quality and performance. BIM implementation in the maintenance management of road bridges has been achieving similar results (Abudayyeh & Al-Battaineh, 2003; Chan et al., 2016; McGuire et al., 2016; Wan et al., 2019).

Abudayyeh and Al-Battaineh (2003) adopted a bridge as-built information model in their study to facilitate maintenance and rehabilitation decision-making by providing necessary data to assist management. As-built data provide historical information related to bridges' design, construction, operation, and maintenance, essential for planning maintenance and rehabilitation programs (Abudayyeh & Al-Battaineh, 2003). Koch et al. (2014) present the current achievements and open challenges in the automation of inspection processes. Although challenges remain under investigation, automated inspection methods are already a reality. Also, as-built 3D modeling, along with damage detection, has the potential to be fully automated to facilitate the management and maintenance of large structures (Koch et al., 2014).

McGuire et al. (2016) presented the implementation of a method and prototype to track and assess the structural condition of bridges. The search used commercial BIM software to link and analyze bridge inspection, evaluation, and management data. This research highlighted BIM’s ability to maintain parametric information about the bridge and visually represent damage, which can be used in damage assessment and maintenance decision-making. The author’s method allows the user to assess damage based on location and provides maintenance recommendations based on comparing current inspection results with previous inspections. Enhanced documentation of damage parameters during inspection processes with BIM capabilities can improve bridge management and maintenance with a more consistent dynamic process and deterioration data. However, for the future practical integration of BIM into bridge management, steps in software development need to be taken to adapt further BIM principles to the operation and maintenance of bridges’ service lives.

Wan et al. (2019) developed a BMS based on BIM technology integrated with a geographic information system (GIS), which contains information on inspections and assessment of technical conditions to improve the efficiency of bridge maintenance management. In addition, IFC and international framework for dictionaries (IFD) standards are developed, implementing Web-BIM-oriented management with collaborative work among users. This Web-BIM-based BMS, coupled with IFC language development, predisposes more features to improve efficiency in managing and maintaining large structures. Other authors have also made advances in bridge management and maintenance using these features (Bazán et al., 2020; Byun et al., 2021; Tanaka et al., 2016).

3. Method

A comprehensive literature review was conducted in this work, aiming to identify the trends and challenges in recent and relevant studies in the area. Figure 3 shows a flowchart that summarizes the methodology adopted. Web of Science and Scopus Databases were adopted for bibliometric analysis since they are the main academic databases covering the study subjects. The bibliometric evaluations were carried out for the search parameter "article title, abstract, keywords", starting with the terms "bridge management" OR "management of bridges". From the results, the documents containing the keywords "bridge maintenance" OR "maintenance of bridges" were selected to subside the discussions.

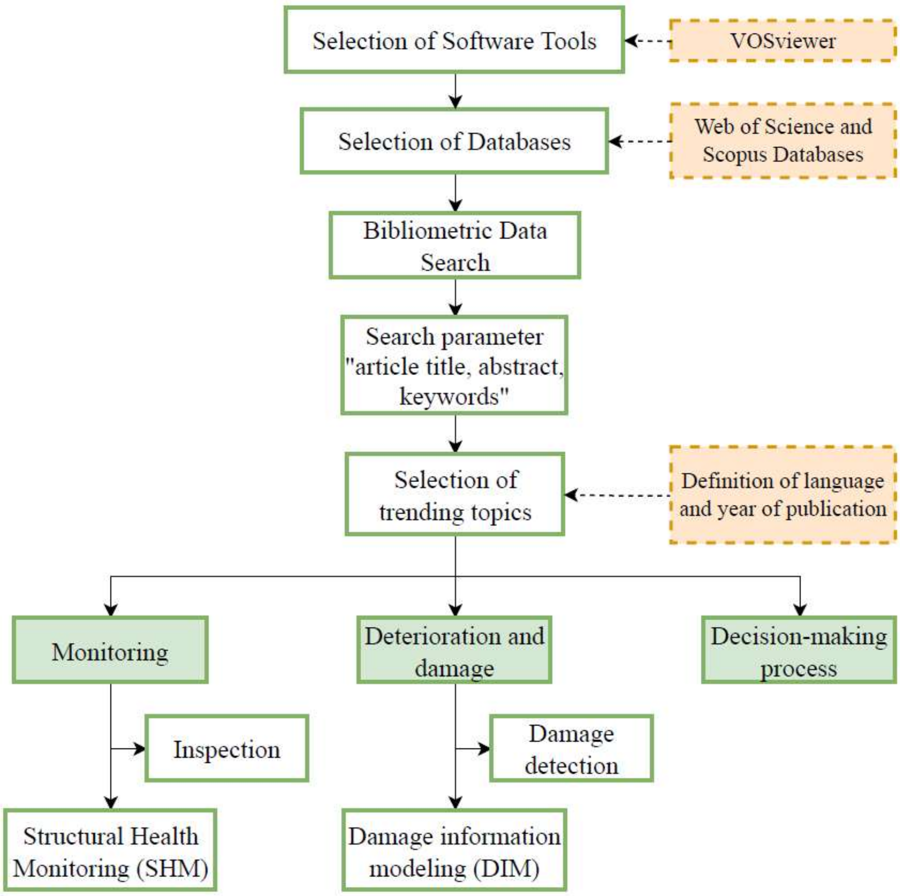

Figure 3. Overview of the search methodology and organization of the review.

The searches were performed in October 2023 and were restricted to journal articles and reviews published in English from 2013 to 2023. A careful review of the subject area and source titles was conducted to filter content out of the scope. The authors understand that the results do not fully represent the literature on Bridge management but bring a consistent sampling considering the database and criteria used.

4. Bridge management: scientific interest and trends

From the databases used and adopted criteria for the bibliometric analysis, 413 articles were identified addressing the central theme (bridge management). Figure 4 shows the occurrence by country (authors' institutions). The United States is the most influential and collaborative country, responding for 31.3% of the scientific production on the subject, followed by China (15.7%), the United Kingdom (5.8%), Italy (5.0%), South Korea (4.4%), Australia (4.0%), Canada (3.8%), and Portugal (3.4%).

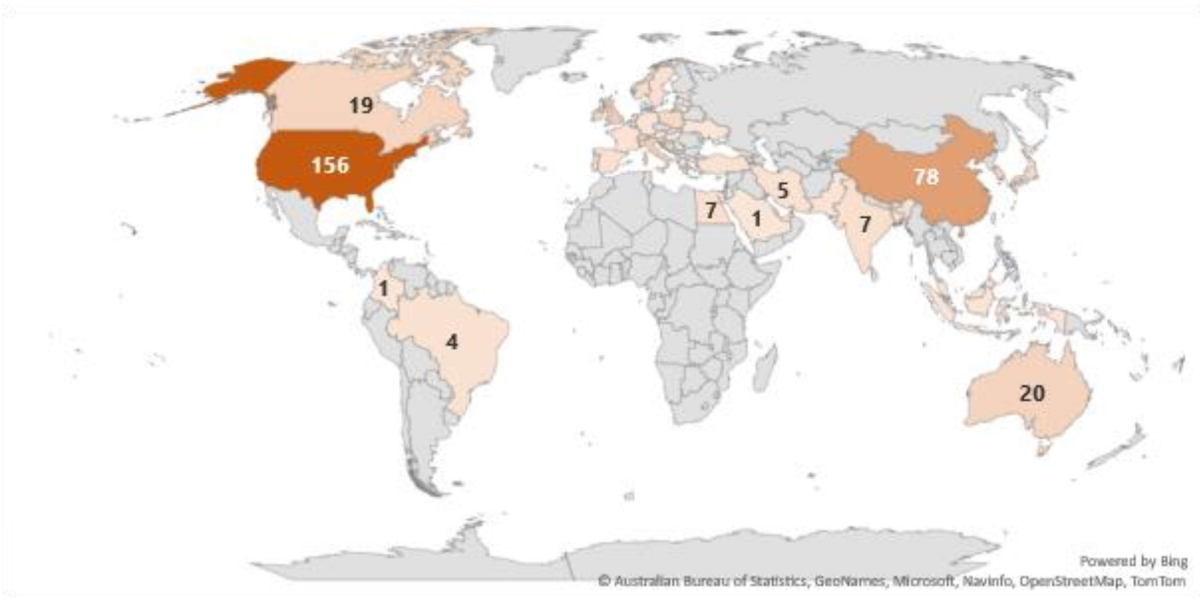

Figure 4. Countries by the number of published articles on the subject.

As expected, large countries have large transportation networks, reflecting their interest and investment in bridge management efficiency and resulting in scientific production. Brazil, however, had until now a discrete international collaborative participation, with only four papers identified in the survey. Notably, 46 of the identified funding sponsors were administration offices or ministries linked to a country or state administration of transportation infrastructure. American Federal and State Offices were the most representatives in this aspect. This trend demonstrates the relevance and economic interest in efficiently managing transportation assets at a governmental level.

The interest in the subject is growing, as shown in Figure 5. After a stagnation between 2013 and 2016 (25 papers on average), significant growth in 2017, and stagnation between 2017 and 2019 (36 papers on average), the number of articles covering the subject consistently grew between 2020 and 2022, reaching 60 articles published in 2022 (2,5 times the number registered in 2013 and a growth of 23% compared to 2021). Fifty articles had already been published in 2023 by the date of completion of this research (October 2023).

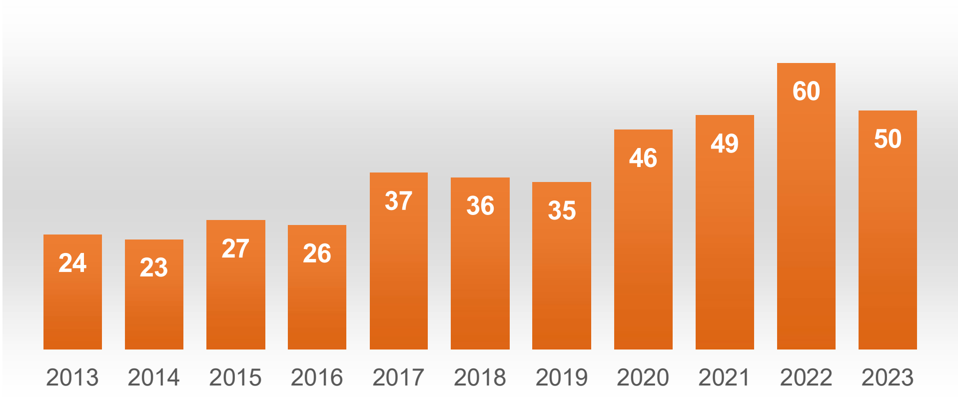

Figure 5. Annual publication trend on the subject from 2013 to 2023.

The evaluation shows that the strongest correlated keywords were optimization, deterioration, inspection, structural health monitoring, prediction, decision-making, information management, and bridge management systems. Figure 6 shows the overlay visualization of the co-occurrence network of the most used keywords weighted by occurrence and scored by publication year. The keywords were filtered, excluding the terms used in the search and generic ones. The analysis results show the trending topics in the bridge management context, summarized in Table 1. Table 2 lists the reviews considered in this work and summarizes the main subject, remarks, and contributions.

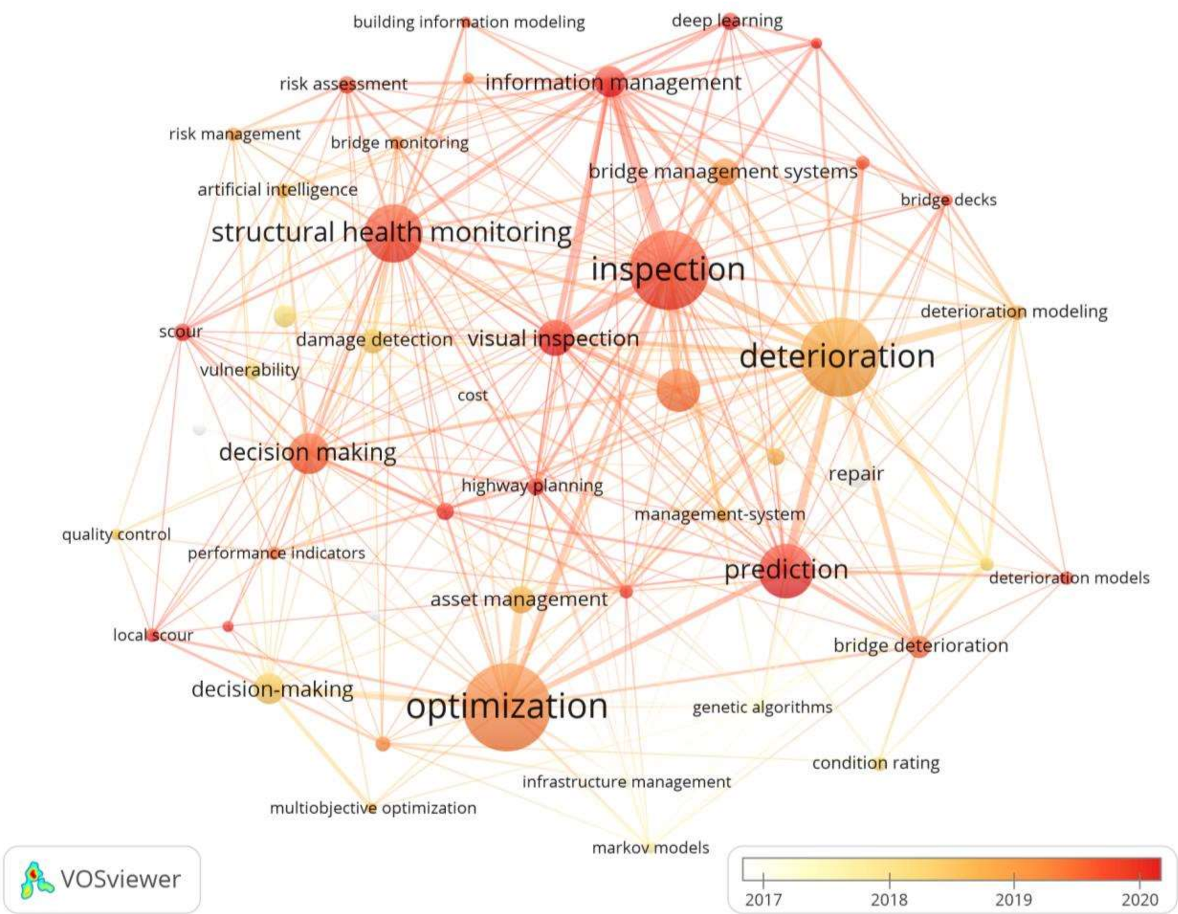

Figure 6. Overlay visualization of the co-occurrence network of the 60 most used keywords (excluding "bridge management", "bridge" and "bridges").

Table 1. Trending topics related to the theme "bridge management" according to the co-occurrence network obtained from the bibliometric analysis.

Trending topic	**Some remarkable related topics**	**Cluster**	**Some recent references (five years)**
Machine Learning	Decision-making Damage detection	Structural Health Monitoring (SHM)	(Althaqafi & Chou, 2022; Asghari & Hsu, 2021; Karaaslan et al., 2021; Mohammed Abdelkader et al., 2020; Saremi et al., 2023; K. Wang et al., 2021; G. Xu & Guo, 2022; D. Y. Yang, 2022)
Life Cycle	Asset management Decision-making	Optimization	(Akiyama et al., 2020; Allah Bukhsh et al., 2019; Asghari & Hsu, 2021; Calvert et al., 2020; Shim et al., 2019; F. Wang et al., 2022; G. Xu & Guo, 2022)
Visual inspection	Prediction Bridge deterioration	Inspection	(Abu Dabous & Feroz, 2020; Alsharqawi et al., 2020; Dizaj et al., 2021; Maroni et al., 2022; Santamaria Ariza et al., 2020; Turksezer et al., 2021)
Building Information Modeling (BIM)	Repair Condition assessment	Bridge Management System (BMS)	(Byun et al., 2021; Deng et al., 2021; Isailović et al., 2020; Kwon et al., 2021; M. Mohammadi et al., 2023; Wan et al., 2019)
Deep learning	Information management Deterioration Modeling	Deterioration	(Hong et al., 2022; Khandel & Soliman, 2021; D. Y. Yang, 2022a; Yue et al., 2022; X. Zhang et al., 2023)

Table 2. List of recent reviews (five years) found in the bibliometric analysis, with the main subject, limitations, and remarks.

References	Year	Main subject	Main remarks and contributions
(Jiménez Rios et al., 2023)	2023	Bridge management using digital twin	Consensus on the adoption of digital twins for bridge design, management, and operation. Lack of software interoperability. Poor performance of anomaly-detection algorithms. Approach definition for integration at macro-scale. Implementation of industry 5.0 concepts.
(Saidin et al., 2022)	2022	Vibration-Based Techniques	Applicability, pros, and cons of Ambient Vibrating Testing and Forced Vibrating Testing; Experimental Modal Analyses; and Benefits of the Stochastic Subspace Identification method.
(Niyirora et al., 2022)	2022	Vibration-based monitoring + machine learning	Vibration-based damage detection; Artificial intelligence and big data in damage detection
(Dayan et al., 2022)	2022	Information modeling	Aspects of using information modeling in bridge management
(J. Yang et al., 2022)	2022	Big data knowledge engineering	Big data characteristics of bridge management
(Hosamo & Hosamo, 2022)	2022	Digital twin using 3D laser scanning	Digital twin and machine learning in BIM integration; laser scanning in bridge maintenance
(Bień & Salamak, 2022)	2022	Management of bridge structures	Classification of current and future generations of Bridge Management Systems
(Saback et al., 2022)	2022	Digital Twins and BIM	Several gaps are to be addressed. There is a lack of consensus on the definition of digital twins. Complex data flow and software compatibility.
(Fabianowski et al., 2021)	2021	Artificial neural network for condition assessment	Application potential of neural networks in bridge management and identification of difficulties as a guideline for further research
(Panah & Kioumarsi, 2021)	2021	BIM in health monitoring and maintenance process	A study on combining BIM with monitoring and maintenance of structures, presenting current limitations, and bringing solutions
(Ivanković et al., 2020)	2020	Performance indicators for sustainable management	Performance indicators (PIs) for road bridges with Structural health monitoring (SHM)
(Sun et al., 2020)	2020	SHM using Big Data (BD) and Artificial Intelligence (AI)	Perspectives and suggestions for using BD and AI in bridge SHM
(Srikanth & Arockiasamy, 2020)	2020	Deterioration models	Advantages and limitations of different bridge deterioration models
(Artus & Koch, 2020)	2020	Damage modeling	State of research and cases for use damage modeling, its types, categories, and frequency

5. Literature review and remarks

5.1 Monitoring

Bridges are vital components of the road system, and to maintain adequate performance, functionality, and safety of structures throughout their service life, periodic inspection, maintenance, and rehabilitation actions must be implemented (Frangopol & Soliman, 2015; Xie et al., 2018). However, such structures are often located in hilly terrain that is difficult to access. Therefore, establishing effective monitoring, inspection methods, and a periodic maintenance strategy is paramount (Rashidi et al., 2020).

Condition monitoring of a bridge focuses primarily on determining in-service performance and detecting material degradation to assess the safety and service life of the structure (Abu Dabous & Feroz, 2020). Information sharing and data exchange keep pace with advances in bridge monitoring and management technologies. Moreover, they enable meaningful uses of information, service improvements, and enhanced bridge operation, maintenance, and safety (Delgado et al., 2018; Jeong et al., 2017).

5.1.1 Inspection

Bridge inspection information is the first step of the complete bridge management process and is the center of any BMS (Hurt & Schrock, 2016; Quirk et al., 2018). The bridge inspector has as one of his main tasks the identification of damage (large or small) and potential problem areas in the structure before they become critical to structural or functional integrity (Bianchi et al., 2023). According to S. Xu et al. (2022), an inspection report contains information that can be divided into three categories: (1) basic inspection information (type of inspection, date of inspection, and personnel responsible); (2) information about individually identified damages; and (3) condition state classifications. Images taken on-site should be attached to improve damage description and subsequent quantitative measurements. The geometric information of the damage includes its shape characteristics (e.g., length, width, or area) and location (e.g., position relative to the bridge element and orientation of development).

Assessing the current condition of deteriorated structures is essential for identifying existing defect types in time and making appropriate repair strategies, and it becomes a challenging task that requires a large dataset and good expert knowledge and judgment (Bolar et al., 2013; Panah & Kioumarsi, 2021; Y. Xu & Turkan, 2019b). Rehabilitation, scheduling, and budget decisions are primarily based on the results of visual inspections of bridges, coupled with considerable uncertainty and subjectivity inherent in human judgments and manual data acquisition, which is labor-intensive and sometimes nearly impossible (Marzouk & Hisham, 2012; McGuire et al., 2016; Moufti et al., 2014; Phares et al., 2004; Wojcik & Zarski, 2020). Visual inspection of bridges suffers from several limitations, including the safety of the inspection team, accuracy in detecting subsurface defects, and subjectivity of the process. Visual inspection is still the most cost-effective detection method; however, it is time-consuming, and the collected data is typically documented by completing standard inspection report forms (Abu Dabous et al., 2017; Agdas et al., 2016; Al-Shalabi et al., 2015; McGuire et al., 2016; Valença et al., 2014). Digital bridge models are necessary to digitalize this process (Artus & Koch, 2022).

The use of Unmanned Aerial Vehicles (UAVs), mainly known as drones, makes inspection data acquisition faster and more reliable. These drones have changed the work routine, and there is great potential in automating this process. They can be equipped with different cameras, radars, laser scanners, infrared, thermal, and other types of sensors (Costin et al., 2018; Jensen, 2019; Wojcik & Zarski, 2020). UAVs have generated considerable interest in the architecture, engineering, construction, and facilities management (AEC-FM) sector due to their notable advantages, such as enhanced security, ease of use, mobility, and cost-effectiveness (Molina et al., 2023; Perry et al., 2020; Y. Xu & Turkan, 2019b). In addition, the use of Terrestrial Laser Scanner (TLS) is also a recent and accurate technology of great potential to be used in inspection processes. Laser scanners capture a large number of points for objects in a short period, forming a so-called "point cloud" (M. Mohammadi et al., 2023; Panah & Kioumarsi, 2021; Rashidi et al., 2020; Sedek & Serwa, 2016; Volk et al., 2014; Y. Xu & Turkan, 2019b).

The Ground Penetrating Radar (GPR) technique uses high-frequency electromagnetic waves to acquire subsurface information. It is a fast, non-destructive method implemented to inspect concrete bridges to detect the size and location of subsurface damage on bridges (Nguyen, Nguyen, et al., 2022; Prasanna et al., 2016; Shamsudin et al., 2015; Y. Xu & Turkan, 2019b). Infrared (IR) thermography is another remote sensing technology whose basic theory is that the amount of heat conducted through a material will change in the presence of a subsurface defect, and it is used in the inspection and evaluation stages of bridges (Abu Dabous et al., 2017; Abu Dabous & Feroz, 2020; Y. Xu & Turkan, 2019b). However, the ability of thermography to detect deep flaws depends on the depth and size of the defect, as well as factors in the environment where the test is being performed: the amount of sunlight, temperature differences, and test time (Y. Xu & Turkan, 2019b, 2019a; Yehia et al., 2007). A comparison between the inspection technologies listed in this section is summarized in Table 3.

Table 3. Comparison between inspection technologies.

Technology	Team safety	Access	Accuracy	Time spent	Cost	Skilled labour
UAVs	✓✓✓	✓✓✓	✓✓	✓	✓	✓✓
TLS	✓✓✓	✓✓	✓✓✓	✓✓✓	✓✓✓	✓✓✓
GPR	✓✓	✓	✓✓	✓✓	✓✓	✓✓✓
IR	✓✓✓	✓✓	✓✓	✓	✓	✓

✓ - Low
✓✓ - Medium
✓✓✓ - High

The state of the bridge is the central point for the operating phase. Registering the state of conservation means registering the damages and defects of a structure (Artus & Koch, 2020). McGuire et al. (2016) developed a BIM-based method in which bridge inspectors capture information about the type of damage found, the amount, severity, and location. The location of the deterioration is essential to assess the bridge load and structure integrity and perform the intervention process (Adhikari et al., 2013; Chan et al., 2016; Estes & Frangopol, 2003; Hüthwohl et al., 2018; Prasanna et al., 2016). The lack of a description or documentation of the damaged site makes comparing results across inspections a limited task. Enhanced documentation of damage parameters with BIM during inspections can improve bridge management and link inspection results to analysis procedures (McGuire et al., 2016).

Al-Shalabi et al. (2015) implemented a 3D BrIM (Bridge Information Modeling) condition inspection framework with mobile device applications and cloud computing for inspection data documentation. In this approach, the information collected from the bridge elements can be accessed by on-site mobile devices such as a tablet computer that allows inspectors to access an accurate and up-to-date 3D information model of the bridge through cloud data storage services. The data cloud can be accessed from a home office and the site, enabling data sharing with all stakeholders simultaneously. This 3D model contains all bridge elements, including its object-level maintenance history. This BrIM-based inspection workflow allows input data such as damage type and dimensions to the database.

Xu and Turkan (2019b) developed a framework to create a BrIM with documented damage using unmanned aerial systems (UASs) to assist management and inspection practice. Images and videos collected more safely and quickly with UASs can be used to automatically detect cracks or other defects with the help of computer vision algorithms. Utilizing BrIM facilitates the allocation of defect information to specific model elements and allows for centralized management of all bridge-related data within a single model throughout the entire bridge's lifecycle (Y. Xu & Turkan, 2019b).

Mohammadi et al. (2023) conducted a study that includes the use of TLS-derived BrIM for creating a detailed digital representation of a bridge, integrating geometrical and non-geometrical information of bridge elements. The study's methodology incorporates a condition assessment model for prioritizing bridge elements based on their health condition and integrates a Decision Support System (DSS) for evaluating remedial strategies and optimizing budget allocation and planning. The research paper validates this methodology through a real case study and demonstrates its effectiveness in improving bridge management, safety, and maintenance.

5.1.2 Structural health monitoring (SHM)

New monitoring technologies and practices are essential to circumvent visual inspection limitations and provide satisfactory results through secure and highly automated analysis procedures (Abu Dabous et al., 2017; Abu Dabous & Feroz, 2020; Agdas et al., 2016; Valença et al., 2014). SHM has played an efficient role in the operation and maintenance phase of structural life cycle management due to the high number of aging infrastructures (Panah & Kioumarsi, 2021; Theiler et al., 2018). SHM encompasses a range of methods and practices designed to assess the condition of a structure based on a combination of measurement, modeling, and analysis to obtain accurate information about them (Agdas et al., 2016; Panah & Kioumarsi, 2021; Pipinato, 2016).

The advances in SHM technology allied to BIM improve the quality of the assessment stages of structure management and decision-making (Boddupalli et al., 2019; Delgado et al., 2017, 2018; Panah & Kioumarsi, 2021; Rashidi et al., 2020). Real-time information collection using wireless sensor networks (WSN) and BIM technologies aims to improve accuracy in monitoring structures to reduce maintenance costs and improve accuracy in decision-making based on data collection and processing (Panah & Kioumarsi, 2021). SHM has been widely investigated and applied to large structures such as bridges (Comisu et al., 2017; Gatti, 2019; Rashidi et al., 2020; Vardanega et al., 2016; Worden & Cross, 2018).

SHM technology is applied to detect bridge quality problems, the need for intervention, identify regions with insufficient load capacity, the need for improvements, and assist in deciding in situations with high-risk factors for reconstruction or strengthening (Agdas et al., 2016; Comisu et al., 2017; Huston et al., 2016; Orcesi & Frangopol, 2011; Zhou et al., 2020).

Surface defects such as cracking, spalling, and efflorescence are indicators of possible subsurface defects (such as reinforcement corrosion and concrete delamination), which are not visible but can directly reduce the structural capacity of the elements and be detrimental to the entire structure and need to be monitored regularly (Y. Xu & Turkan, 2019b, 2019a).

Developing sensors and data acquisition technologies have enabled the installation of extensive monitoring systems on various structures (Comisu et al., 2017; Panah & Kioumarsi, 2021; Vardanega et al., 2016). SHM has been perceived as an expensive resource, performed only in large structures with specialized professionals. Making the structural monitoring system popular in small bridges and easy to apply has been addressed in several studies using Internet of Things (IoT) based real-time wireless sensors and mobile communication technology (Feldbusch et al., 2017; Guzman-Acevedo et al., 2019; Sitton et al., 2020; Y. Yu et al., 2015).

The specific components of monitoring and maintenance are application-dependent and can vary significantly; however, most systems have the same fundamental elements, which are: (i) measurements by sensors and instrumentation; (ii) assessment of structural condition, and (iii) evaluation and prognosis to support decision-making related to maintenance and rehabilitation (Agdas et al., 2016; Alampalli & Ettouney, 2008; Huston et al., 2016). Automatically assessing structure integrity and locating damage can significantly reduce costs and improve safety in operations (Boddupalli et al., 2019). Table 4 summarises the studies that have used SHM, showing the objective of the research, the structure to which it was applied, its strategies, and the technologies used for monitoring.

Table 4. Summary table of SHM strategies and technologies.

References	Aim	Structure application	Phase	Tools
(Y. Yu et al., 2015)	Verify the feasibility of the mobile-SHM sensors and external sensors board	Concrete bridge with one tower and double cable plane	Operation	Smartphone sensors SHM
(Delgado et al., 2017)	Investigate the effect of concrete shrinkage and thermal strain transfer from the cast-in-situ deck and infill to the prestressed concrete girders	Prestressed concrete railway bridge	Construction	BIM + fibre-optic-based SHM
(Feldbusch et al., 2017)	Development of an "iDynamics" app to study the differences between professional accelerometers and smartphone sensors	Pedestrian bridge	Operation	Smartphone sensors SHM + "iDynamics" app
(Delgado et al., 2018)	Present a BIM approach to harness structural monitoring data dynamically with the automatic generation of parametric BIM models of systems	Steel-composite railway bridge	Construction	BIM + fibre-optic-based SHM
(Guzman-Acevedo et al., 2019)	Investigate the application of various sensors (GPS receivers, accelerometers, and smartphones) integrated with a smart sensor for the SHM of bridges	Reinforced concrete bridge	Operation	Smartphone sensors
(Boddupalli et al., 2019)	Enable the automated inventory of sensor data in the BIM environment to facilitate systematic maintenance and risk management	Reinforced concrete bridge	Operation	BIM + sensor data SHM
(Gatti, 2019)	Compare a static load test, required by Italian law, with a dynamic structural health monitoring (SHM) test, carried out at different times, to assess the structural reliability of a medium-length bridge built in the late 1960s.	Prestressed reinforced concrete	Operation	Measurement sensors
(Previtali et al., 2022)	Test the feasibility of using portable mobile laser scanning for surveying large, complex infrastructures and compare it with TLS survey	Masonry old bridge	Operation	TLS + Mobile mapping systems (MMS) + photogrammetry
(Fawad et al., 2023)	Automating an existing bridge SHM system of a bridge by using BIM and finite element (FE) model	Concrete bridge	Operation	BIM + FE + sensors + IoT

Since monitoring is an integral part of the operation and maintenance phases, it is favorable to enable semantic descriptions of SHM systems using BIM to make monitoring information accessible, practical, and understandable (Davila Delgado & Oyedele, 2020; Panah

& Kioumarsi, 2021; Theiler et al., 2018). BIM includes tools, processes, and technologies for documenting and exchanging 3D models and can facilitate monitoring structures throughout the life cycle (Panah & Kioumarsi, 2021; Volk et al., 2014). The BIM database is represented by the IFC standard for the exchange phase, which allows the construction process to be standardized. However, not all monitoring information to describe and exchange construction information is supported by IFC (Ait-Lamallam, Sebari, et al., 2021; Ait-Lamallam, Yaagoubi, et al., 2021; Theiler & Smarsly, 2018). Several studies propose extensions of the IFC schema to facilitate systems documentation and life cycle change management (Borrmann et al., 2015; Davila Delgado & Oyedele, 2020; Delgado et al., 2018; Ji et al., 2013; Rio et al., 2013).

Combining the collection and analysis of data from SHM sensors with BIM capabilities has been examined in several studies (Boddupalli et al., 2019; Davila Delgado & Oyedele, 2020; Delgado et al., 2017, 2018; Theiler et al., 2018; Zhou et al., 2020). Delgado et al. (2017) described a new approach that enables modeling sensor-based structural performance monitoring systems in a BIM environment. However, the interpretation of sensor data for decision-making purposes of long-term management strategies still requires the skills of an experienced and competent professional.

Delgado et al. (2018) developed a dynamic BIM approach based on structural monitoring data to assist the decision-making process in a complementary study to the previously cited (Delgado et al., 2017). Parametric and semantically rich BIM models of structural monitoring systems were developed, allowing data visualization in a 3D environment. By incorporating BIM provisions during the operational phase of an asset, significant cost reductions can be provided by reducing tactile and visual inspections and maintenance. In more recent studies, Delgado et al. (2020) investigated current IFC open standard BIM data models to describe monitoring systems and circular economy precepts for constructed assets. However, they found that the IFC is not mature enough, limiting the interoperability and implementation of monitoring system modeling, data management, and analysis.

Boddupalli et al. (2019) used SHM coupled with BIM to improve the damage assessment of critical structures to facilitate maintenance and rehabilitation decision-making. The BIM visualization tool proposed in the study was implemented and validated using a real bridge, and SHM data were collected under varying temperature conditions. This approach integrated the sensor system and BIM to improve data management and visualization. The results showed the usefulness of the proposal in detecting and visualizing potential hazards during the life cycle of bridges, which benefits infrastructure owners in deciding on cost-effective future maintenance strategies.

5.2 Deterioration and damage

5.2.1 Damage detection

Deterioration is associated with operational factors, natural events, environmental effects, construction quality, age, geometry, and materials used. Each of these parameters can individually or jointly contribute differently to the failure of the structure (Bolar et al., 2013). Automatic damage detection methods have been implemented, especially for cracks, which are recurrent damage to concrete structures and can trigger failures (Adhikari et al., 2013; Prasanna et al., 2016; Torok et al., 2014; Y. Xu & Turkan, 2019b; Z. Yu et al., 2021; Q. Zhang et al., 2020).

For crack analysis, identification and quantification of crack patterns are necessary to reveal the state of the bridges. Adhikari et al. (2013) proposed an integrated model based on digital image processing to detect and quantify cracks in concrete bridges, with 3D visualization that mimics local visual inspection. The proposed model comprised crack quantification, change detection, neural networks, and 3D visualization models. Furthermore, the authors noted that the numerical representation of concrete defects (quantification model) depends heavily on the camera resolution and imaging criteria, such as orthogonality.

Prasanna et al. (2016) presented a new automatic crack detection algorithm, the STRUM (spatially tuned robust multifeatured) classifier, combined with a robotic bridge scanning system, and as a result, 90% accuracy was obtained in thousands of tested cracks. In addition, the results can be quantified, archived, and compared over time. Zhang et al. (2020) also used a trained algorithm to detect cracks and fissures in concrete bridge decks, and the model accuracy was 99.25% in the tests. Yu et al. (2021) proposed a new YOLOv4-FPM model for real-time crack detection using UAVs or other fast-acquisition devices. The results show that the detection speed matches the real-time detection task, and the detection accuracy is sufficient to replace manual work.

In studies by Xu and Turkan (2019b), the defect information (type, severity) can be assigned to the 3D BrIM model, improving the visualization of the inspection data. This information is stored in a central object-oriented database in the IFC schema. However, several challenges and limitations associated with the implementation of the system were identified, primarily concerning the accuracy of crack detection, highly affected by the way images are collected and processed, and the difficulty with modeling the bridge geometry in 3D. The proposed framework did not offer support for automatic damage measurement, requiring manual data processing to build the BrIM and project the location of the damage on structural elements (Y. Xu & Turkan, 2019b).

Valença et al. (2017) proposed a new method called MCrack-TLS to automatically assess cracks in concrete bridges based on combining image processing and terrestrial laser scanner (TLS) technology. TLS allows a precise orthorectification of images, solving one of the main disadvantages of applying image processing for crack characterization in large structures. The parameters evaluated were the width, length, orientation, and location of the cracks. These characteristics show that the proposed method can help define and optimize maintenance interventions on concrete bridges.

Wójcik and Zarski (2020) evaluated the applicability of modern methods of building bridges with BIM, 3D reconstruction, and Artificial Intelligence (AI). They concluded that the IFC scheme used in this way could describe a complex bridge geometry, damage information model, and geometry. Furthermore, it is possible to enrich this model with data captured by 3D reconstruction in the form of textured meshes. However, no currently available IFC viewer supports textured models, creating the need to develop and customize viewer apps in BIM.

Hüthwohl et al. (2019) proposed an objective classification of concrete damage, making it possible to classify various areas of potentially damaged bridges into their specific defect type following existing bridge inspection guidelines. Three separate pre-trained deep neural networks were tuned based on a multi-source dataset consisting of automatically collected image samples as well as various Department of Transportation inspection databases. In that study, they showed that this approach can reliably classify various types of defects with an average score of 85%. According to the authors, the limitations of the approach presented are related to training data. Some classes of defects were under-represented compared to others. This is the main reason why the multiclassifier caused misclassification and bias (Hüthwohl et al., 2019). Isailović et al. (2020) described an IFC-based classification method for detecting and modeling fragmentation defects in BIM with more than 70% accuracy.

Based on the information about defects collected by the mobile terminal of the BMS developed by Wan et al. (2019), the evaluation module can perform automatic component analysis according to the maintenance pattern on the bridges. The BrIM displays different colors on bridge elements to intuitively describe the updated technical state at different levels. The green-colored elements remained in a safe condition, and the yellow-colored ones suffered slight damage. The red color means the elements have been severely damaged (Wan et al., 2019). Chan et al. (2016) used a similar modeling system, identifying the condition status attributed to elements with the colors green (fair condition), yellow (bad condition), and red (very bad condition), and included the white color to identify new elements or good condition.

Bridge repair and reinforcement information are stored in the system and can be consulted by users. When the defect develops to some extent and threatens the safety of the structure, the system automatically sends messages to bridge managers to remind them to create repair and reinforcement projects (Wan et al., 2019). The BIM-based system regularly generates statistics, graphs, and tables according to inspection and monitoring information, which help to make auxiliary maintenance decisions. After the reinforcement and repair procedure, it is possible to determine whether the maintenance is qualified or not, according to the actual situation. Maintenance can be viewed through the template, and managers can check repair results (Wan et al., 2019). Table 5 summarizes the damage detection studies mentioned.

Table 5. Summary table of damage detection studies.

References	Component	Measurements	Tools	Resolution	Accuracy
(Prasanna et al., 2016)	Bridge Deck	Crack map: number of cracks per region	On-site robotic bridge scanning system + SCRUM algorithm	0.6 mm/px	90%
(Valença et al., 2017)	Concrete Bridge	Crack width, length, and orientation	TLS technology (MCrack-TLS) + image processing	0.35 mm/px	-
(Hüthwohl et al., 2019)	Concrete Bridge	Concrete bridge defects	UAV + textured models	0.1 mm/px	85%
(Y. Xu & Turkan, 2019b)	Concrete Bridge	Detect cracks automatically	UAS + computer vision algorithms + BrIM	-	-
(Isailović et al., 2020)	Double girder concrete bridge	Spalling damage	Point-cloud + BIM + IFC schema	-	70%
(Q. Zhang et al., 2020)	Concrete bridge decks	Crack detection	Neural network + long short-term memory	-	98.9%
(Wojcik & Zarski, 2020)	Prestressed box girder bridge	Crack	BIM + 3D reconstruction + AI + IFC schema	0.1 mm/px	97.5%

With the help of equipment and the development of methods for damage detection and modeling, essential parameters are defined to optimize the maintenance stage. Locating the damage to the elements of the bridge structure is critical to improving inspection procedures and assisting in correct on-site intervention. Automatic damage detection methods represent significant advances in identifying and quantifying these data for bridge condition analysis.

However, challenges and limitations are still associated with implementing these techniques and the total accuracy of the data collected and processed by such equipment.

5.2.2 Damage information modeling (DIM)

Creating a damage information model (DIM) first requires the BIM of the structure since the damage is associated with the building element, its properties, and its material. BIM contains geometric and semantic construction information needed to model damage comprehensively, such as information about materials, actors, functions, and relations, assisting in planning new inspections, model simulations, maintenance planning, and execution of intervention services (Artus & Koch, 2020, 2022).

A DIM aims to address the issue of unsatisfactory interoperability resulting from the widespread use of BIM in operation and maintenance by providing a concept for the damaged data exchange between multiple processes. Standardizing damage information can help reduce information loss and cost (Artus & Koch, 2020, 2022; Hüthwohl et al., 2018). This standard needs to contain an information delivery manual (IDM), a model view definition (MVD), and a data format comparable to IFC, among others (Artus & Koch, 2020). An MVD is a computer implementation of an IDM (Sacks et al., 2018).

Studies from Sacks et al. (2018) bring a semantic enrichment method called SeeBridge, which introduces a novel approach to acquiring and compiling information for bridge inspection and systems management. The SeeBridge process utilizes an IDM to facilitate open data exchange, formally specifying user requirements and ensuring that the final model possesses semantic significance. Subsequently, based on the IDM, a Model View Definition (MVD) was prepared for the IFC4 Add2 data schema standard to facilitate the exchange of building information models.

The damage detection algorithm iterates over each BIM element and analyzes the images, form, and function in structure. Initially, images are used exclusively to locate visually detectable damage clusters. These findings undergo further refinement to identify specific damage types (structural crack, non-structural crack, fragmentation, flaking, efflorescence, corrosion) using additional extracted properties such as element type, damage position, and damage location. Significant damage parameters (damage type, absolute, and relative size measurements) are extracted from the findings and incorporated into the BIM model (Sacks et al., 2018).

In a related study, Tanaka et al. (2016) proposed an information model for supporting the bridge inspection process based on the IFC and IFC-Bridge for BIM. Their work introduced entities that provide information about inspection tasks (measured regions and degradation elements), inspection results, and time variations of degradation were considered in the degradation elements. Also, the relation between the degradation and civil elements, and the civil elements and measured region were defined.

Hüthwohl et al. (2018) categorized in their study inspection information on reinforced concrete bridges using the IFC standard to integrate damage information into the BIM model. They listed different damage classes with their respective properties, such as diameter, depth, width, location, corrosion, stains, and cracks, with data taken from existing bridge inspection manuals. It can be noted that not all classes occur exclusively, several pathological manifestations occur together. It has been shown that the existing IFC4 standard can model bridge defects and general inspection information following existing bridge inspection guidelines. Limitations to this method exist in the extraction of defect properties, the general modeling approach, and the selection of IFC entities. Wan et al. (2019) also included parameters and attributed definitions to damage information, such as length, direction, and width.

Isailović et al. (2020) proposed an IFC semantic enrichment framework to inject the extracted and reconstructed damage features into the as-is IFC model. Semantic enrichment must meet two requirements: the damage characteristics must conform to the BMS damage classification, and the semantic data structure needs to conform to the IFC schema. The semantic information of damage includes damage type (classification of a visible surface defect), deterioration process (physical-chemical process causing surface defects), damage position (rough distance measure, relative to the dimension of the inspected element), damage extend (an approximate measure of the damage region), and damage severity (damage condition rating).

Studies from Artus and Koch (2022) focused on modeling damage information to support bridge review and structural analysis. A comprehensive DIM incorporating geometric, visual, and semantic damage data were studied and applied. Since so far, there are no damage-specific entities implemented in IFC, the authors have analyzed the available alternatives for modeling. A test of the IFC implementation concept was performed, and the alternatives were according to IFC 4 and a thorough visualization evaluation. Revit was used to design and export the beam model to IFC 4. The main results are the definition of the required data for damage, an object-oriented damage model that supports multiple use cases, and the implementation of the model in a standard. In addition, tests have shown that the standard is adequate for providing damaged information; however, several software does not adequately implement the standard.

In their research, Xu et al. (2022) introduced a novel approach to document and represent inspection-related information in bridge BIM models, focusing specifically on the geometric aspects of defects. The method involved modeling defects' spatial placement and shape representation parametrically. By leveraging the latest version of IFC, this work showcased a parametric-driven representation of defect information, contributing to the establishment of an integrated BIM environment for the lifecycle management of civil assets. The proposed IFC-based method offered three primary aspects of modeling within the BIM environment:

1. Inspection activity: This aspect focused on capturing and documenting the various inspection activities carried out on the bridge.

2. Individual defects: The method aimed to accurately model and represent the geometry and characteristics of individual defects found during inspections.

3. Logical relationships: The proposed approach also addressed defining and establishing logical relationships around the defects, providing a comprehensive understanding of their interconnections and implications.

By incorporating these elements into the BIM model, Xu et al. (2022) work presented an effective and systematic way to manage inspection-related information in bridge projects using BIM technology.

Semantic and geometric data are required to damage information processing, which includes measurements, such as crack width, length, orientation, and position of the element, and textual information, such as alphanumeric material descriptions (Artus & Koch, 2022). However, the integration of information related to inspection and specifically to damage within the BIM model of the bridge has not yet been fully accomplished. Current methods for describing the logical relationships between defects and other IFC entities are non-existent or incomplete (Hüthwohl et al., 2018; Isailović et al., 2020; Tanaka et al., 2016; S. Xu et al., 2022). There is no single way to model damage, so the input parameters differ from one study to another, as do the representation and material changes obtained. Specific entities for damage modeling have not yet been implemented in the IFC scheme, and an additional extension adds more complexity. Table 6 summarizes the main entities in the current IFC documentation for inspection and damage applied in some studies.

Table 6. Summary table of the IFC entities for inspection and damage used in some of the studies cited.

IFC entity	Definition[1]	Application	References
IfcTask	Identifiable unit of work	Inspection process	(Hüthwohl et al., 2018; Isailović et al., 2020; Tanaka et al., 2016; S. Xu et al., 2022)
IfcElementAssembly	Represents complex element assemblies aggregated from several elements	Inspection finding	(Isailović et al., 2020; Sacks et al., 2018)
IfcSurfaceFeature	It is a modification on the surface of an element	Modeling defects that only affect the surface of a component	(Artus & Koch, 2022; Hüthwohl et al., 2018; Isailović et al., 2020; Sacks et al., 2018; G. Xu & Azhari, 2022)
IfcBuildingElementProxy	It is a proxy definition of an element, without a predefined meaning	Represent a defect	(Artus & Koch, 2022)
IfcAnnotation	It is an information element within the geometric context of a project	Add textual annotations about a defect to the component	(Artus & Koch, 2022)
IfcVoidingFeature	It is a modification of an element that reduces its volume	Modeling defects adding a void to a component	(Artus & Koch, 2022)
IfcImageTexture	It is a 2-dimensional texture that can be applied to the surface of a geometric item	Link the defect images on the surface of an object to the IFC model	(Hüthwohl et al., 2018; Sacks et al., 2018)

[1]*buildingSMART International*

5.3 Decision-making process

The BMS has as one of its most important functions the decision-making process in bridge management, especially regarding the prioritization of maintenance, repair, rehabilitation, and replacement activities to optimize the restricted budgets (Contreras-Nieto et al., 2019; Lee & Kim, 2007). Decision-making is critical to selecting which bridges require maintenance and repair, and detailed information is necessary to select the most adequate and economical intervention strategies (Lee & Kim, 2007; Yehia et al., 2008). There are considerable pressures to extend the lifetime of existing infrastructure, considering sustainability and its impact on the environment. This situation requires the industry to provide more durable and effective measures for protecting and repairing concrete structures (Matthews, 2007).

The decision-making process for repair and rehabilitation projects in bridges is influenced by several crucial factors. Yehia et al. (2008) identified some of these key considerations: (i) Nature, extent, and severity of the defect; (ii) Effect of the proposed repair method on the bridge's lifespan; (iii) Disruption to traffic flow during the repair process; and (iv) Availability of funds.

The first and most critical step in repairing a structure is correctly determining the cause of the damage. Knowing what caused the damage and reducing or eliminating that cause will repair last longer (von Fay, 2015). Like any reinforced concrete structure, infrastructure works suffer the loss of integrity over their lifetime due to degradation caused by chemical agents (alkali-aggregate reaction, corrosion, leaching, chloride and sulfate attacks, carbonation, efflorescence), physical (gradient of temperature, fatigue, overload, retraction, freeze-thaw cycles), biological (accumulation of organic matter, living organisms) or mechanical (DNIT, 2010; P. Helene, 2005; TxDOT, 2021; von Fay, 2015). Different deterioration processes generate different types of damage. Reinforcement corrosion is considered the predominant problem that causes several subsequent physical effects such as cracking, scaling, chipping, and delamination of concrete (Bolar et al., 2013; Cadenazzi et al., 2020; Moufti et al., 2014; Omar et al., 2017).

For every bridge that requires intervention, several strategies are available. These strategies range from "doing nothing" to "complete replacement", as not all damaged concrete requires an immediate repair unless the damage affects the safety or operating condition of the structure (Rashidi, 2013; von Fay, 2015). A decision tree is a helpful tool for classifying all possible alternatives and decision-making (Rashidi, 2013; Rashidi & Lemass, 2011). In many situations, the budget needed to carry out the intervention procedures is unavailable, and bridge managers must allocate the budget to higher-priority structures. In this case, "doing nothing and monitoring" is a very common strategy that does not require investment (Rashidi & Lemass, 2011). This alternative is associated with the general monitoring of the condition of the elements, keeping them in service until an important action is needed, such as rehabilitation or replacement (Rashidi, 2013).

Yehia et al. (2008) proposed a decision support system for bridge maintenance. They suggest repair and rehabilitation strategies for common problems in reinforced concrete bridge decks, including the three most common issues, which are corrosion, delamination, and cracking. The authors developed a decision tree using knowledge obtained from the literature and research with experts. The decision tree starts with two main questions: the age of the bridge deck and the average daily traffic. Based on this last variable, the repair method can be managed differently. The next branches of the decision tree are the damages that will lead to a repair strategy. Once this strategy is selected, the tree moves to the level where it specifies the intervention method and ends with the repair material (Yehia et al., 2008).

Repair and minor rehabilitation lower the damage rate and restore bridge performance. Studies conducted by Bolar et al. (2013) proposed a hierarchical logic trial network to assess the condition of bridges. In this paper, the authors demonstrated the difficulty of establishing a classification system for intervention actions for bridge elements. Parameters such as available materials and technologies, location, cost, urgency, and the current bridge condition, affect the selection criteria of repair techniques. It is also necessary to consider the different parameters to select the most appropriate repair technique (Mahdi et al., 2019).

Mahdi et al. (2019) developed a decision support system for concrete bridges that assists in assessing the prioritization of the bridge maintenance strategy, helping to identify the level of urgency for repair and selecting the most appropriate maintenance plan, considering budget constraints. A database was built, incorporating different factors into the assessment process, such as bridge defects, repair techniques, and associated costs.

Intervention selection involves a case-by-case assessment to determine the potential risks associated with any specific course of action. Bridge maintenance managers must analyze several criteria and consider constraints when proposing the best solution to rehabilitate a structure. Rashidi et al. (2010) developed a risk management framework for decision-support steps for bridge maintenance. This support system can provide appropriate intervention options based on cost, service life, product durability/sustainability, client preferences, and legal and environmental constraints.

Reinforcement corrosion is one of the most recurrent manifestations in concrete structures. Some studies bring intervention solutions for this specific damage to indicate repair to protect these severely deteriorated structures (S. Kim et al., 2011; Whitmore, 2018). A literature review allowed observing the lack of studies focused on intervention processes and procedures for reinforced concrete bridges. This information is commonly found in books, maintenance, and repair manuals for concrete structures and concrete bridges, with specific solutions for each type of damage (DNIT, 2010; P. Helene, 2005; P. R. Helene, 1992; JICA, 2014, 2017; NYSDOT, 2008; PennDOT, 2012; Souza & Ripper, 1998; TxDOT, 2021; VicRoads, 2018; von Fay, 2015; Whitmore, 2018).

5.4 Challenges and limitations

The constant expansion of transportation infrastructure and the aging and deterioration of existing infrastructure represent considerable and persistent challenges that require efficient and appropriate management. The high operational costs associated with BIM implementation (Lu et al., 2014) can be compensated by reducing costs related to bridge assessment, maintenance operations, and condition inspection (Al-Shalabi et al., 2015). BIM is planned to solve problems such as communication, integration, collaboration, and information interoperability (Al-Shalabi et al., 2015; Bradley et al., 2016; Jiang et al., 2019; Lu et al., 2014; Tawelian & Mickovski, 2016). However, the effective implementation of BIM in the BMS depends on tools and software that communicate efficiently with each other and the stakeholders (Floros & Ellul, 2021; Hajdin & Samec, 2022; Matarneh et al., 2022).

There is a considerable interoperability problem between the different software due to the lack of a standardized neutral format for exchanging information (Ali et al., 2014; Costin et al., 2018; Jiménez Rios et al., 2023). Between the same software company, there is usually a high level of data compatibility. However, interoperability is generally low between different companies, with a loss of information when exchanging data between software (Jiang et al., 2019). Interoperability is understood as the ability to exchange data between applications, facilitating workflows and process automation (Eastman et al., 2011).

OpenBIM is a collaborative project management process that uses BIM based on open standards and workflows, enhancing the benefits of BIM by ensuring the accessibility, reliability, management, and sustainability of digital data throughout the structure's life cycle (Ait-Lamallam, Yaagoubi, et al., 2021; Ciccone et al., 2022; Jiang et al., 2019; Moretti et al., 2020; Pour Rahimian et al., 2019). OpenBIM standards have been developed by buildingSMART to promote interoperability, and mainly include five basic standards (IFC - Industry Foundation Classes, IDM – Information Delivery Manual, MVD – Model View Definitions, BCF – BIM Collaboration Format, and bsDD – buildingSMART Data Dictionary) (Jiang et al., 2019).

Most BIM creation software supports the import/export functionality of the IFC data schema, the main neutral data model developed by buildingSMART. The IFC schema is an extensible object-oriented data model divided into basic entities and sub-entities. This format classifies and structures data, allowing different sets of information to be easily extracted (Afsari et al., 2017; Pour Rahimian et al., 2019). The IFC schema is represented by logic-based EXPRESS language, and the semantic relationship is limited to the representation and sharing of inferred knowledge (K. Kim et al., 2018). The COBie standard promotes the use of open data formats, such as Extensible Markup Language (XML), SpreadsheetML, or the IFC STEP format, to guarantee interoperability between different systems and neutrality, making it easier to exchange information between the project's stakeholders (Bose et al., 2021; K. Kim et al., 2018; Schwabe et al., 2018).

Traditional inspection and management systems have proven inefficient for this new reality of the infrastructure network (Agdas et al., 2016; Shamsudin et al., 2015), and system modernization and automation are required (Boddupalli et al., 2019; Isailović et al., 2020). The inspections performed with the help of synchronized models in the data cloud can be accessed by on-site mobile devices and home office computer interfaces, making it possible for stakeholders to exchange data simultaneously (Al-Shalabi et al., 2015; Ding et al., 2016). In addition, SHM is also an expensive resource, so IoT is an alternative to enable the monitoring of small structures at lower costs (Y. Yu et al., 2015). However, one of the challenges of using mobile equipment on site is the availability of cell phone signals since most bridges are located in rural areas, far from the cities, and where cell phone service is unavailable (Al-Shalabi et al., 2015; Tsai et al., 2014). To solve these problems, the researchers (Al-Shalabi et al., 2015; Tsai et al., 2014) suggest an offline approach to the BrIM system, allowing the inspector to download the files before arriving at the inspection site.

With advances in SHM technology and the automated inspection process combined with BIM, it is expected to improve the quality of the evaluation, management, damage detection, and decision-making stages. The semantics of information in the IFC schema is required to exchange data between the 3D models and the monitoring data throughout the life cycle of the structure. However, not all information associated with the monitoring step can be described and exchanged within the IFC schema since IFC open standard models are not mature enough.

Damage detection and modeling in a BIM-based system have been developed and support the decision-making process for interventions. The correct identification and location of defects found in the structure are of great importance for proper repair decisions. Many advances have been made in damage modeling through image capture equipment and the development of data processing and analysis methods. However, there are still challenges and limitations in the implementation of these techniques and the automatic and accurate detection of defects, in addition to insertion into BIM models. The common and recurring challenges mentioned in this section are summarised in Table 7.

Table 7. Common challenges for damage detection and modeling in a BIM-based system.

Challenge	Solution	References
BIM implementation costs	Cost-benefit analysis	(Al-Shalabi et al., 2015; Bryde et al., 2013; Lu et al., 2014; Tawelian & Mickovski, 2016)
Time required	Time-saving by optimization and collaborative work	(Al-Shalabi et al., 2015; Bryde et al., 2013; Lu et al., 2014)
Expensive resource	Internet of Things (IoT), wireless sensors, and mobile communication technology	(Ding et al., 2016; Feldbusch et al., 2017; Guzman-Acevedo et al., 2019; Sitton et al., 2020; Y. Yu et al., 2015)
Visual inspections limitations	Monitoring technologies	(Abu Dabous et al., 2017; Abu Dabous & Feroz, 2020; Agdas et al., 2016; Isailović et al., 2020; McGuire et al., 2016; Shamsudin et al., 2015)
Low cell phone signals	Offline tool for inspection	(Al-Shalabi et al., 2015; Tsai et al., 2014)
Damage detection	Automated analysis procedures	(Adhikari et al., 2013; Boddupalli et al., 2019; Prasanna et al., 2016; Tran et al., 2018; Y. Xu & Turkan, 2019b, 2019a; Q. Zhang et al., 2020)
IFC limitations	Specific entities on the IFC scheme	(Ait-Lamallam, Sebari, et al., 2021; Ait-Lamallam, Yaagoubi, et al., 2021; Artus & Koch, 2022; Hüthwohl et al., 2018; Isailović et al., 2020; Rio et al., 2013; Tanaka et al., 2016; Theiler & Smarsly, 2018)

Thus, one way to circumvent these limitations and challenges is to combine visual inspections with SHM capabilities and technologies. Using portable non-destructive testing equipment, tablets, and smartphones to monitor the progression of damage and failures identified during a visual inspection is a valuable strategy for bridge maintenance management. This approach allows continuous monitoring of the problems identified by the inspector, maintaining the safe use of the structure and providing the necessary time for planning the intervention processes.

6. Concluding remarks

This review aimed to identify and discuss emerging topics in bridge maintenance focusing on comprehensive and integrated BIM-based BMSs. Advances, perspectives, and challenges in implementing such methods and technologies have been raised and discussed. Some concluding remarks are listed below:

- Aging structures, coupled with the increasing emergence of damage and failure, have led to an increase in research on damage modeling, with the approach of SHM and automatic damage detection using technological resources and process automation.
- From the bibliometric analysis, it was possible to observe an increase in the number of articles in this area between the years 2020 and 2022, showing the importance of the

topic, especially in countries with large transportation networks, reflecting the interest in research and investment to improve the bridge management system.

- Visual inspection of bridges has limitations ranging from the subjectivity of the analysis to the inspection team's safety. Automatically assessing structure integrity through new monitoring technologies and practices enables more accurate, secure, and highly automated detection of damage and failures, significantly reducing operating costs and improving bridge safety. It does not mean substituting human inspection since the responsibility of validating the information cannot be delegated. However, it points to optimization with inspection assisted by a larger set of tools, with more data that could be processed by algorithms assisted by artificial intelligence.
- The implementation of automatic damage detection methods has been addressed, and it is observed that a large portion of the studies is directed mainly at cracking, which is recurring damage to concrete structures that cause subsequent damage.
- Semantic descriptions of inspections, SHM, and DIM using the IFC standard have been studied and implemented. As not all information is currently available in open standard data models, limiting the interoperability and implementation of these systems in BIM, several studies are investigating and proposing extensions to the IFC specifications.
- A BIM-based BMS represents centralized approaches that can improve information management and visualization processes, optimizing structure performance and reducing life cycle costs. Combined with SHM technologies, maintenance decision-making is accomplished by evaluating the state of the structure in real-time and monitoring any changes with the aid of sensors, laser scanners, and infrared thermography, among other technologies.
- Indeed, while the initial implementation of BIM may be perceived as a high-cost investment, its benefits can significantly outweigh these costs over the long term. BIM offers various advantages that can help offset expenses and improve overall project efficiency. Some of the key benefits of BIM include (i) Cost reduction in assessment, maintenance, and inspections; (ii) Improved communication and collaboration; (iii) Enhanced integration of disciplines; (iv) Efficient project management; and (v) Data-driven decision making.

The current reality of bridge management is characterized by rapid and continuous changes. Within this context, various mature technologies and methodologies are already available. However, there remain significant challenges related to geographical coverage, data acquisition, transmission, computer processing, and analysis of large datasets. Moreover, the availability of equipment, trained personnel, and limitations in BIM data schema and model interoperability continue to pose barriers to implementation, particularly in the short term. It is also important to note that transportation authorities possess a substantial amount of data that requires consolidation in a BIM-based management system. In this regard, the use of Information Container for Linked Document Delivery (ISO Standard) is considered a pragmatic approach.

BMS tends to be multi-methodological, incorporating a diverse range of existing and emerging tools and methods. These include traditional human inspection techniques and highly automated SHM systems. BMSs must be highly flexible in processing data sets from different origins, complexity, and volume. Managing such diverse datasets is the main challenge to ensuring the compatibility and stratification of valuable and comprehensive information for safe and accurate decision-making. It involves sophisticated artificial intelligence, statistical and deterministic algorithms. Conversely, BIM is an essential part of the system, a data source, and a fundamental information repository. Standardization and well-defined protocols become indispensable to ensure interoperability, data sharing, and cost-effectiveness. These considerations extend to aspects such as the training and contracting of personnel, the production, and management of models, considering time and equipment constraints.

To the best of the authors' knowledge, there are currently no operational BIM-based BMS in practical use. However, ongoing initiatives by road authorities, such as the establishment of the Brazilian DNIT BIM nucleus driven by the Brazilian presidency's Act 10306 mandating BIM use in public administration engineering projects, signify progress. These efforts, in collaboration with academia and the private sector, are laying the groundwork for the creation of a new BMS that can adapt into a BIM-based system.

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CHAPTER III

Consideration for developing parametric models for preliminary cost estimation of widening and strengthening intervention in old reinforced concrete bridges

Abstract

A significant part of Brazil's paved federal highway network, built between 1940 and 1984, has a geometry and load capacity incompatible with the current traffic demands. Intervention actions of widening and strengthening highway bridges become necessary to promote the rehabilitation of these structures and adaptation to the mobile loads of the current standardization. Accurately estimating each service package's quantities and costs is crucial for efficiently planning and allocating resources. This paper explores the development of parametric models for the preliminary cost estimation of these interventions, highlighting the expected benefits for management support. Parametric models provide greater accuracy and flexibility in cost estimation by considering variables specific to each project, such as the bridge type, geometric parameters, and employed technical solutions. The methodology involves defining the bridge type, analyzing actual rehabilitation projects provided by DNIT (National Department of Infrastructure and Transportation), and evaluating common solutions applied. This approach contributes to a more reliable and transparent cost prediction process, reducing uncertainties and facilitating decision-making in structural interventions.

Keywords: rehabilitation; widening; reinforced concrete bridge; parametric models; preliminary cost estimation.

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1. Introduction

The integrity and stability of concrete bridges are compromised when their structure is damaged or when the acting loads are greater than those foreseen at the time of design, and also by problems related to deterioration over the years (Baloch et al., 2021; Ma et al., 2017). Transportation infrastructure plays a significant role in economic development, so maintenance is crucial to ensure the system's and its users' safety (Wu et al., 2021). Reinforcement and rehabilitation interventions involve a wide range of activities associated with various stages of implementation, including inspection and diagnosis of structural conditions, planning, and development of executive designs, site preparation and mobilization of resources, and execution of the strengthening works. Each stage requires considerable technical, human, and financial resource allocation to ensure effective and safe interventions (Hu; Liu, 2019).

The evolution of the paved Brazilian highway network occurred in the 1940s when the first Brazilian Standards regarding the calculation and execution of reinforced concrete structures were also edited (DNIT, 2004). Since 1940, the calculation tools for concrete structures have evolved, as well as the vehicles that use the highways, the materials employed in the works, and the construction techniques (Carvalho; Calixto, 2019; DNIT, 2004; Vitório; Barros, 2012). These changes over time resulted in several updates of the standards, providing the formation of a heterogeneous profile of bridges characteristic of each construction era, designed following different sizing criteria, coupled with the fact that some bridges have already undergone intervention procedures such as replacement, recovery, strengthening, and widening (Carvalho; Calixto, 2019; DNIT, 2004; Vitório; Barros, 2012).

Most of the reinforced concrete (RC) bridges that constitute the Brazilian federal highway system were built between 1940 and 1984, and in the current scenario, these bridges have geometry and load capacity incompatible with the actual traffic (Carvalho; Calixto, 2019). Thus, it is evident that there is a need to promote rehabilitation actions to adapt to the mobile loads required by current standards and transmitted by the vehicle fleet and problems of a structural nature. According to Vitório (2013), the interventions of widening and strengthening highway bridges in Brazil only started to gain importance among the technical community in the mid-1990s, when some duplication works and widening of federal and state highways began.

Widening and strengthening procedures are essential to ensure the safety load-bearing capacity and durability of existing old bridges that were designed many years ago and may no longer meet current traffic requirements or design standards. In this context, this research proposes a methodology for developing parametric models to assist in the preliminary cost estimation for widening and strengthening reinforced concrete bridges in Brazil since these parametric models are not used yet and have great potential for application.

Parametric models allow cost estimates to be automated using predefined variables and parameters that reflect the specific characteristics of a bridge and its structural elements. When integrated into a broader system with the support of advanced algorithms, these models can quickly process large bridge databases, generating cost estimates efficiently across multiple projects. This approach provides decision-makers with a solid, data-driven basis for comparing intervention scenarios and identifying the most cost-effective solutions in terms of time, budget, and resources.

The proposed methodology not only improves the accuracy of intervention cost estimation but also offers the advantage of scalability, facilitating batch analysis of several bridges. By leveraging integrated and automated systems, this methodology can simplify the estimation process, allowing for more informed and timely decisions in large-scale infrastructure management. The study involves defining the bridge typology by selecting cases for analysis, evaluating existing projects for widening and strengthening, identifying the main parameters, and generating preliminary cost scenarios through parametric modeling.

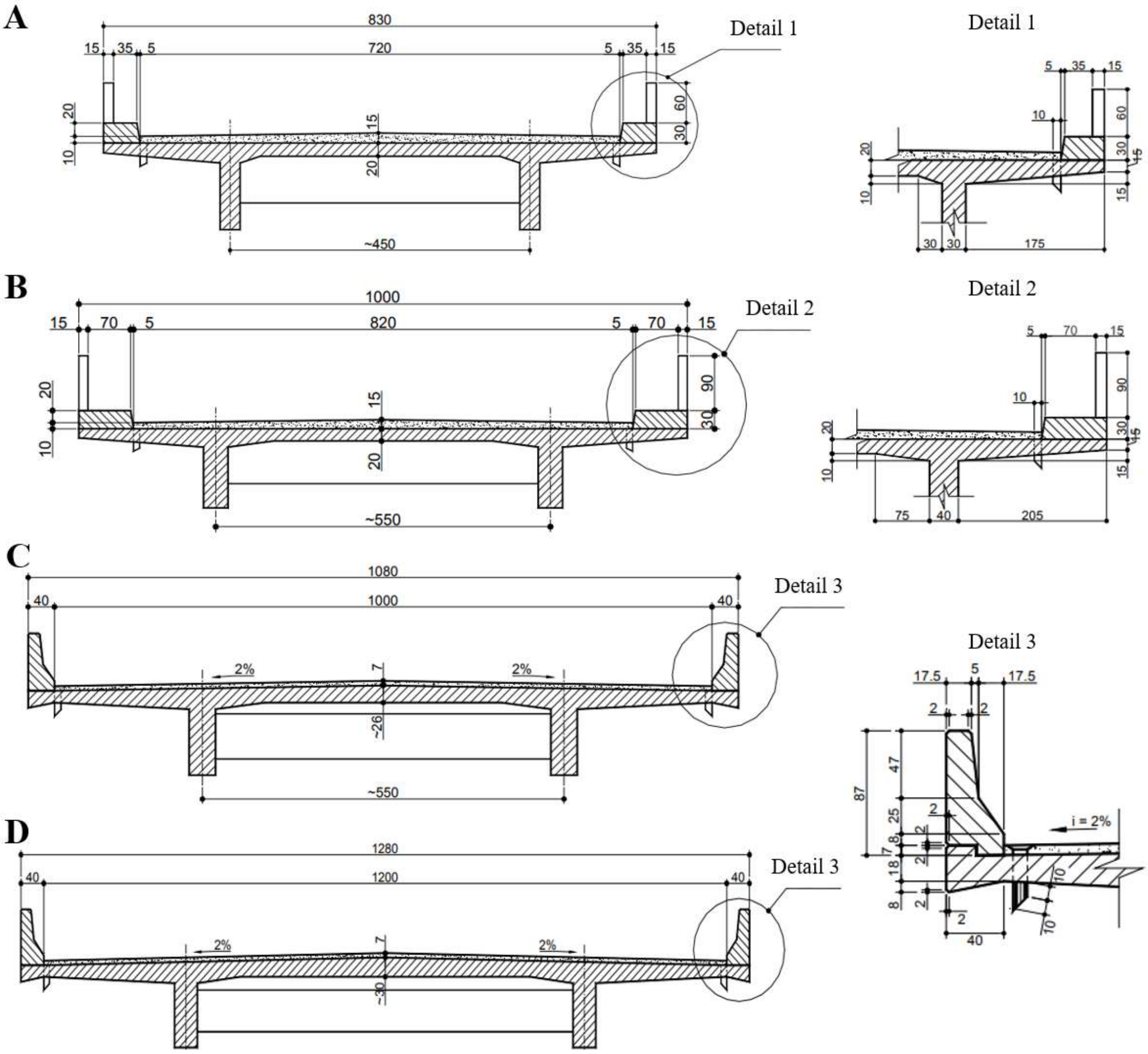
2. Background

2.1 Evolution of Brazilian bridge design standards

Brazilian road bridges have undergone changes in cross-section over the years (Figure 1). Before the 1960s (Figure 1.A), the cross-section was 8.30m and did not include the roadside. However, since 1985, the DNIT (Brazilian National Department of Transport Infrastructure) has adopted a 12.80 m cross-section for most federal bridges, including the roadside, to enhance user safety (Figure 1.D).

In addition to changes in cross-section, the loads acting on bridges have evolved significantly over time. The initial standard for mobile loads for road bridges, NB-6/1946, introduced the Class 24 (24tf) design vehicle and remained in effect until 1960, when NB-6/1960 introduced Class 36 (36tf). The most recent modification occurred with the publication of NB-6/1982, now NBR 7188/84, which established the Class 45 (45tf) design vehicle. Table 1 summarizes the evolution of Brazilian federal highway bridges over time.

Figure 1 – Evolution of the cross-section of Brazilian highway bridges: A. 1940 to 1960; B. 1960 to 1975; C. 1975 to 1985; D. After 1985.



Font: Adapted from DNIT (2004)

Table 1 – Evolution of Brazilian federal highway bridges over time.

Effective period	Cross-section	Lane width	Mobile loads	Standards
1940 to 1960	8,30 m	7,20 m	24 tf	NB-1/1946, NB-2/1946, and NB-6/1946
1960 to 1975	10,00 m	8,20 m	36 tf	NB-1/1960, NB-2/1960, and NB-6/1960
1975 to 1985	≥ 10,80 m	≥ 10,00 m	36 tf	NB-1/1978, NB-2/1960, and NB-6/1960
After 1985	12,80 m	12,00 m	45 tf	NB-1/1978, NB-2/1987, and NB-6/1982

2.2 Widening and strengthening of old bridges

Economic development and population growth put pressure on a country's infrastructure. In this context, many old bridges cannot meet the continuously increasing traffic demands and have become functionally obsolete. Widening and reinforcing old bridges is aimed at saving investment and time to improve the capacity of existing bridges, which is not to say that these interventions are simpler than building a new one, but, usually, are more economical than complete replacement (ACI Committee 345, 2013; Hong; Park, 2015; Shao et al., 2019; Wen, 2011).

The widening process refers to expanding the bridge's width to accommodate increased traffic, which can be caused by urban growth, increased vehicles, or changes in transport needs. Widening can be undertaken on different bridges' parts, such as adding new roadways, roadsides, or pedestrian pavements. According to the design instructions of the Department of Highways of the São Paulo State - DER/SP (2006), the widening procedures may or may not alter the existing structure, depending on the structural condition and solution adopted, prioritizing the adequacy of the design vehicle calculation of class 45.

To ensure the structural integrity and optimal driving comfort of widened bridges, the upper structures are frequently expanded directly with the original old bridges in a transverse manner. However, it is crucial to carefully consider long-term effects, especially when dealing with concrete bridges, where concrete shrinkage and creep become significant factors that demand thorough assessment to prevent potential issues (Hong; Park, 2015; Hosseini; Jefferson, 1998; Wen, 2011). ACI Guide for Widening Highway Bridge (2013) discusses problems caused by widening concrete bridges, primarily focusing on bridge decks. It addresses the effects of differential movements between existing and new parts and makes general recommendations on the choice of structure type, design details, construction methods, and materials (ACI Committee 345, 2013).

On the other hand, strengthening involves implementing measures that reinforce the load-bearing capacity and strength of the existing bridge to handle the new requirements or to correct possible structural deficiencies arising from aging or wear over time. Strengthening interventions may include using new materials, structural reinforcement techniques, introducing additional elements, or even partially replacing damaged or weakened structural components (Baloch et al., 2021; Carvalho; Calixto, 2019; Chen et al., 2022; Ma et al., 2017; Shao et al., 2019; Xie; Hu, 2013).

2.3 Brazilian bridge management system

A Bridge Management System (BMS) is a comprehensive tool designed to oversee and control the complete lifecycle of structures. BMS entails a range of essential tasks, including data collection, inspection processes, condition assessments, maintenance scheduling, repair or replacement initiatives, financial resource optimization, and an overall enhancement of user safety (Alonso Medina; León González, 2022; Hurt; Schrock, 2016; Marzouk; Hisham, 2012; Shepard, 2005).

Brazil's main bridge management system is the SGO - Sistema de Gerenciamento de Obras de Arte Especiais, developed by DNIT. This system is responsible for registering, assessing, and monitoring bridges on Brazil's federal highways. Around 137,000 bridges are estimated to exist in Brazil (Fausto Da Silva; Almeida De Melo, 2021), of which around 6833 are registered with the SGO and make up the federal highway network (DNIT, 2024b). Bridges located on municipal and state roads, which are not the responsibility of the DNIT, are not included in this inventory, which explains the discrepancy between the two figures presented.

2.4 Reference cost system for construction work (sicro)

The SICRO - Sistema de Custos Referenciais de Obras is the Brazilian system of reference costs for construction, which encompasses all the technical knowledge required for the preparation of design cost estimation and services at DNIT, facilitating the analysis of budgets for public construction requested by the organization. SICRO provides detailed information on labor, materials, and equipment costs, taking into account regional and seasonal variables (DNIT, 2017).

Currently, the SICRO table has more than six thousand different cost breakdowns. The construction of the cost breakdown system considers other factors, such as price variations caused by an increase or decrease in the supply of a given product. It also recognizes the seasonality of certain materials, the distance between the capital and other production centers, and the demand for materials concerning local construction investments (DNIT, 2024a). Thus, it can be emphasized that there is a variation in product values according to the region of the country. The most recent version available for consultation at the time of writing is January 2024. It is important to note that new versions of SICRO may be made available after the article is published.

3. Research methodology

This research proposes a methodology for defining essential considerations for developing parametric models for widening and reinforcement procedures in actual Brazilian reinforced concrete bridges, whose original design is Class 36, becoming Class 45 after the intervention, focusing on typically employed solutions.

For this study, the typology of the bridges was determined and defined for the structural system of the deck consisting of two girders, cross beams, and a reinforced concrete slab. A group of bridges in Bahia (highway BR-030/BA) was selected for analysis. The cross-section of the selected real bridges ranged from 9.55 to 10.05 meters, and the longitudinal section ranged from 23.50 to 128.50 meters (Table 2). The variation of the parameters and the solutions employed for the widening and strengthening interventions made it possible to evaluate the commonly performed services, the estimated quantities, and the associated costs.

Table 2 – Dimension parameters of the bridge set selected for methodology application.

ID	Bridge identification	Length (m)	Width (m)	Number of spans	Longitudinal overhang
1	Valentim River Bridge	65.00	9.60	3 spans (15.5 m + 23.0 m + 15.5 m)	2 overhangs (5.5 m each)
2	Urubá II River Bridge	54.00	9.55	2 spans (21.0 m + 21.0 m)	2 overhangs (6.0 m each)
3	Água Sumida River Bridge	44.90	10.05	3 spans (13.2 m + 18.0 m + 13.2 m)	-
4	Gongogi River Bridge	128.50	10.00	6 spans (20.0 m each)	-
5	Jibóia River Bridge	23.50	10.05	1 span (12.9 m)	2 overhangs (5.3 m each)

3.1 Design analysis of the selected bridges

Design analysis for the selected reinforced concrete bridges consists of identifying and defining specific parameters that describe the characteristics and requirements of the structural components created or modified, allowing a more accurate and efficient approach to widening and strengthening designs. This process was carried out by dividing the elements into categories: infrastructure, mesostructure, superstructure, and complimentary. Thus, the corresponding components were grouped according to the solutions identified in the designs utilized for calibration.

Enabling the bridge manager to automatically generate a wide range of alternative design solutions for elements in a bridge rehabilitation process is a great advantage offered by parametric modeling in supporting geometric design explorations. Pile caps, Footings, and Drilled Pier Foundation solutions were identified and parameterized for infrastructure. In the mesostructure, New Columns, New Column Brackets, Existing Jacketed Columns, and Existing Column Brackets. In the superstructure Deck Widening, New Girders, the Reinforcement of Existing Girders, and Crossbeams extension (Table 3).

Table 3 – Widening and strengthening of bridge elements.

Component category	Widening/ New elements	Reinforced elements
Infrastructure	Pile Cap Footing Drilled Pier Foundation	-
Mesostructure	New Columns New Column Bracket Existing Columns Bracket	Existing Jacketed Columns
Superstructure	Deck Widening New girders Crossbeam extension	Reinforcement of existing girders

3.2 Unit cost analysis and service cost estimation

The methodology for the cost analysis involved listing the essential services needed to widen, construct, and reinforce the bridge elements. These services include making resin plywood forms, CA-50 rebar, concrete for pumping, mechanical concrete pumping, concrete compacting, and wet shotcrete. Each service has its own unit cost composition provided by the SICRO reports, the Brazilian cost reference system, which presents data by region of the country (North, Northeast, Centre-West, Southeast, South) and individually for each state. This study used the specific report for Bahia state. SICRO is updated quarterly, the most recent version available for consultation is from January 2024.

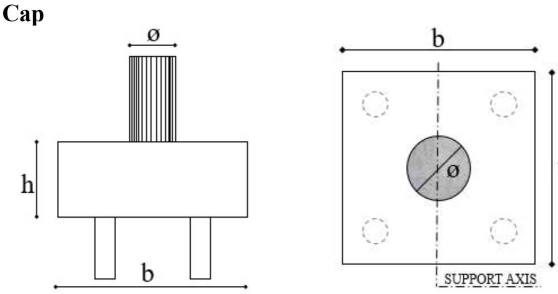
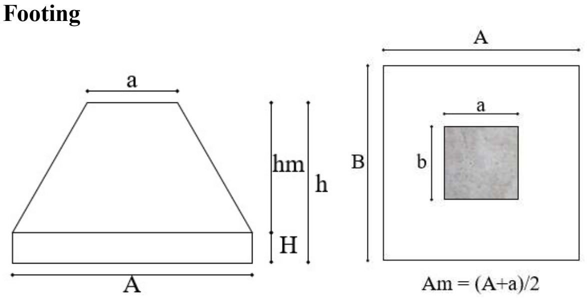
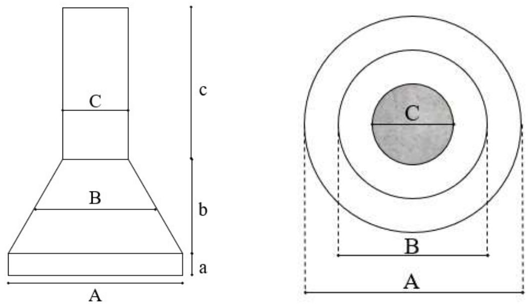
With the specific quantities of each element of the bridge and the unit cost of the services, the total direct costs of the infrastructure, mesostructure, and superstructure services were calculated. It is important to note that these calculations refer exclusively to direct costs - which include labor, materials, and equipment - as defined in the SICRO Manual, Volume 1 (DNIT, 2017). These costs do not include indirect costs, such as transportation of inputs, construction administration, and other charges.

4. Definition of parameters and design values

4.1 Infrastructure

Three different structural solutions were identified for the infrastructure: pile cap, footing, and drilled pier foundation. Specific geometric parameters were defined to characterize the elements, the quantity used in each bridge design, the concrete volume, and the corresponding rates of plywood forms and CA-50 rebar (Table 4).

Table 4 – Parameters of infrastructure elements.

Infrastructure solutions		
Pile Cap		**Parameters** **b** = pile cap base (m) **h** = pile cap height (m) **ø** = column diameter (m) **N** = number of pile caps (unit) **V** = volume of concrete (m^3) **PF** = plywood forms (m^2/m^3 of concrete) **R_{CA-50}** = rebar CA-50 (kg/m^3 of concrete)
Footing		**Parameters** **A** = larger footing size (m) **a** = smaller footing size (m) **Am** = average footing size (m) **H** = base footing height (m) **hm** = average footing height (m) **h** = footing height (m) **N** = number of footings (unit) **V** = volume of concrete (m^3) **PF** = plywood forms (m^2/m^3 of concrete) **R_{CA-50}** = rebar CA-50 (kg/m^3 of concrete)
Drilled Pier Foundation		**Parameters** **A** = larger diameter (m) **a** = smaller height (m) **B** = base diameter (m) **b** = base height (m) **C** = shaft diameter (m) **c** = shaft height (m) **N** = number of drilled pier foundations (unit) **V** = volume of concrete (m^3) **PF** = plywood forms (m^2/m^3 of concrete) **R_{CA-50}** = rebar CA-50 (kg/m^3 of concrete)

Each bridge adopted a different structural solution for the infrastructure. Bridges 1 and 2 (Valentim River Bridge and Urubá II River Bridge) adopted Pile Cap. Bridge 3 (Água Sumida River bridge) adopted the Footing and Drilled Pier Foundation for the infrastructure. Bridge 4 (Gongogi River Bridge) adopted Footing, and Bridge 5 (Jiboia River Bridge) adopted the Drilled Pier Foundation. The values of each corresponding parameter are shown in Table 5. In addition, a range of values was identified and the average values were determined.

The average values and ranges identified for the individual parameters can be adjusted according to the complexity or specificity of the project. This flexibility makes the parametric approach more adaptable to different contexts.

The parameterization proposed for infrastructure elements contributes directly to the development of parametric budget models by providing a basis for the preliminary calculation of materials and services. These parameters, when associated with cost databases, allow for a more agile and accurate estimation of costs, improving the decision-making process in the early stages of planning.

Table 5 – Infrastructure design parameters for the selected bridges.

Pile Cap

Parameters	Bridge ID 1	2	3	4	5	Range	Average values
b (m)	2.5	2.5	*	*	*	2.5	2.5
h (m)	1.2	1.2	*	*	*	1.2	1.2
ø (m)	0.92	0.92	*	*	*	0.92	0.92
N (unit)	8	6	*	*	*	6 - 8	-
V (m^3)	60.0	45.0	*	*	*	45.0 – 60.0	-
PF (m^2/m^3)	1.6	1.6	*	*	*	1.6	1.6
R_{CA-50} (kg/m^3)	81.6	81.6	*	*	*	81.6	81.6

Footing

Parameters	Bridge ID 1	2	3	4	5	Range	Average values
A (m)	*	*	3.0	2.7	*	2.7 – 3.0	2.85
a (m)	*	*	1.1	1.12	*	1.1 – 1.12	1.11
Am (m)	*	*	2.05	1.91	*	1.91 – 2.05	1.98
H (m)	*	*	0.5	0.5	*	0.5	0.5
hm (m)	*	*	0.8	0.8	*	0.8	0.8
h (m)	*	*	1.3	1.3	*	1.3	1.3
N (unit)	*	*	4	14	*	4 - 14	-
V (m^3)	*	*	31.45	91.89	*	31.45 – 91.89	-
PF (m^2/m^3)	*	*	0.76	0.82	*	0.76 – 0.82	0.79
R_{CA-50} (kg/m^3)	*	*	86.36	85.32	*	85.32 – 86.36	85.84

Drilled Pier Foundation

Parameters	Bridge ID 1	2	3	4	5	Range	Average values
A (m)	*	*	2.5	*	2.5	2.5	2.5
a (m)	*	*	0.2	*	0.2	0.2	0.2
B (m)	*	*	1.85	*	1.85	1.85	1.85
b (m)	*	*	1.0	*	1.0	1.0	1.0
C (m)	*	*	1.2	*	1.2	1.2	1.2
c (m)	*	*	2.0	*	3.4	2.0 – 3.4	2.7
N (unit)	*	*	4	*	4	4	-
V (m^3)	*	*	23.73	*	30.06	23.73 – 30.06	-
R_{CA-50} (kg/m^3)	*	*	1.0	*	1.0	1.0	1.0
PF (m^2/m^3)	*	*	42.32	*	48.30	42.32 – 48.30	45.31

4.2 Mesostructure

The mesostructure typology was the same for all five bridges, consisting of new lines of columns, brackets, and the strengthening of hexagonal reinforced concrete columns. After jacketing, the hexagonal columns became circular. Table 6 shows the specific parameters for each element, the quantity used in the bridge, the amount of concrete, and the corresponding rates of plywood forms and CA-50 rebar.

Table 6 – Parameters of mesostructure elements.

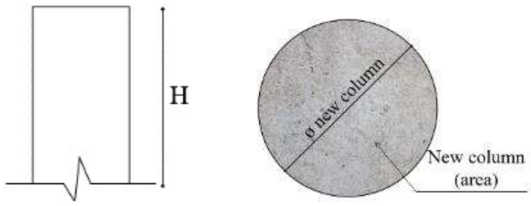
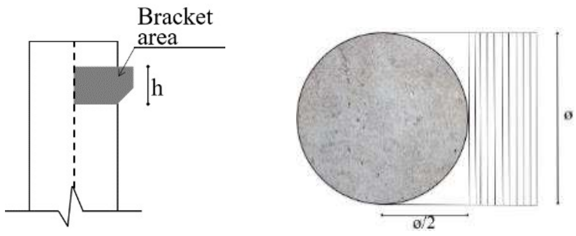
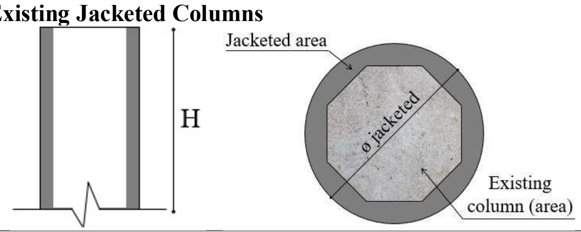
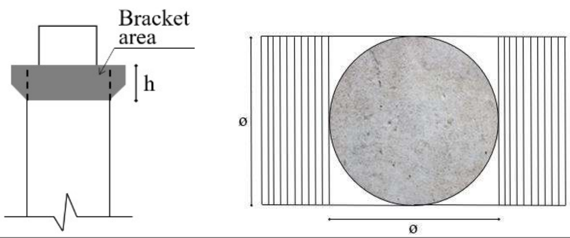
Mesostructure solutions	
New Columns 	**Parameters** **ø** = column diameter (m) **H** = average column height (m) **N** = number of columns (unit) **V** = volume of concrete (m^3) **PF** = plywood forms (m^2/m^3 of concrete) $\mathbf{R_{CA\text{-}50}}$ = rebar CA-50 (kg/m^3 of concrete)
New Column Bracket 	**Parameters** **ø** = column diameter (m) **h** = bracket height (m) $\mathbf{B_a}$ = bracket area (m^2) **P** = bracket perimeter (m) $\mathbf{C_a}$ = Column area (m^2) **N** = number of columns (unit) **V** = volume of concrete (m^3) **PF** = plywood forms (m^2/m^3 of concrete) $\mathbf{R_{CA\text{-}50}}$ = rebar CA-50 (kg/m^3 of concrete)
Existing Jacketed Columns 	**Parameters** **ø** = jacketed column diameter (m) **H** = column height (m) $\mathbf{J_a}$ = Jacked area (m^2) **N** = number of columns (unit) **V** = volume of concrete (m^3) **PF** = plywood forms (m^2/m^3 of concrete) $\mathbf{R_{CA\text{-}50}}$ = rebar CA-50 (kg/m^3 of concrete)
Existing Columns Bracket 	**Parameters** **ø** = jacketed column diameter (m) **h** = bracket height (m) $\mathbf{B_a}$ = bracket area (m^2) **P** = bracket perimeter (m) $\mathbf{C_a}$ = **c**olumn area (m^2) **N** = number of columns (unit) **V** = volume of concrete (m^3) **PF** = plywood forms (m^2/m^3 of concrete) $\mathbf{R_{CA\text{-}50}}$ = rebar CA-50 (kg/m^3 of concrete)

Table 7 shows the design parameters for the mesostructure of the bridges analyzed. The diameter of the new columns was the same for all five bridges (0.92 m). The average height of the columns and the number of elements varied according to each design, considering the topography of the terrain in which the structure is placed to determine the heights of the columns and the length of the bridge to determine the quantity required. The volume of concrete and the steel rate varied from bridge to bridge, but the coefficient of plywood form area per volume of concrete remained the same for all structures (4.35 m^2/m^3). In the case of the brackets for the new columns, all the parameters were standardized, varying only in the number of elements per bridge, the volume of concrete, and the steel rate. The existing jacketed columns presented a short difference in diameter between the bridges, ranging from 1.05 m to 1.15 m. In addition, the average height and number of elements also varied according to each specific design. The existing columns bracket had some variable parameters according to the diameter of the columns and specific parameters with standardized values, ranging from the number of elements per bridge, the volume of concrete, and other services dependent on this volume.

Table 7 – Mesostructure design parameters for the selected bridges.

New Columns

Parameters	Bridge ID 1	2	3	4	5	Range	Average values
ø (m)	0.92	0.92	0.92	0.92	0.92	0.92	0.92
H (m)	4.78	6.27	5.87	3.41	4.0	3.41 – 6.27	4.87
N (unit)	8	6	8	14	4	4 – 14	-
V (m^3)	25.43	25.0	31.2	31.78	10.64	10.64 – 31.78	-
PF (m^2/m^3)	4.35	4.35	4.35	4.35	4.35	4.35	4.35
$R_{CA\text{-}50}$ (kg/m^3)	89.76	101.62	87.43	97.35	86.97	86.97 – 101.62	92.63

New Column Bracket

Parameters	Bridge ID 1	2	3	4	5	Range	Average values
ø (m)	0.92	0.92	0.92	0.92	0.92	0.92	0.92
h (m)	0.5	0.5	0.5	0.5	0.5	0.5	0.5
B_a (m^2)	0.34	0.34	0.34	0.34	0.34	0.34	0.34
P (m)	0.62	0.62	0.62	0.62	0.62	0.62	0.62
C_a (m^2)	0.66	0.66	0.66	0.66	0.66	0.66	0.66
N (unit)	8	6	8	14	4	4 – 14	-
V (m^3)	1.17	0.88	1.17	2.05	0.59	0.59 – 2.05	-
PF (m^2/m^3)	8.53	8.53	8.53	8.53	8.53	8.53	8.53
$R_{CA\text{-}50}$ (kg/m^3)	709.36	709.37	818.50	709.37	709.37	709.36 – 818.50	731.19

Existing Jacketed Columns

Parameters	Bridge ID 1	2	3	4	5	Range	Average values
ø (m)	1.05	1.05	1.15	1.05	1.15	1.05 – 1.15	1.09
H (m)	5.35	5.18	5.77	3.41	3.7	3.41 – 5.77	4.68
J_a (m^2)	0.34	0.34	0.37	0.34	0.4	0.34 – 0.4	0.36
N (unit)	8	6	8	14	4	4 – 14	-
V (m^3)	14.54	10.57	17.09	16.26	5.92	5.92 – 17.09	-
PF (m^2/m^3)	9.7	9.7	9.76	9.7	9.03	9.03 – 9,76	9.58
$R_{CA\text{-}50}$ (kg/m^3)	102.49	108.64	90.91	109.38	93.92	90.91 – 109.38	101.07

Existing Columns Bracket

Parameters	Bridge ID 1	2	3	4	5	Range	Average values
ø (m)	1.05	1.05	1.15	1.05	1.15	1.05 – 1.15	1.09
h (m)	0.5	0.5	0.5	0.5	0.5	0.5	0.5
B_a (m)	0.65	0.65	0.65	0.65	0.7	0.65 – 0.7	0.66
P (m)	1.09	1.09	1.09	1.09	1.09	1.09	1.09
C_a (m)	0.87	0.87	1.04	0.87	1.04	0.87 – 1.04	0.93
N (unit)	8	6	8	14	4	4 – 14	-
V (m^3)	2.0	1.5	1.83	3.49	1.14	1.14 – 3.49	-
PF (m^2/m^3)	9.8	9.8	11.19	9.8	9.29	9.29 – 11.19	9.97
$R_{CA\text{-}50}$ (kg/m^3)	512.92	512.92	587.32	512.92	497.10	497.10 – 587.32	524.64

These parameter variations reflect the project's adaptation to the specific conditions of each bridge, respecting safety standards and guaranteeing the necessary structural durability. The uniformity of some coefficients, such as plywood forms and CA-50 steel rates, demonstrates the standardization of some procedures to optimize execution and reduce costs without compromising the quality of the structural reinforcement.

4.3 Superstructure

The structural solution for widening and strengthening the superstructure elements was the same for the five bridges analyzed. The designs involved deck widening, new girders, reinforcing existing girders, and extending the crossbeams to accompany the deck. For the girders and crossbeams, the parameters were separated for the bridge span regions and the support regions. Table 8 shows the specific parameters for each element, the quantity used in the bridge, the amount of concrete, and the corresponding rates of plywood forms and CA-50 rebar.

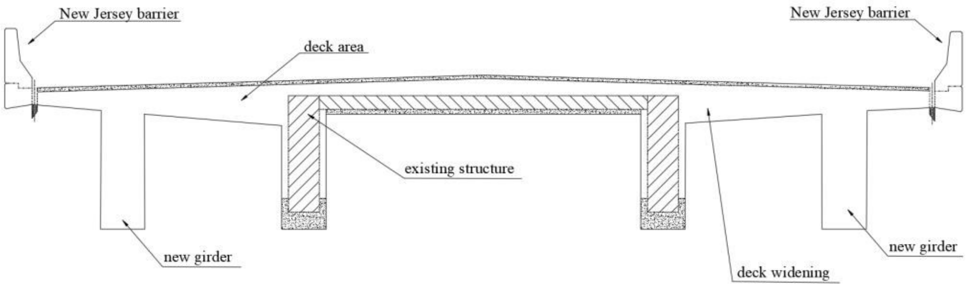
Table 9 shows the design parameters for the superstructure of the bridges analyzed. The initial width of the bridges analyzed ranged from 9.55 m to 10.05 m, and all were widened to a final dimension of 13.00 m. Thus, the widening of the deck has different values from bridge to bridge, ranging from 6.5 m to 7.23 m. Similarly, there is a difference between the area of the bridge section and the perimeter.

The new girders in the span area had a base set at 0.62 m and a height of 2.06 m. The only bridge that varied in height was the Jiboia River Bridge since it is the shortest bridge (23.50 m) among the others and has just one span. The ratio of bridge length to span zone varied between 0.7 and 0.88, with an average value of 0.8. The ratio of plywood area to concrete volume was 3.71, less for the Jiboia River Bridge due to the lower height of the stringer. In addition, the concrete volume and the rate of steel were variable according to each specific design. The base was set at 0.92 m in the support region, with the same heights as in the span region. The proportion of the bridge span to the support region varied from 0.12 to 0.3, with an average value of 0.2. The ratio of the plywood area to the concrete volume was 2.17. The concrete volume and the rate of steel were varied according to each specific design.

In the existing reinforced girders, the initial base was 0.5 m, and after the jacketing process, it increased to 0.62 m in the span. The average height of the stringers ranged from 1.29 to 1.79 m, and the ratio of the length of the bridge to the span had an average value of 0.8. The other parameters showed variations in their values. In the support region, the base was 0.8, and after reinforcement, it increased to 0.92 m in all bridges. The height also varied from 1.29 to 1.8 m, and the proportion of the bridge's length to the support had an average value of 0.2. Finally, the crossbeams extension, whose parameter values varied from bridge to bridge, both in span and support.

Table 8 – Superstructure elements parameters.

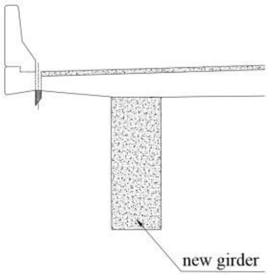
Deck Widening



Parameters
D_w = deck widening (m)
D_a = deck area (m²)
D_p = deck perimeter (m)
ø = column diameter (m)

Input parameters
B_l = Bridge length (m)
V = volume of concrete (m³)
PF = plywood forms (m²/m³ of concrete)
R_{CA-50} = rebar CA-50 (kg/m³ of concrete)

New Girder

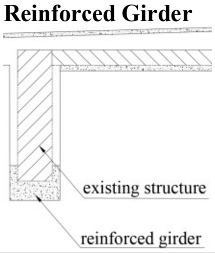


Input parameters

SPAN
B = girder base (m)
H = girder height (m)
N = number of new girders (unit)
S_{lr} = span length ratio
V = volume of concrete (m³)
PF = plywood forms (m²/m³ of concrete)
R_{CA-50} = rebar CA-50 (kg/m³ of concrete)

SUPPORT
B = girder base (m)
H = girder height (m)
S_{ulr} = support length ratio
V = volume of concrete (m³)
PF = plywood forms (m²/m³ of concrete)
R_{CA-50} = rebar CA-50 (kg/m³ of concrete)

Reinforced Girder

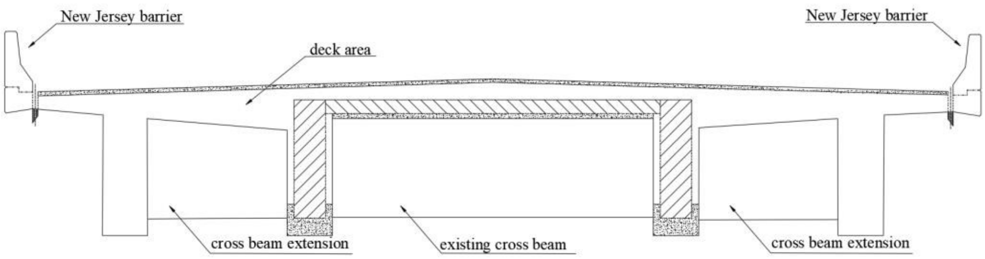


Input parameters

SPAN
b = original girder base (m)
B = reinforced girder base (m)
H = girder height (m)
S_{lr} = span length ratio

SUPPORT
b = original girder base (m)
B = reinforced girder base (m)
H = girder height (m)
S_{ulr} = support length ratio

Crossbeam Extension



Input parameters

SPAN
N = Number of cross beans on the span
B = cross beam base on span (m)
L = cross beam length (m)
H = cross beam height (m)

SUPPORT
N = Number of cross beans on support
B = cross beam base on support (m)
L = cross beam length (m)
H = cross beam height (m)

Table 9 – Superstructure design parameters for the selected bridges.

Deck Widening

Parameters	Bridge ID 1	2	3	4	5	Range	Average values
D_w (m)	7.15	7.23	6.75	7.15	6.5	6.5 – 7.23	6.96
D_a (m)	2.73	2.75	2.65	2.73	2.6	2.6 – 2.75	2.69
D_p (unit)	6.31	6.73	6.28	6.31	6.17	6.17 – 6.73	6.36
ø (m)	1.05	1.05	1.15	1.05	1.15	1.05 – 1.15	1.09
B_l (m)	65.0	54.0	44.9	128.5	23.5	23.5 – 128.5	63.18
V (m^3)	177.45	148.28	118.99	350.81	61.1	61.1 – 350.81	-
PF (m^2/m^3)	2.31	2.45	2.37	2.31	2.37	2.31 – 2.45	2.36
R_{CA-50} (kg/m^3)	96.09	103.05	117.17	96.03	107.23	96.03 – 117.17	103.91

New Girder

	Parameters	Bridge ID 1	2	3	4	5	Range	Average values
SPAN	B (m)	0.62	0.62	0.62	0.62	0.62	0.62	0.62
	H (m)	2.06	2.06	2.06	2.06	1.45	1.45 – 2.06	1.94
	Slr	0.78	0.80	0.88	0.83	0.7	0.7 – 0.88	0.8
	N (unit)	2	2	2	2	2	2	-
	V (m^3)	130.02	110.43	100.9	273.19	29.58	29.58 – 273.19	-
	PF (m^2/m^3)	3.71	3.71	3.71	3.71	3.92	3.71 – 3.92	3.75
	R_{CA-50} (kg/m^3)	116.15	140,92	158,86	139,03	112,01	112,01 – 158,86	133.39
SUPPORT	B (m)	0.92	0.92	0.92	0.92	0.92	0.92	0.92
	H (m)	2.06	2.06	2.06	2.06	1.45	1.45 – 2.06	1.94
	Slr	0.22	0.2	0.12	0.17	0.3	0.12 – 0.3	0.2
	N (unit)	2	2	2	2	2	2	-
	V (m^3)	53.44	40.82	20.47	81.68	18.81	18.81 – 81.68	-
	PF (m^2/m^3)	2.17	2.17	2.17	2.17	2.17	2.17	2.17
	R_{CA-50} (kg/m^3)	116.15	140.92	158.86	139.03	112.01	112.01 – 158.86	133.39

Reinforced Girder

	Parameters	Bridge ID 1	2	3	4	5	Range	Average values
SPAN	b (m)	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	B (m)	0.62	0.62	0.62	0.62	0.62	0.5	0.62
	H (m)	1.74	1.79	1.29	1.75	1.75	1.29 – 1.79	1.66
	Slr	0.78	0.8	0.88	0.83	0.7	0.7 – 0.88	0.8
	N (unit)	2	2	2	2	2	2	-
	V (m^3)	33.88	29.24	19.58	71.44	10.99	10.99 – 71.44	-
	PF (m^2/m^3)	15.38	15.41	16.63	15.39	15.39	15.38 – 16.63	15.64
	R_{CA-50} (kg/m^3)	398.78	321.89	431.57	299.66	241.01	241.01 – 431.57	338.58
SUPPORT	b (m)	0.8	0.8	0.8	0.8	0.8	0.8	0.8
	B (m)	0.92	0.92	0.92	0.92	0.92	0.92	0.92
	H (m)	1.75	1.8	1.29	1.75	1.75	1.29 – 1.8	1.67
	Slr	0.22	0.2	0.12	0.17	0.3	0.12 – 0.3	0.2
	N (unit)	2	2	2	2	2	2	-
	V (m^3)	5.92	4.65	1.67	9.05	2.96	1.67 – 9.05	-
	PF (m^2/m^3)	16.67	16.67	16.67	16.67	16.67	16.67	16.67
	R_{CA-50} (kg/m^3)	398.78	321.89	431.57	299.66	241.01	241.01 – 431.57	338.58

Crossbeam Extension

	Parameters	Bridge ID 1	2	3	4	5	Range	Average values
SPAN	B (m)	0.2	0.2	0.2	0.2	0.2	0.2	0.2
	L (m)	2.38	2.41	2.18	2.38	2.13	2.13 – 2.41	2.3
	H (m)	1.71	1.84	1.2	1.6	1.22	1.2 – 1.84	1.51
	N (unit)	3	2	3	6	3	2 – 6	-
	V (m^3)	4.88	3.55	3.14	9.14	3.12	3.12 – 9.14	-
	PF (m^2/m^3)	10.58	10.54	10.83	10.63	10.82	10.54 – 10.83	10.68
	R_{CA-50} (kg/m^3)	229.13	200.14	256.12	223.87	315.55	200.14 – 315.55	244.96
SUPPORT	B (m)	0.25	0.25	0.25	0.25	0.25	0.25	0.25
	L (m)	2.08	2.11	1.88	2.08	1.69	1.69 – 2.11	1.97
	H (m)	1.76	1.71	1.2	1.6	1.25	1.2 – 1.76	1.5
	N (unit)	4	3	4	5	2	2 – 5	-
	V (m^3)	7.32	5.41	4.51	8.32	2.11	2.11 – 8.32	-
	PF (m^2/m^3)	8.57	8.58	8.83	8.63	8.8	8.57 – 8.83	8.68
	R_{CA-50} (kg/m^3)	206.51	269.95	182.18	289.66	280.24	182.18 – 289.66	245.71

The design parameters and material quantities for the superstructure elements provided a detailed understanding of the structural solution for the widening and strengthening interventions. By segmenting the parameters for span and support regions, a more accurate estimation of the materials needed for the concrete, plywood forms, and rebar was achieved, which varied according to the specific dimensions of each bridge.

5. Preliminary cost estimation

As specified in the methodology, the essential services were identified in the January 2024 SICRO report for the Bahia state. Each service was recognized with an ID to facilitate its identification, the corresponding SICRO code, the description of the service as it appears in the reports, the unit of measurement, and unit cost. (Table 10). Based on the quantities obtained from the designs for each bridge, the associated costs were calculated for each set of bridge elements. The direct cost of the services for each bridge was determined (Table 11).

Table 10 – SICRO services description.

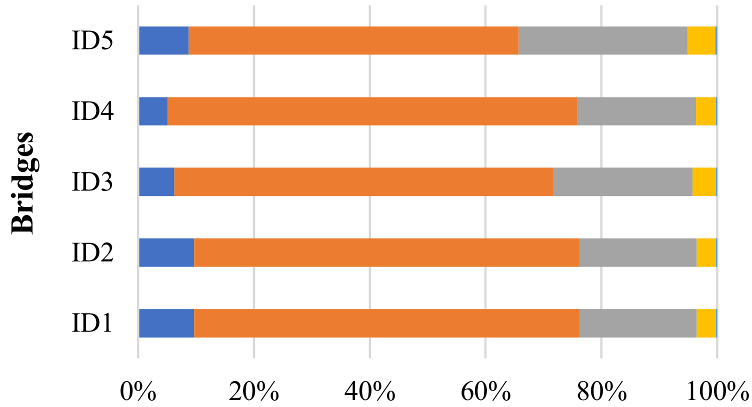
ID	SICRO Code	Services Description	Unit	Unit cost (R$)
A	3108005	Resin plywood forms 14 mm - general use - 3-time use - manufacture, installation, and removal	m²	88.06
B	0407819	CA-50 rebar - supply, preparation, and installation	kg	11.89
C	1116268	Concrete for pumping fck = 30 MPa - made in 40 m³/h batching plant - sand extracted and gravel produced	m³	293.35
D	1106128	Mechanical concrete pumping with a towable pump with a capacity of 41 m³/h - production in a 40 m³/h batching plant	m³	48.66
E	1100657	Concrete compacting by immersion vibrator	m³	3.33
F	1208333	Wet shotcrete fck = 40 MPa applied in class I tunnels with a section greater than 90 m²	m³	932.72

By separating the costs of services by a set of elements of infrastructure (Figure 2), mesostructure (Figure 3), and superstructure (Figure 4), it is possible to analyze those that most influence the estimate direct cost of the structure. CA-50 rebar is predominantly the service with the most impact on the final cost in all elements set. Concrete is the second service with the highest associated value in the infrastructure, followed by plywood forms. Plywood forms are more costly than concrete in the mesostructure and superstructure. In addition, in the reinforced girder intervention, the wet shotcrete service appears, which has a high associated unit cost, however it is used in small volumes.

Table 11 – Estimate services cost per bridge analyzed.

	Element	Services ID	Bridge ID 1		2		3		4		5	
			Quant.	**Direct cost (R$)**	**Quant.**	**Direct cost (R$)**	**Quant.**	**Direct cost (R$)**	**Quant.**	**Direct cost**	**Quant.**	**Direct cost (R$)**
Infrastructure	*Pile Cap, Footing or Drilled Pier Foundation*	A	96.0	8,453.76	72.0	6,340.32	47.73	4,202.83	75.6	6,657.34	30.06	2,647.08
		B	4,896.0	58,213.44	3672.0	43,660.08	3,719.97	44,230.44	7,839.95	93,217.01	1,452.0	17,264.28
		C	60.0	17,601.0	45.0	13,200.75	55.17	16,184.12	91.89	26,955.93	30.06	8,818.1
		D	60.0	2,919.6	45.0	2,189.7	55.17	2,684.57	91.89	4,471.37	30.06	1,462.72
		E	60.0	199.8	45.0	149.85	55.17	183.72	91.89	305,99	30.06	100.1
				87,387.6		65,540.7		67,485.95		131,607.63		30,292.28
Mesostructure	*New Column + New Column Bracket*	A	120.58	10,618.27	116.17	10,229.93	145.67	12,827.70	155.69	1,3710.06	51.24	4,512.19
		B	3,115.0	37,037.35	3,164	37,619.96	3,688.0	43,850.32	4,550.0	54,099.50	1,341.0	15,944.49
		C	26.6	7,803.11	25.88	7,591.90	32.37	9,495.74	33.83	9,924.03	11.23	3,294.32
		D	26.6	1,294.36	25.88	1,259.32	32.37	1,575.12	33.83	1,646.17	11.23	546.45
		E	26.6	88.58	25.88	86.18	32.37	107.79	33.83	112.65	11.23	37.40
	Existing Jacket Column + Existing Column Bracket	A	160.61	14,143.32	117.19	10319.75	187.34	16497.16	191.93	16901.36	64.08	5642.88
		B	2,514.00	29,891.46	1916.00	22781.24	2626.00	31223.14	3570.00	42447.30	1124.00	13364.36
		C	16.54	4,852.01	12.07	3540.73	18.92	5550.18	19.75	5793.66	7.06	2071.05
		D	16.54	804.84	12.07	587.33	18.92	920.65	19.75	961.04	7.06	343.54
		E	16.54	55.08	12.07	40.19	18.92	63.00	19.75	65.77	7.06	23.51
				106,588.37		94,056.53		122,110.81		145,661.53		45,780.20
Superstructure	*Deck Widening*	A	410.15	36,117.81	363.42	32,002.77	281.97	24,830.28	810.84	71,402.57	145.00	12,768.70
		B	17,051.0	202,736.39	15,281.0	181,691.09	13941.0	165,758.49	33687.0	400,538.43	6,552.00	77,903.28
		C	177.45	52,054.96	148.28	43,497.94	118.99	34,905.72	350.81	102,910.11	61.10	17,923.69
		D	177.45	8,634.72	148.28	7,215.30	118.99	5,790.05	350.81	17,070.41	61.10	2,973.13
		E	177.45	590.91	148.28	493.77	118.99	396.24	350.81	1,168.20	61.10	203.46
	New Girder	A	598.71	52,722.40	498.56	43,903.19	418.96	36,893.62	1191.46	104919.97	156.70	13,799.00
		B	2,1309.29	253,367.46	21,314.05	253,424.05	19,280.35	229,243.36	49,338.43	586633.93	5,419.77	64,441.07
		C	183.46	53,817.99	151.25	44,369.19	121.37	35,603.89	354.87	104,101.11	48.39	14,195.21
		D	183.46	8,927.16	151.25	7,359.83	121.37	5,905.86	354.87	17,267.97	48.39	2,354.66
		E	183.46	610.92	151.25	503.66	121.37	404.16	354.87	1,181.72	48.39	161.14
	Reinforced Girder	A	619.92	54,590.16	528.00	46,495.68	353.34	31,115.12	1,250.30	110,101.42	218.46	19,237.59
		B	15,871.86	188,716.42	10,909.95	129,719.31	9,170.02	109,031.54	24,120.71	286,795.24	3,361.99	39,974.06
		C	12.62	37,02.08	10.72	3,144.71	7.35	2,156.12	26.52	7,779.64	4.08	1,196.87
		D	12.62	614.09	10.72	521.64	7.35	357.65	26.52	1,290.46	4.08	198.53
		E	12.62	42.02	10.72	35.70	7.35	24.48	26.52	88.31	4.08	13.59
		F	27.18	25,351.33	23.17	21,611.12	13.90	12,964.81	53.97	50,338.90	9.87	9,205.95
	Crossbeam Extension	A	114.42	10,075.83	83.86	7,384.71	73.87	6,504.99	168.86	14,869.81	49.63	4,370.42
		B	2,631.00	31,282.59	2,171.00	25,813.19	1,626.00	19,333.14	4,456.00	52,981.84	1,576.00	18,738.64
		C	12.20	3,578.87	8.96	2,628.42	7.65	2,244.13	17.46	5,121.89	5.23	1,534.22
		D	12.20	593.65	8.96	435.99	7.65	372.25	17.46	849.60	5.23	254.49
		E	12.20	40.63	8.96	29.84	7.65	25.47	17.46	58.14	5.23	17.42
				988,168.37		852,281.09		723,861.37		1,937,469.70		301,465.09
Direct intervention cost				**1,182,144.34**		**1,011,878.33**		**913,458.13**		**2,214,738.86**		**377,537.57**

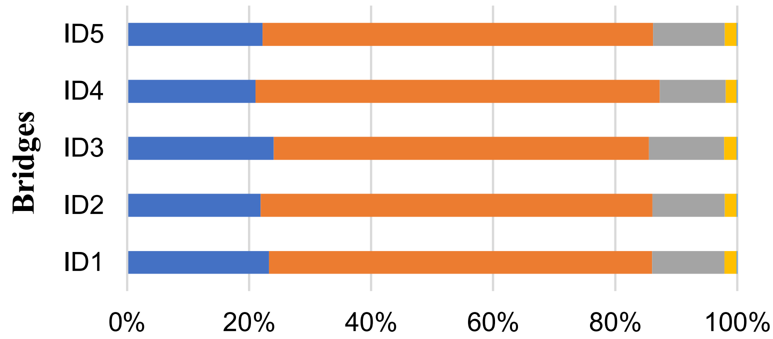
Figure 2 – Proportion of services cost in infrastructure



	ID1	ID2	ID3	ID4	ID5
A (Plywood forms)	9.67%	9.67%	6.23%	5.06%	8.74%
B (CA-50 rebar)	66.62%	66.62%	65.54%	70.83%	56.99%
C (Concrete for pumping)	20.14%	20.14%	23.98%	20.48%	29.11%
D (Mechanical pumping)	3.34%	3.34%	3.98%	3.40%	4.83%
E (Immersion vibrator)	0.23%	0.23%	0.27%	0.23%	0.33%

Proportion of total infrastructure cost

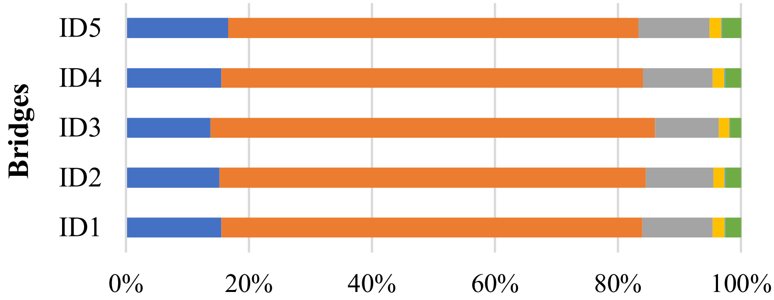
Figure 3 – Proportion of services cost in mesostructure



	ID1	ID2	ID3	ID4	ID5
A (Plywood forms)	23.23%	21.85%	24.01%	21.02%	22.18%
B (CA-50 rebar)	62.79%	64.22%	61.48%	66.28%	64.02%
C (Concrete for pumping)	11.87%	11.84%	12.32%	10.79%	11.72%
D (Mechanical pumping)	1.97%	1.96%	2.04%	1.79%	1.94%
E (Immersion vibrator)	0.13%	0.13%	0.14%	0.12%	0.13%

Proportion of total mesostructure cost

Figure 4 – Proportion of services cost in superstructure

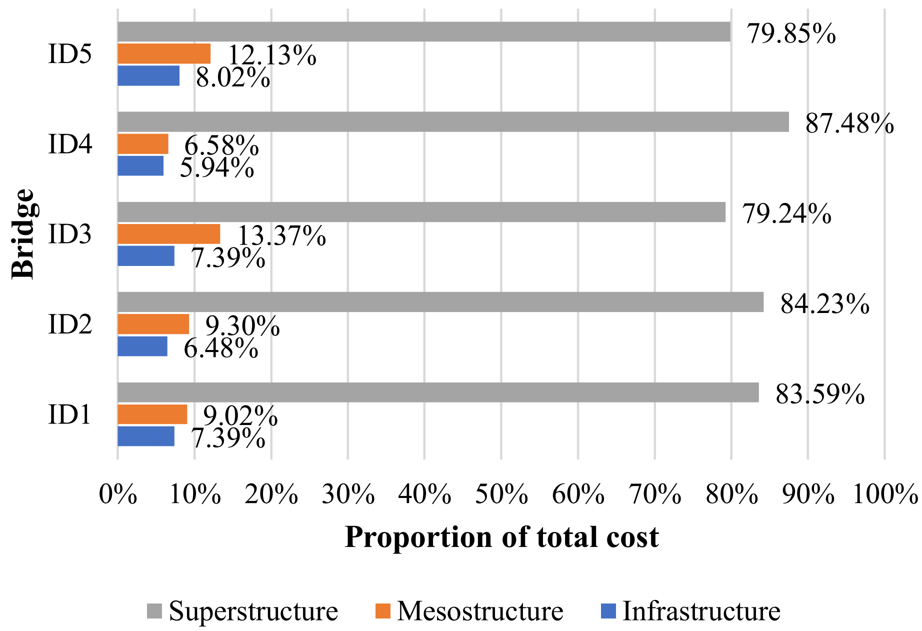


	ID1	ID2	ID3	ID4	ID5
A (Plywood forms)	15.53%	15.23%	13.72%	15.55%	16.64%
B (CA-50 rebar)	68.42%	69.30%	72.30%	68.49%	66.69%
C (Concrete for pumping)	11.45%	10.99%	10.35%	11.35%	11.56%
D (Mechanical pumping)	1.90%	1.82%	1.72%	1.88%	1.92%
E (Immersion vibrator)	0.13%	0.12%	0.12%	0.13%	0.13%
F (Wet shotcrete)	2.57%	2.54%	1.79%	2.60%	3.05%

Proportion of total superstrucutre cost

Another possible analysis is the proportion of values per set of elements concerning the total value of the preliminary cost estimation. Figure 5 shows that the costs of the superstructure elements range between 79.24% and 87.48%, indicating the high impact of these elements on the final value of the widening and strengthening for all the bridges analyzed. The costs of the mesostructure represent between 6.58% and 13.37% of the total value, and the infrastructure impacts between 5.94% and 8.02% of the final total cost.

Figure 5 – Proportion of cost per set of elements



By associating the length of the bridge with the direct cost of the services, there was a significant variation in the price per meter (R$/m) between the five bridges, with values ranging from R$ 16,065.43/m to R$ 20,344.28/m (Table 12). The Água Sumida River Bridge, with a length of 44.90 m, has the highest R$/m value, while the Jibóia River Bridge, with only 23.50 m, has the lowest value. An interesting pattern is that, although the smaller bridges tend to show higher R$/m values due to the lower dilution of fixed costs, the Jibóia River Bridge, with the shortest length in the sample, has the lowest cost per meter. This relation contradicts the expectation that shorter bridges have a higher price per meter. This deviation can be explained by factors specific to the intervention carried out on this bridge, such as the simplicity of the intervention or lower structural complexity.

On the other hand, the Água Sumida River bridge, which has an intermediate length (44.90 m), has the highest value of R$/m, which indicates that length is not always the only determining factor in this relationship. The influence of variables such as the type of intervention, previous structural conditions, and the materials used also play a significant role in the final cost.

Finally, the 128.50 m Gongogi River bridge has the lowest cost per meter among the longer bridges, suggesting that interventions on longer structures may show greater economies of scale. However, this economy was not consistently reflected among all the bridges analyzed, indicating that the R$/m parameter needs to be considered with caution and complemented with other technical and economic criteria, such as the type of intervention and the complexity of the work, before being used for direct comparisons.

Table 12 – Analysis of bridge price per meter.

Bridge ID	Bridge Name	Length (m)	Direct Intervention Cost (R$)	Price per Meter (R$/m)
1	Valentim River Bridge	65.00	1,182,144.34	18,186.84
2	Urubá II River Bridge	54.00	1,011,878.33	18,738.49
3	Água Sumida River Bridge	44.90	913,458.13	20,344.28
4	Gongogi River Bridge	128.50	2,214,738.86	17,235.32
5	Jibóia River Bridge	23.50	377,537.57	16,065.43

6. Research limitations

This study has some limitations that should be considered when interpreting the results and applying the findings to other contexts:

- The study analyzed only five bridges with similar geometric characteristics and the same mesostructure typology. Although this approach allowed for a detailed and controlled analysis, the limited sample reduces the representativeness of the results. It may restrict the applicability of the parametric models developed to other bridges with different structural characteristics and located in varied contexts.

- The widening and strengthening solutions considered in this study were similar in all the cases analyzed, reflecting the designs available for the selected bridges. This uniformity limits the ability to generalize the parametric models for interventions involving different strengthening techniques or construction methods.
- The estimates developed do not include transportation costs for the inputs to the intervention sites nor the associated indirect costs, such as administrative and managerial expenses and unforeseen risks during the execution of the works. This omission could result in cost underestimates in different scenarios applications.
- The bridges selected for the study are located in the same region of the country and were designed for specific load classes (design-vehicle). Therefore, the parametric models developed may not directly apply to bridges in other regions, designed for different design classes, or requiring other interventions.
- Limited access to detailed project data restricted the scope of the study to available bridges with complete documentation. This restriction suggests the need to broaden the database for future research to validate and adjust the models developed for a more diverse range of structural configurations and operational contexts.

Given the preliminary nature of this study, it is crucial to exercise caution when extrapolating the results to other scenarios. Future studies should consider a more diverse sample of bridges and incorporate additional variables to increase the robustness and applicability of the proposed parametric models.

7. Conclusions

The analysis of the five bridges revealed uniformity in the mesostructure typology, featuring new lines of columns, brackets, and reinforcement of hexagonal reinforced concrete columns. Following jacketing, the hexagonal columns transitioned to circular. While geometry and specific parameters varied based on terrain topography and bridge length, coefficients, such as plywood form area per volume of concrete, remained constant across designs.

Superstructure widening and reinforcement designs followed a general structural solution, including deck widening, introduction of new girders, reinforcement of existing girders, and extension of crossbeams. Although these structural elements varied in specific details like concrete volume and steel rate, they were standardized in terms of basic dimensions and proportions. Initial bridge widths ranged from 9.55 m to 10.05 m, all widened to 13.00 m, with deck extension varying from 6.5 m to 7.23 m.

Variations in dimensions and parameters of reinforced elements reflect necessary adaptations to meet each bridge's specific conditions, such as girder height and the ratio of bridge length to span and support zones. Uniformity in coefficients used for plywood forms and concrete volume suggests an effort to maintain efficiency and consistency in material application, regardless of individual design variations. In summary, the analysis indicates that, although there are variations in dimensions and specific details due to the unique site characteristics, there has been a standardized and efficient approach to the use of materials and the execution of structural reinforcement, ensuring the robustness and durability of the reinforced bridges.

Analyzing the costs of essential services for bridge reinforcement and widening in Bahia state, as specified in the January 2024 SICRO report, reveals crucial insights into the distribution and financial impact of structural elements. Each service was identified with a specific ID, SICRO code, description, unit of measurement, and unit cost, allowing a detailed assessment of costs associated with each set of bridge elements.

Results show that the superstructure has the highest impact on the direct design cost, accounting for between 79.24% and 87.48% of the total value of the analyzed bridges. This underscores the significant influence of superstructure components, such as girders and crossbeams, on the final cost. The mesostructure and infrastructure contribute less to the direct cost, with the mesostructure ranging from 6.58% to 13.37% and the infrastructure from 5.94% to 8.02%.

Among services, CA-50 rebar stands out as the most financially impactful item across all sets of elements, followed by concrete in the infrastructure. Plywood forms in the mesostructures and superstructures prove more expensive than concrete. Although shotcrete has a high unit cost, its usage volume is low, affecting the direct cost less.

In conclusion, financial planning for bridge reinforcement and widening designs should particularly focus on the superstructure, given its significant impact on the final cost. Standardization of certain elements can contribute to economic efficiency, while variation in costs per meter underscores the importance of considering the specificities of each bridge when developing cost estimation and execution plans.

This study makes a valuable contribution by highlighting the applicability of parameterization methodologies for preliminary estimates in bridge strengthening and widening projects. The standardization observed in the application of materials and structural solutions suggests that parametric models can assist in planning and decision-making, particularly in preliminary phases, before preparing the detailed budget. This approach can be advantageous for optimizing resources and offering more agile cost forecasts for projects with similar characteristics.

However, it is essential to recognize that the applicability of parameterization must be analyzed on a case-by-case basis, especially for bridges with geometric or structural conditions different from those examined in this study. Furthermore, employing parametric models as a complement to the usual budgeting process requires the integration of regional variables, such as logistical and indirect costs, which were not considered in this analysis.

Future research should explore broader and more diverse samples of bridges, incorporating different structural configurations and geographical regions. In addition, it is recommended to include indirect costs and other regional factors that may impact the estimates. The validation of parametric models in more varied contexts could confirm their effectiveness and generate more comprehensive recommendations for their application on a national scale. In addition, new digital tools, integrated with bridge management systems, could facilitate data collection and analysis, further improving the accuracy of preliminary estimates.

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CHAPTER IV

Challenges in parameterizing maintenance service quantities and damage data for preliminary budgeting in bridge interventions

Abstract

The growing demand for bridge interventions due to structural deterioration and increased traffic loads highlights the need for efficient preliminary budgeting methods. This study investigates the challenges in parameterizing damage information and maintenance service quantities to support early-stage budgeting decisions in bridge interventions. A dataset of real maintenance actions from highway bridges was analyzed to explore the feasibility of using simplified parametric models based on multiplicative coefficients. While the proposed method allows for rapid estimation of service quantities using readily available data, the results reveal significant limitations in predictive accuracy, particularly across different service types and contexts. Issues related to data variability, scale sensitivity, and model generalization are discussed. The study does not intend to replace traditional budgeting methods but to contribute insights into the potential and constraints of using parametric modeling as a decision-support tool in bridge management practices. Future research should focus on enhancing model robustness and integrating such approaches into digital asset management platforms.

Keywords: Parametrization. Inspection data. Damage. Bridge. Maintenance interventions. Repair services.

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1. Introduction

Inspection and assessment activities are crucial to ensure functionality, operability, and user safety in bridge structures. However, traditional inspection techniques, which rely on visual and manual assessments, face significant limitations, such as subjectivity in data collection, delay in the process, and difficulty correlating observed damage with necessary interventions (Marzouk & Hisham, 2012; McGuire et al., 2016; Moufti et al., 2014; Phares et al., 2004; Wojcik & Zarski, 2020). These challenges hinder the effectiveness of maintenance planning and resource allocation, particularly in regions with extensive and diverse infrastructure networks, such as Brazil. In this context, structuring and parameterizing inspection data emerges as a critical step to improve consistency and support maintenance decision-making.

Reinforced concrete structures suffer degradation over time due to exposure to various factors, including chemical agents, physical stresses, and biological influences (DNIT, 2010; Helene, 2005; von Fay, 2015). Corrosion of reinforcement is one of the most recurrent damages, leading to subsequent physical effects such as cracking, exfoliation, and concrete delamination. This damage compromises structural integrity and increases the need for precise, scheduled interventions (Bolar et al., 2013; Cadenazzi et al., 2020; Moufti et al., 2014; Omar et al., 2017).

The bridge inspection process often fails to ensure consistency and accuracy in damage documentation, resulting in uncertainties in the maintenance and repair processes (Al-Shalabi et al., 2015; Bianchi et al., 2023; Bolar et al., 2013). Parametric modeling is an effective solution for structuring and standardizing inspection data, allowing quick and consistent changes to information and facilitating the reuse of models (Xu et al., 2022). However, parameterizing damage in a way that enables it to be effectively and automatically associated with repair interventions remains a complex task, requiring detailed semantic and geometric information that often varies across cases. Parameterizing geometric and semantic damage data can reduce information loss and increase accuracy in documentation and intervention planning (Artus & Koch, 2020, 2022; Hüthwohl et al., 2018).

Although several researchers have studied the structuring of damage data for implementation in the Industry Foundation Classes (IFC) schema and its integration into Building Information Modeling (BIM) models (Artus et al., 2022; Artus & Koch, 2022; Hüthwohl et al., 2018; Isailović et al., 2020; Sacks et al., 2018; Xu et al., 2022), there is still a gap when it comes to automated correlation between damage types and the necessary maintenance interventions. Most studies approach defect parameterization in isolation, without linking this data directly to repair services, which limits its applicability in intervention planning.

This study presents a methodology to parameterize the semantic and geometric information of damage identified during inspections of reinforced concrete bridges based on a database of bridges inspected in Brazil. The primary contribution of this research lies in linking parameterized damage to corresponding repair interventions. This association enables more precise estimates of the quantities of materials and services required for maintenance, streamlining the preparation of preliminary budgets and maintenance plans. By automating this correlation, the proposed approach introduces an innovative solution for bridge maintenance management, enhancing the accuracy of repair estimates and supporting faster, more informed decision-making.

2. Literature review

2.1 Parameterization of bridge defects

Damage parameterization in bridges is essential in maintenance management. It allows defect identification and characterization based on semantic information and geometric data. It includes location, extent, and severity—essential to planning corrective measures and optimizing resource allocation. Several studies have addressed the need to categorize and parameterize structural damage, such as cracks, efflorescence, concrete spalling, and reinforcement corrosion (Artus & Koch, 2020, 2022; Hüthwohl et al., 2018; Sacks et al., 2018; Xu et al., 2022).

Sacks et al. (2018) proposed a data model that classifies common defects and enables integration with BIM platforms, improving condition assessment. Hüthwohl et al. (2018) incorporated damage data into the IFC schema, promoting standardized information exchange and reuse across stakeholders. Artus et al. (2022) introduced an object-oriented model that supports structured collection and digital management of damage information. Their approach enhances inspection efficiency but highlights ongoing challenges in fully implementing standards in current software tools.

Xu et al. (2022) proposed a methodology for modeling bridge defects, identifying critical parameters such as cracks, delamination, spalling, honeycombing, and abrasion. The study suggests using these parameters to improve the accuracy of damage assessment and support informed decisions when planning maintenance interventions. However, their model focuses on defect characterization without establishing a direct link to specific repair actions, which limits its use in planning.

These studies highlight the relevance of a well-defined parametric model to capture the essential characteristics of damage and correlate them directly with the interventions required. While previous studies have focused mainly on the categorization and parameterization of defects, the methodology proposed in this study fills this gap by automating the correlation between inspection data and repair services, enabling precise service quantification and facilitating preliminary budgeting. It represents a significant advancement by integrating damage assessment and intervention planning into a unified framework.

2.2 Parametric estimation technique

Parametric cost estimating is widely used in construction projects for bidding, cost-benefit analysis, and pre-planning phases. According to Kwak and Watson (2005), this technique enhances decision-making in technology-driven environments by using independent variables—such as functional and geometric attributes—to predict project outcomes. Integrating it into systems such as BIM or bridge management systems (BMS) combines historical data with model-based logic to improve forecasting and simplify pre-planning processes (Mandolini et al., 2024).

Developing parametric models typically involves identifying relevant variables, collecting structured historical data, and applying statistical or machine learning methods such as multivariate regression and factor analysis. Trost and Oberlender (2003) demonstrated that such techniques can improve the reliability of early-stage cost estimates by reducing subjectivity and supporting repeatability in complex engineering projects.

In this study, parametric estimation is adapted to the context of bridge maintenance by correlating specific types of structural damage with the quantities of required services. Rather than estimating costs directly, the methodology focuses on quantifying interventions based on damage characteristics, allowing for more accurate planning and resource allocation. This approach promotes greater automation and standardization in maintenance management and supports preliminary budgeting in bridge intervention planning.

3. Research Methodology

3.1 Data Collection and Analysis

The dataset used in this study comprises 515 bridges managed by the Brazilian National Department of Transport Infrastructure (DNIT), all of which were analyzed under the Program for Maintenance and Rehabilitation of Structures (PROARTE). These bridges include detailed records of visual inspections and work plans with estimated service quantities and costs.

To ensure representativeness, the sample covers bridges from all five Brazilian regions—Northeast, Southeast, North, South, and Midwest—and a wide range of structural lengths classified into small, medium, and large categories. This diversity in geographic distribution and structural characteristics reflects the heterogeneity of the national bridge network and provides a solid foundation for analyzing damage-service relationships. A summary of regional and dimensional classifications is presented in Table 1 and Table 2.

Table 1. Categorization of bridges by region.

Region	Sample universe	Percentage (%)
Northeast	177	34.37
Southeast	94	18.25
North	93	18.06
South	101	19.61
Midwest	50	9.71

Table 2. Categorization of bridges by longitudinal extent.

Longitudinal extent	Sample universe	Percentage (%)
Small bridge: ≤ 30,0 m	228	44.27
Medium bridge: 30,0 - 80,0 m	204	39.61
Large bridge: > 80,0 m	83	16.12

All bridges in the dataset have documented damages based on routine visual inspections. Condition ratings follow the Brazilian standards (NBR 9452 (ABNT, 2019) and DNIT 010/2004 – PRO (DNIT, 2004)), using a 1-to-5 scale. The majority of bridges were classified as being in good to fair condition (grades 4 and 3), while approximately 22.5% received grades 2 or 1, indicating more critical maintenance needs. These condition grades were used to help guide the prioritization of services in the parametric modeling process.

3.2 Parametric Models and Damage-Intervention Association

Building on methodologies proposed by Martins et al. (2023), this study refines the parameterization of recurrent bridge damages and their associated maintenance interventions using a national dataset of 515 bridges. The objective was to develop parametric models capable of standardizing damage data from inspections and linking them to typical repair services through adjustment coefficients.

Key input parameters—length, width, and depth—were defined for each damage type (e.g., cracks, spalling, and efflorescence), standardizing data collection and enabling automated repair quantification. This enabled the establishment of associations between damage characteristics and corresponding maintenance services. For example, superficial damage like damp patches and efflorescence is typically treated with surface cleaning and protective coating, whereas cracks may require structural adhesive injection.

In more complex cases, the type and extent of the intervention also depend on contextual factors, such as the structural element affected and whether there is a loss of reinforcement. To address this, simplified correlation diagrams were developed to represent service-decision logic, aiding in the interpretation of typical scenarios observed in the dataset (Figure 1 and Figure 2).

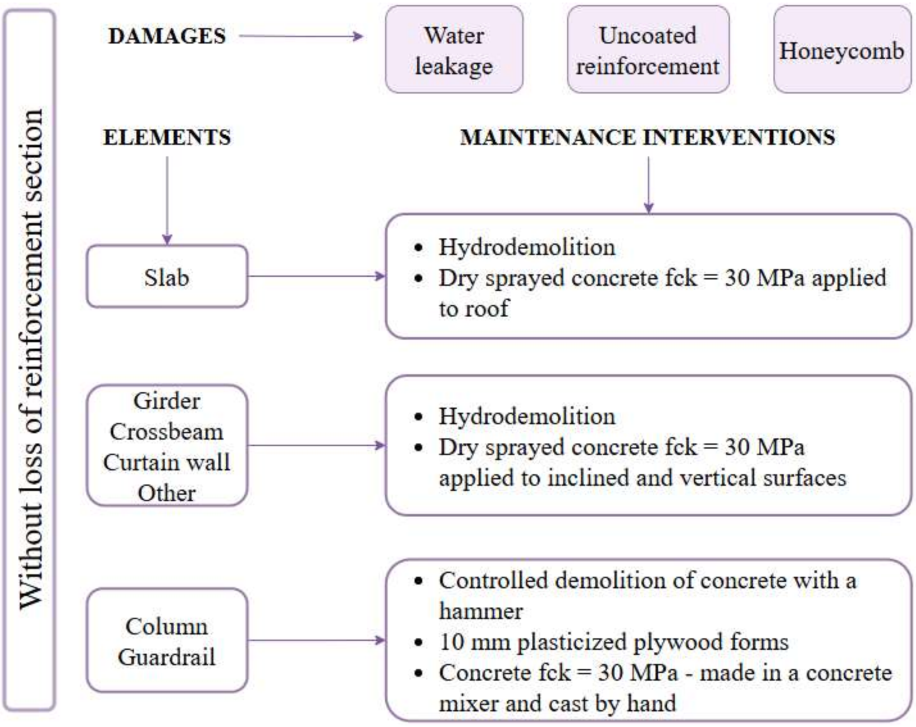

Figure 1. Diagram to maintenance intervention without loss of reinforcement section.

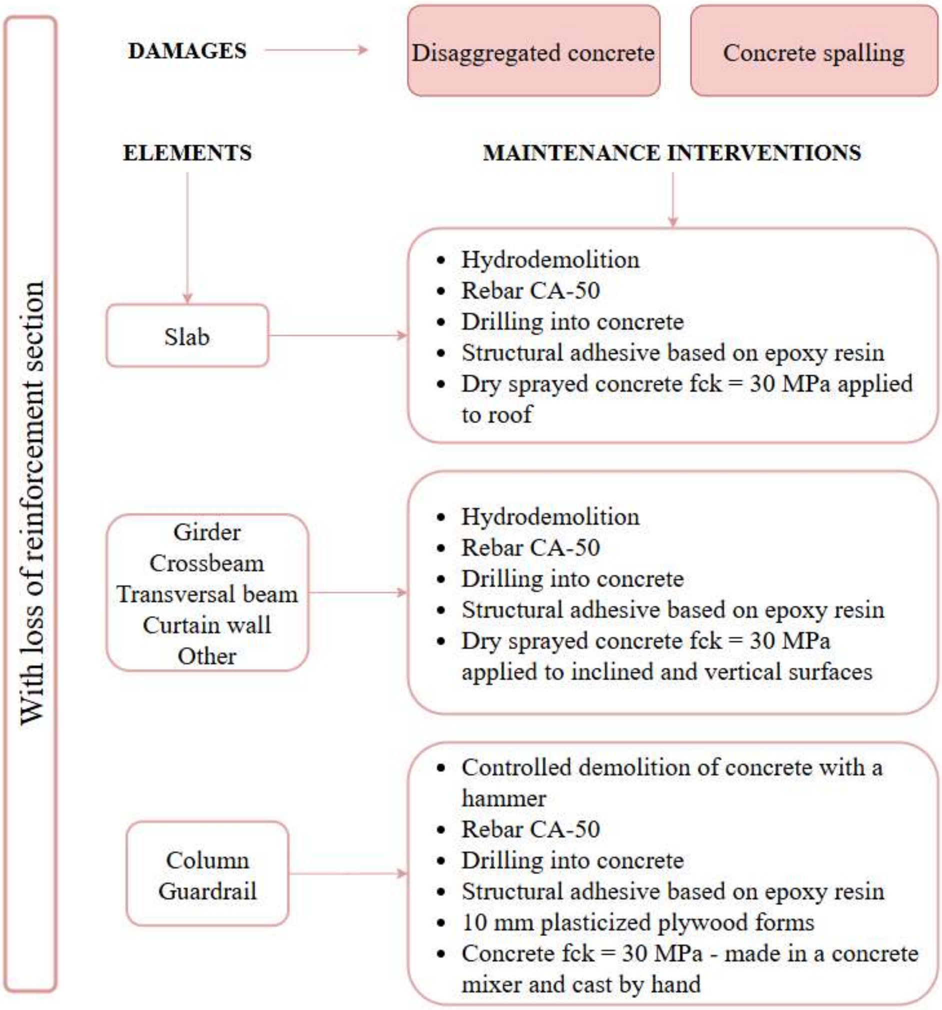

Figure 2. Diagram to maintenance intervention with loss of reinforcement section.

Parametric models were created to estimate service quantities based on these associations. The models use standardized geometric parameters the user o provided or obtained from inspection records. A summary of the equations and default values used is presented in Table 3. The CA-50 nomenclature is a Brazilian notation for steel rebar with a characteristic strength of 500 MPa. Certain services, such as rebar placement, concrete drilling, and structural adhesive, depend on detailed inputs (e.g., bar diameter, spacing) that were not consistently reported in the dataset. To overcome this, average ratios were calculated based on the damage area, allowing standardization. For instance, 1.0 kg of CA-50 steel per square meter of related damage was adopted as a base coefficient based on patterns observed across hundreds of bridges.

Table 3. Models for quantitative maintenance services

Service	Input parameters (related with the damages)	Calculate service quantity
Concrete surface cleaning Manual painting	Length (m): Provided by the user Width (m): Provided by the user	**Cleaning/Painting (m^2) =** Length (m) × Width (m)
Crack injection	Length (m): Provided by the user Width (m): 0.05 (default) Depth (m): 0.005 (default)	[1]**Crack injection (kg) =** Length (m) × Width (m) × Depth (m) × 1000 × 1.5 (kg/l) Crack injection (kg) = 0.375 x Length (m)
Hydrodemolition Controlled demolition	Length (m): Provided by the user Width (m): Provided by the user Depth (m): 0.03 (default value)	**Hydrodemolition/Controlled demolition (m^3) =** Length (m) x Width (m) x 0.03 (m)
Plywood forms	Perimeter (m): Provided by the user Height (m): Provided by the user	**Plywood forms (m^2) =** Perimeter (m) x Height (m)
Rebar CA-50	Ø: Provided by the user (mm) Length (m): Provided by the user Quantity (unit): Provided by the user	**Rebar CA-50 (kg) =** [($Ø^2$/1000 x π/4) x 7850] x Length (m) x Quantity (unit)
Mixer Concrete Dry sprayed concrete	Length (m): Provided by the user Width (m): Provided by the user Depth (m): 0.05 (default value)	**Mixer Concrete/Dry sprayed concrete (m^3) =** Length (m) x Width (m) x 0.05 (m)
Concrete Drilling	Quantity (unit): Provided by the user Extension (m): Provided by the user	**Concrete Drilling (m) =** Quantity (unit) x Extension (m)
Structural adhesive	Rebar Length (m): Provided by the user	**Structural adhesive (kg) =** Rebar Length (m) x [(π x $0{,}02^2$)/4] x 1.2 (kg/l)

[1]1000 = Conversion factor from cubic meters to liters; 1.5 = density of the epoxy resin (kg/l)

This variation can be attributed to several factors, including the specific characteristics of each structure, the severity and extent of the identified damage, and whether structural reinforcement is required. Additionally, some maintenance activities—such as sidewalk repairs or the complete restoration of a beam—may not be directly related to the observed damage but are executed concurrently, influencing material consumption. These context-dependent decisions lead to fluctuations in the amount of steel used per damaged area. Therefore, the simplifications adopted in the parametric models reflect typical variations in real-world conditions and the influence of project-specific maintenance strategies.

3.3 Data Extraction and Adjustment Coefficient Calculation

The proposed methodology aims to support bridge maintenance planning by estimating service quantities based on damage characteristics obtained from inspection data. To achieve this, a dataset of 515 bridges was processed to identify recurring damage-service relationships, which were then used to develop parametric estimation equations.

3.3.1 Calibration and Validation Strategy

The dataset was randomly divided into a calibration set (80%) and a validation set (20%), following established practices in statistical modeling and machine learning. This division ensured that the models were trained and tested on independent subsets, improving generalizability and avoiding overfitting.

3.3.2 Development of Parametric Equations

Equations were defined to estimate the quantities of maintenance services required based on the extent of damage. These equations were then applied to the calibration set, and the predicted values were compared to the actual quantities specified in work plans and budgets. The discrepancies between predicted and actual values informed the computation of adjustment coefficients to refine the estimates.

3.3.3 Adjustment Coefficient Analysis

To align the base estimation equations with the actual service quantities observed in the dataset, an adjustment coefficient (C_{Adj}) was calculated for each damage-service pair. This coefficient corresponds to the ratio between the value recorded in the work plan and the quantity predicted by the parametric model, as expressed in Equation (1).

$$C_{Adj} = \frac{Work\ Plan\ Service\ Quantity}{Predicted\ Service\ Quantity} \tag{1}$$

While this approach is based on a single multiplicative factor per service type, it was selected due to the limitations of available data, which lacked detailed descriptors such as structural element dimensions, reinforcement specifications, and contextual variables that would allow for more complex modeling. Given these constraints, the adjustment coefficient is a practical way of reducing systematic discrepancies between observed and predicted values.

It is important to note that this methodology aims to be an initial approximation of the baseline to support budgeting at an early stage. Although simplistic, using a single coefficient provides a replicable framework for incorporating inspection data into preliminary estimation routines. Future studies should explore more robust modeling strategies, including multivariate regression or supervised learning techniques, to increase accuracy and generalizability.

3.3.3.1 Outlier Detection and Filtering

To ensure robust calibration, outliers were identified and removed using three statistical techniques:

- Tukey's Method (IQR-Based Outlier Detection): The interquartile range (IQR) method was applied to detect values beyond 1.5xIQR from Q1 or Q3;
- Z-Score analysis, flagging values beyond ±3 standard deviations;
- Local Outlier Factor (LOF), a density-based algorithm used to detect anomalous data points.

These steps helped reduce distortion caused by extreme cases and enhanced the consistency of coefficient calibration.

3.3.3.2 Optimization of Adjustment Coefficients

To improve model accuracy, the adjustment coefficients were optimized using the Optuna framework, a machine learning-based hyperparameter optimization tool. The objective function minimized the Mean Absolute Error (MAE) between predicted and observed service quantities. A search space was defined for each coefficient, and Optuna iteratively identified the optimal values over multiple trials.

3.3.4 Model Validation and Performance Metrics

The optimized coefficients were applied to the validation set to evaluate model accuracy. Three metrics were used:

- MAE (Mean Absolute Error): measures average absolute deviation;
- RMSE (Root Mean Square Error): emphasizes larger errors;
- R^2 (Coefficient of Determination): indicates model fit.

These metrics provided a quantitative evaluation of the model's ability to translate damage data into service quantity estimates. Despite the simplicity of the approach, the results serve as a foundation for further refinement and integration into bridge maintenance workflows.

4. Results

4.1 Adjustment coefficients

This section presents the adjustment coefficients (CAdj) obtained through calibration with a reference dataset. The objective was to evaluate the consistency between the quantities estimated by simplified parametric models and those observed in actual interventions. The optimization process was conducted using the Optuna framework, which identified the coefficient values that minimized the Mean Absolute Error (MAE). Table 4 summarizes the results of this calibration.

Table 4. Adjustment Coefficients and Accuracy with OPTUNA.

Services	**C_{Adj}**	**MAE**	**Linear regression coefficient**
Crack injection	1.12	1.09	0.27
Hydrodemolition	0.63	0.31	0.79
Controlled demolition	2.16	0.22	2.97
Plywood forms	1.23	1.24	1.08
Rebar CA-50	1.22	41.08	2.69
Mixer Concrete	2.23	0.21	2.18
Dry sprayed concrete (ceiling)	0.66	0.53	0.48
Dry sprayed concrete (inclined surface)	0.18	0.20	0.04
Concrete Drilling	1.29	1.2	0.38
Structural adhesive	0.53	1.73	0.29

C_{Adj} (Adjustment Coefficient): Represents the efficiency of the adjustment for the service analyzed. Values close to 1 indicate a balanced adjustment.
MAE (Mean Absolute Error): Measures the accuracy of the fit. Lower values indicate greater precision.
Linear Regression Coefficient: Represents the relationship between estimated and actual values. Positive values indicate a direct correlation, while negative values indicate significant discrepancies.
OPTUNA Optimization: was used to optimize the adjustment coefficients, maximizing the accuracy of the estimates (MAE) while adjusting the C_{Adj}. The methodology applied offers a more reliable model for predicting the costs of interventions, enabling a more efficient and informed analysis.

The values of CAdj indicate the extent to which model predictions align with field data. A coefficient close to 1.00 suggests a good agreement between estimated and observed quantities. Deviations from this value reflect either underestimation (CAdj > 1) or overestimation (CAdj < 1) by the model. Notably, services such as controlled demolition (CAdj = 2.16) and mixer concrete (CAdj = 2.23) presented values significantly higher than 1, indicating that the actual quantities used on site were more than double those predicted. These discrepancies may result from factors not captured in the parametric model, such as unforeseen construction challenges or inefficiencies during execution.

Conversely, services such as dry sprayed concrete on inclined surfaces (CAdj = 0.18) and structural adhesive (CAdj = 0.53) exhibited much lower-than-expected quantities. This may be attributed to limited use in practice, conservative modeling assumptions, or restricted application areas in the case studies. These results suggest the need for further refinement of the predictive parameters for these services or for incorporating additional explanatory variables into the models.

The MAE values offer an additional layer of interpretation regarding prediction accuracy. Services such as mixer concrete (MAE = 0.21) and controlled demolition (MAE = 0.22) show high adjustment coefficients and low error rates, indicating that the model consistently accounted for the observed deviations. On the other hand, rebar CA-50 (MAE =

41.08) exhibited substantial prediction error, indicating poor model performance for this service.

An analysis of one specific case highlights this issue: for a bridge located in the Southeast region, the model estimated only 7.52 kg of rebar CA-50, whereas the actual work plan specified 200 kg. The inspection report revealed minimal damage directly associated with the reinforcement, but significant deterioration of the guardrails, which likely required a large volume of additional steel. This suggests that the current model does not fully capture certain types of demand that emerge from structural components not directly linked to the quantified damage.

Despite some high MAE values, several services presented reasonably accurate results with moderate adjustment coefficients, such as crack injection (CAdj = 1.12, MAE = 1.09), plywood forms (CAdj = 1.23, MAE = 1.24), and concrete drilling (CAdj = 1.29, MAE = 1.20). These results indicate an acceptable level of predictive performance, although further calibration may improve precision. Additionally, hydrodemolition (CAdj = 0.63, MAE = 0.31) stands out for achieving a low MAE despite a moderate deviation coefficient. This result highlights the capacity of the optimization method to handle services with higher variability in usage while still producing reliable estimates.

In summary, the Optuna-based calibration approach allowed the identification of service-specific adjustment coefficients that enhance the reliability of the proposed parametric models. While some services require further refinement, the methodology demonstrated robustness in adapting to different material and service consumption. These findings reinforce the potential of this approach as a decision-support tool during the early stages of budgeting and planning in bridge management systems.

4.2 Validation of the coefficients

Table 5 presents the validation results for the predictive model, including MAE, RMSE, R^2, and the linear regression coefficient for each maintenance service.

Among the services analyzed, crack injection demonstrated the best overall performance, with low error metrics (MAE = 0.3, RMSE = 0.43) and a high R^2 value (0.91), indicating strong model reliability. The linear regression coefficient of 0.91 confirms the close alignment between predicted and actual quantities. Dry sprayed concrete (inclined surface) also performed well, with low MAE (0.19) and a high regression coefficient (2.42), despite a slightly negative R^2 (-0.11), suggesting that while absolute predictions were close to actual values, the model explained little of the variance.

Table 5. Metric Analysis Validation Results.

Service	**Metrics Analysis**			
	MAE	RMSE	R^2	Linear regression coefficient
Crack injection	0.3	0.43	0.91	0.91
Hydrodemolition	0.27	0.46	-0.09	0.46
Controlled demolition	0.12	0.18	-0.35	0.24
Plywood forms	4.61	5.91	-1.0	-0.19
Rebar CA-50	43.61	89.28	-0.17	4.75
Mixer Concrete	0.45	0.74	-0.37	-0.05
Dry sprayed concrete (ceiling)	0.35	0.61	-0.04	1.20
Dry sprayed concrete (inclined surface)	0.19	0.37	-0.11	2.42
Concrete Drilling	0.72	1.06	0.02	0.98
Structural adhesive	1.23	1.64	-1.17	0.12

MAE (Mean Absolute Error): The average of the absolute differences between the predicted and observed values.
RMSE (Root Mean Square Error): The square root of the average of squared differences between predictions and observations, more sensitive to large errors.
R^2 (Coefficient of Determination): Indicates the proportion of variance in the observed data explained by the model. Negative values suggest the model performs worse than a simple mean.
Linear Regression Coefficient: Represents the relationship between estimated and actual values. Positive values indicate a direct correlation, while negative values indicate significant discrepancies.

On the other hand, services such as plywood forms and rebar CA-50 showed the weakest performance. Plywood forms had the most negative R^2 (-1.0) and a negative regression coefficient (-0.19), indicating a poor fit and an inverse relationship between predictions and actual values. Rebar CA-50 exhibited similar issues, with a high MAE (43.61), high RMSE (89.28), and a regression coefficient of 4.75, which suggests overestimation and poor generalizability.

Other services, including hydrodemolition, controlled demolition, and mixer concrete, had moderate errors and negative R^2 values, indicating that the model predictions are close in absolute terms but fail to capture data variability. Regression coefficients for these services remained low, reflecting weak predictive alignment. Finally, concrete drilling and dry sprayed concrete (ceiling) showed balanced results, with moderate errors and near-zero or slightly negative R^2, but high regression coefficients (0.98 and 1.20, respectively), suggesting reliable proportionality between predicted and observed values.

In summary, the model's performance varied significantly across different services. The most accurate predictions were observed for services directly related to quantifiable pathological manifestations, such as crack injection. In contrast, the poorest results were associated with services heavily influenced by contextual factors or design decisions, such as plywood formwork and rebar CA-50. These discrepancies indicate that while the model performs well for services linked to objective inspection data, its predictive capacity is limited for services whose execution depends on site-specific adaptations, construction strategies, or design adjustments not accounted for in the initial parameters.

4.3 Impact of Error on Cost Estimates in Analysis

This section evaluates how errors in estimated quantities affect the preliminary budgeting of bridge maintenance interventions. The analysis is based on the Mean Absolute Error (MAE), which quantifies the discrepancy between the model's predictions and the quantities defined in the work plans. To assess the financial relevance of these errors, average unit costs (R$/unit) were applied to each service, reflecting standard market prices. Additionally, the contribution (%) of each service to the overall financial impact was calculated to identify those with the highest influence on the total budget.

By linking estimation errors with monetary values, this analysis enables a more comprehensive understanding of their consequences on financial planning. It supports prioritizing model refinements, particularly for services that exhibit large prediction errors or have high unit costs. Table 6 presents the results of this analysis.

Table 6. Analysis of the Influence of Error on Costs per Service.

Service	**MAE**	**Mean Unit Cost (R$/unit)**	**Financial Impact (R$)**	**Contribution (%)**
Crack injection	0.30	376.45	112.93	4.32
Hydrodemolition	0.27	485.48	131.08	5.02
Controlled demolition	0.12	750.45	90.05	3.45
Plywood forms	4.61	88.40	407.52	15.61
Rebar CA-50	43.61	13.48	587.86	22.51
Mixer Concrete	0.45	491.89	221.35	8.48
Dry sprayed concrete (ceiling)	0.35	1783.21	624.12	23.9
Dry sprayed concrete (inclined surface)	0.19	1249.88	237.48	9.09
Concrete Drilling	0.72	161.45	116.24	4.51
Structural adhesive	1.23	67.26	82.73	3.17

The analysis reveals two critical dimensions of financial impact: estimation variance (MAE) and unit cost. For example, Rebar CA-50, despite its low unit cost (R$13.48), registers the highest MAE (43.61), resulting in a substantial financial impact of R$587.86—approximately 22.51% of the total error-related costs. This highlights the necessity of refining the model's predictive performance for services with large quantity variability, even when their unit costs are low. Conversely, dry sprayed concrete (ceiling) demonstrates the opposite case: a relatively low MAE (0.35) but an exceptionally high unit cost (R$1783.21), leading to the largest financial impact of R$624.12 and a 23.90% contribution. This finding underscores the importance of ensuring high estimation precision for high-cost services, as even small deviations can lead to significant budget distortions.

Plywood forms and mixer concrete also emerged as influential services, contributing 15.61% and 8.48%, respectively. While their MAEs are moderate, their cumulative financial influence is considerable, emphasizing the need for targeted model adjustments. Other services, such as hydrodemolition, controlled demolition, and concrete drilling, showed lower contributions to total costs (ranging from 3.45% to 5.02%), yet still warrant attention. Though individually less impactful, the collective influence of these mid-tier services may become significant in large-scale interventions.

In summary, services characterized by high quantity variation (e.g., Rebar CA-50) or elevated unit prices (e.g., dry sprayed concrete) must be prioritized in model refinements to enhance the accuracy of cost predictions. Improving the parametric model's performance for these services is essential for optimizing resource allocation, preventing budget overruns, and increasing stakeholder confidence in early-stage cost estimates.

5. Discussion

Damage parameterization and its association with maintenance services play a key role in the preliminary cost planning of bridge management systems. The analysis conducted in this study demonstrates that parametric models can effectively predict quantities for various maintenance services, providing a solid foundation for early-stage budgeting.

Services such as hydrodemolition (MAE = 0.27) and crack injection (MAE = 0.30) achieved high levels of accuracy, indicating that the proposed parametric modeling approach performs well in managing the uncertainty inherent to the early phases of infrastructure projects. These outcomes validate the practical potential of the model for supporting preliminary budgeting efforts in bridge maintenance.

In contrast, some services—particularly rebar CA-50 (MAE = 43.61)—exhibited substantial estimation errors, aligning with the challenges described in the literature (AACE, 2004; Elmousalami, 2019, 2020). Despite its relatively low unit cost, this service accounted for a significant share of the total financial impact (22.51%), due to the high variability in estimated quantities. This result highlights the importance of refining the parameterization for services characterized by large quantity deviations, which may stem from modeling limitations or the complexity of associating such services with direct damage parameters.

Furthermore, the influence of estimation errors on financial planning is not solely linked to the magnitude of the error. For instance, dry sprayed concrete (ceiling) showed a relatively low MAE of 0.35, yet due to its high unit cost (R$1,783.21), it had the highest financial impact (R$624.12) and contributed 23.9% to overall budget distortion. This finding reinforces the need for precise modeling of high-cost services, as even small discrepancies can result in significant budget implications.

These findings are consistent with the cost estimation ranges defined by the AACE (2004), where for Class 5 estimates (conceptual screening level), the acceptable margin of error ranges from -50% to +100%, and for Class 4 estimates (feasibility studies), it ranges from -30% to +50%. The results for several services in this study fall well within these bounds, supporting the use of parametric models in early decision-making processes.

Parametric modeling proves advantageous by establishing direct links between cost-related predictors—such as physical dimensions and material specifications—and the expected service quantities. Compared to analogy-based or capacity factor methods, this approach allows for greater consistency and detail. However, the reliability of the model is still dependent on data availability and the adequacy of predictor selection. The results of this study, such as those obtained for hydrodemolition and sprayed concrete services, demonstrate that the proposed approach meets or exceeds these margins of accuracy in specific services, even in scenarios of high uncertainty. This accuracy is essential, as strategic decisions on feasibility and planning depend directly on the reliability of estimates at the early stages of the project (AACE, 2004; Elmousalami, 2019, 2020).

In summary, the analysis confirms that parametric models can serve as a powerful tool for early cost planning, particularly when supported by well-structured data and continuous validation. Services with either high unit costs or high quantity variability should be prioritized for model refinement, ensuring that cost forecasts remain reliable and useful for decision-makers.

To further enhance the predictive performance of the models, future studies should consider adopting multivariate regression techniques or machine learning approaches. Additional explanatory variables such as damage severity level, environmental exposure class, and material characteristics could allow more precise differentiation between intervention needs. For services with high variability, such as CA-50 reinforcement, these advanced modeling strategies may significantly improve the robustness and generalizability of the predictions. Moreover, leveraging larger and more detailed historical datasets will be key to training and validating more sophisticated models capable of capturing the complexity of bridge maintenance interventions.

6. Conclusions

This study developed and validated an innovative methodology for parameterizing damage information in reinforced concrete bridges, establishing direct and automated correlations with the necessary maintenance services. Applying this approach to 515 Brazilian bridges demonstrated the feasibility of accurately quantifying services, especially interventions such as hydrodemolition (MAE = 0.27) and crack injection (MAE = 0.30), which exhibited high predictive performance in the analysis.

Although the methodology yielded promising results, it is important to emphasize that it is intended primarily as a preliminary screening tool to support early budgeting decisions. It does not aim to replace detailed budgeting procedures that require comprehensive field investigations, refined damage characterization, and full design specifications.

In contrast, services such as plywood forms and rebar CA-50 showed considerable variability, with mean absolute errors exceeding 40, highlighting specific challenges in modeling these cases. These results underscore the importance of improved parameter definitions for services with higher deviations to reduce uncertainty and enhance estimate reliability.

Moreover, the financial impact of estimation errors varied according to the unit cost of services. For example, sprayed concrete on ceilings, despite a relatively low MAE of 0.35, had the greatest absolute budget impact due to its high unit cost (R$ 1,783.21), accounting for 23.9% of the total budget distortion. This finding reinforces the importance of precise modeling for high-cost services, even when absolute errors are moderate.

Overall, the proposed methodology proved effective for the preliminary estimation of maintenance services based on inspection data and damage information, offering greater speed, scalability, and standardization in the budgeting process. Integrating inspection data and parametric models significantly reduced the time needed to generate preliminary budgets, optimizing maintenance management and facilitating application to more complex infrastructure networks.

Future research should aim to expand the dataset, incorporate additional explanatory variables, and explore hybrid techniques—such as machine learning—to further improve model accuracy and applicability across different contexts. This methodology consolidation represents a significant step toward modernizing the planning and management of bridge maintenance activities.

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CHAPTER V

BIM-based Mixed Reality Application for Bridge Inspection

Abstract

Traditional bridge inspection methods have limitations, driving the need for advanced techniques. The primary objective of this paper is to explore and evaluate the potential of combining Mixed Reality (MR) technologies with Building Information Modeling (BIM) and damage information to overcome these challenges. The paper aims to improve communication, collaboration, and the accuracy of structural damage identification during inspections. Parametric objects were developed to accurately represent and locate damage within the BIM model of the Coimbra I Viaduct in Brazil, using detailed geometric parameters. On-site inspections leveraged MR technologies, enabling real-time integration of damage information into the BIM. This approach allowed full-scale interaction with the model in augmented reality (AR), facilitating direct comparison with actual structural features and improving the accuracy and efficiency of inspections. The findings demonstrate the feasibility of a simplified MR-based inspection process, offering a complementary method within a multi-platform Bridge Management System, thereby enhancing bridge maintenance.

Keywords: Building Information Modeling (BIM). Virtual reality (VR). Augmented reality (AR). Mixed reality (MR). Bridge inspection. Damage information.

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1. Introduction

The conventional visual inspection method for bridges has inherent limitations, such as safety concerns for the inspection team, difficulty in accurately identifying subsurface defects, and subjectivity. These factors can impact the efficiency of decision-making and resource allocation in maintenance programs [1–6]. A bridge incurs annual operating, inspection, and maintenance costs and demolition expenses at the end of its service life, which usually vary between 0.4% and 2.0% of its initial construction cost. Ultimately, these costs can make up to 80% of the total construction expenditure [7]. Conducting inspections to assess the condition of bridges is crucial for evaluating the status of deteriorating structures. It helps identify the nature, extent, and location of any issues, ensuring ongoing functionality, operability, and safety for users [8].

Globally, there is a significant demand for annual structure inspections. In China, about one-third of its 800,000 highway bridges exhibit structural failures, necessitating safety monitoring and maintenance [9]. Japan, which has about 730,000 bridges, 39% of them to be over 50 years old by 2023 [10]. In the United States, of the 617,000 bridges averaging 44 years of age, 7.5% are considered structurally deficient [11]. Brazil has an estimated 137,000 bridges, managed by various government agencies [12], with the National Department of Transportation Infrastructure (DNIT - Departamento Nacional de Infraestrutura e Transportes) overseeing 6,833 bridges' operation, maintenance, and rehabilitation.

During the operational phase of a bridge, various inspections are carried out, including regular, detailed, and special ones, using diverse methods and technologies. The lifecycle of a structure generates substantial data, and inefficient management of this information hinders the assessment of structural conditions and maintenance decision-making [13].

To address these limitations, Mixed Reality (MR) has been chosen for its advanced integration and visualization capabilities. MR combines Augmented Reality (AR) and Virtual Reality (VR) to overlay digital information in the physical environment, allowing interactive and detailed visualization of structural damages. This technology provides several benefits, such as the ability to inspect and simulate interventions directly on-site, improving the accuracy of problem identification, and facilitating inspection team training [13,16–19].

MR is complemented by Building Information Modeling (BIM), an efficient methodology for digitally representing a structure's physical and functional characteristics, acting as a repository of information throughout the life cycle [14,15]. When integrated with MR, BIM enables digital data to be visualized and manipulated in a real-world context, enhancing the analysis and communication of structural conditions. The IFC (Industry Foundation Classes) schema standardizes this data, ensuring consistency and precision in the representation of project elements. IFC is an open standard created by BuildingSMART and is widely used for sharing data [20]. This model uses an object-oriented data structure, making it possible to organize geometric data and design information in a standardized manner [21]. The BIM Collaboration Format (BCF) supports communication about issues in a BIM model, working independently of the 3D model and including descriptions, status, and illustrative images of problems [22,23].

Researchers have explored immersive technologies like MR and VR to enhance bridge inspection and maintenance, demonstrating on-site inspection prototypes [24], point cloud data integration for database management [25], BIM-based MR applications for remote inspections [13,26], and holographic overlays for precise damage detection [27]. To the best of our knowledge and according to the review, this article presents an unprecedented approach in the literature that deals with the MR technologies and BIM methodology integrated with inspection techniques and specific damage information to improve bridge maintenance management.

This novel methodology involves the development of specific parametric models to represent damage information in the model, enabling the identification, classification, sharing, and exchange of information on structural issues. An on-site case study was conducted in a small Brazilian town. The aim is to help establish an inspection routine based on simplified MR, with the insertion of specific information for the pathological manifestations identified in the BIM model. This will make information available to other users in the model, assisting in the decision-making process for maintenance, estimating the budget for repair interventions, and creating a history of active and repaired damage to the structure throughout its service life.

2. Literature review

A concise survey of the infrastructure inspection domain employing immersive technologies was conducted to scrutinize primary research themes, technological advancements, scholarly output, and challenges highlighted in recent and pertinent studies within this domain. The Scopus Database was selected for analysis, given its status as one of the principal academic search engines encompassing the subject. The search was carried out in April 2024, using the terms “bridge” OR “infrastructure” AND “inspection” AND “reality” AND “augmented” OR “virtual” OR “mixed” search within “Article title, Abstract, and Keywords”. Only Journal Articles and Conference Papers in English published in the last years

(2019-2024) were considered. A total of 42 Journal Articles and 61 Conference Papers were found.

From this set, a systematic approach was applied to identify and select the most relevant studies. This selection involved an initial screening of titles and abstracts to filter out irrelevant papers, followed by an analysis of the full text of the selected studies. The final selection included only those articles and documents that directly addressed the use of immersive technologies in visual inspection and damage identification, which were then analyzed in depth.

2.1 Conceptualization

Virtual Reality (VR) offers a computer-generated reality in which the users have immersive experiences in an environment that enables them to interact with the virtual features or objects of the virtual models. A head-mounted display (HMD) or multi-projected environment is the most common VR tool [13,16–19,28]. Augmented Reality (AR) enhances the interaction between the real and virtual worlds by overlaying through smartphones, tablets, and AR glasses. AR applications generally enhance the real-world environment with digital objects, creating minimal interaction with the virtual content [13,16–18].

Mixed Reality (MR) combines the resources provided by VR and AR, merging the real and virtual environments somewhere through the mixed-reality spectrum; a real-world object interacts with a virtual object [13,17,29]. MR blends the 3D project model in a real-world representation based on computing technologies. It augments virtual information into the actual environment and allows the user to change information in real-time [13,17,18,30].

An MR environment has three main features, which are (1) combining the real-world object and the virtual object; (2) interacting in real-time; and (3) mapping between the virtual object and the actual object to create interactions between them [29]. Thus, MR, based on a BIM model, presents itself as an alternative for inspection, given that it is possible to interact with the model created in VR, insert it in full scale in AR, and compare it with the physical characteristics.

2.2 Mixed reality inspection vs. conventional visual inspection

Mixed reality inspection and conventional visual inspection represent two distinct approaches to assessing bridge conditions. The current bridge inspection procedure relies primarily on experienced inspectors manually recording data through checklists and paper notes, by observation, while the mixed reality inspection incorporates advanced digital technologies such as BIM models, VR and AR devices. The conventional visual inspection approach is subjective, inefficient, and costly, particularly for complex bridges [1,18,36,37]. These inspections, conducted element by element, are time-consuming, with the duration depending on the size of the bridge. They can lead to considerable disruption in traffic flow. Moreover, inspectors encounter various safety risks, particularly when utilizing lifting equipment to access hard-to-reach areas of bridges [1,37].

Conducting field inspections with the assistance of digital BIM models and MR technology holds significant potential for supporting bridge inspections. This approach streamlines the visualization process, aids in damage identification, and enhances information gathering for inspectors [13,24]. Utilizing new equipment such as tablets, smart glasses, and technologies like Unmanned Aerial Vehicles (UAVs), Terrestrial Laser Scanner (TLS), Ground Penetrating Radar (GPR), and Infrared (IR) thermography in the field has accelerated the collection of inspection data, automated processes, improved safety for inspection teams, enhanced reliability, and proven more cost-effective [6,38,39].

Numerous studies explore the utilization of mixed reality glasses to streamline the inspection and maintenance of structures [13,25,27,30,40,41]. These intelligent glasses function as autonomous holographic computers, enabling users to interact with 3D digital content in the real world hands-free. Additionally, they facilitate image capture using the glasses' integrated camera. Nevertheless, certain studies indicate that experienced inspectors prefer tablets as their primary field inspection tool over smart glasses like Microsoft HoloLens [24,34].

The tablet is considered a practical tool with a more intuitive shape and handling, and it is also more cost-effective and readily accessible compared to smart glasses. The estimated cost of a HoloLens is approximately three times higher. Moreover, smart glasses exhibit limitations in terms of field of vision, individual user experience, and gesture input systems, while tablets offer the advantage of simultaneous viewing of the actual structure and the digital model. Additionally, tablets facilitate interaction and collaboration among multiple users [33,34].

2.3 Related works

Riedlinger et al. [24] developed MR and VR prototypes to provide digital support for on-site bridge inspectors utilizing BIM data. The MR system was implemented on a tablet, and the authors established the process requirements through expert interviews with nine field specialists. The inspection process was delineated into three primary phases: (1) preparation of the bridge inspection using a computer or tablet, synchronizing the required data from a CDE (common data environment) with the terminal device; (2) structural inspection including investigating and documenting damage using photos and additional details, storing in a BCF file with photos and coordinates, and synchronizing with the CDE online or in the office for collaborative analysis; (3) post-processing of the structural inspection in the office, using VR/AR to visualize the existing damage on the bridge.

Nguyen, Kang, et al. [25] introduced an innovative concept of a Mixed Reality (MR)-based Digital Twin Model (DTM) designed to enhance the visualization of semantic information within a Bridge Maintenance System (BMS). This involved collecting a point cloud with geometric information about the bridge, which was then incorporated into a visual programming routine. Parametric families of structural elements were created for Revit. The study focused on integrating the DTM with MR using Microsoft HoloLens 2 through Unity, facilitating the visualization of bridge data in an office setting. The DTM model efficiently integrates, overlays, and manages maintenance databases. However, the pilot implementation of MR indicated potential enhancements in visualizing and integrating maintenance data.

In a subsequent study, Nguyen, Nguyen, et al. [13] proposed "HoloBridge," a novel framework that integrates a BIM-based Mixed Reality (MR) application and HoloLens to enhance off-site bridge inspection and maintenance. This system includes a Bridge Information Model (BrIM) and an MR-based application with functional modules, such as inspection, evaluation, and damage mapping modules, enabling users to make decisions about inspection and maintenance progress. HoloBridge brings the 3D bridge model into the real world, allowing users to query the inspection database for real-time structural condition monitoring. Using a damage mapping algorithm, users can assess damage progression over time, aiding in more reliable decision-making for maintenance.

Al-Sabbag et al. [27] presented a visual inspection method for the interactive detection and quantification of structural defects. The method involves a holographic overlay of information on the spatial environment, utilizing the advanced 3D spatial mapping capabilities of the Microsoft HoloLens 2. Inspectors can capture structure images, identify visual damage, estimate its area, and visualize it as holographic objects overlaid on the scene. This allows real-time interaction with the damage detection process, providing quantitative damage information. The study demonstrated that the system can accurately estimate spalling damage extent with less than 10% error through image processing. The system facilitates human-machine collaboration, real-time analysis, and immersive data visualization.

In another study, Al-Sabbag et al. [30] introduced a pioneering system termed Human-Machine Collaborative Inspection (HMCI). This system facilitates collaboration among inspectors through the utilization of MR and a robotic data collection platform for structural inspections. The MR headset's holographic display is spatially aligned to the robot in real-time, creating an interactive and immersive environment for the user to conduct visual inspection tasks. This capability enables the inspector to visualize and localize real-world information efficiently.

A general workflow of HMCI involves collecting data from 2D sensors (visual, thermal, stereo cameras) and 3D sensors (LiDAR) mounted on a robot targeting a structure. This data, encompassing a substantial volume, is transmitted to a remote server. Subsequently, vision-based inspection algorithms are applied to identify and locate structural damage. Once detected, the MR headset receives this information, generating holograms of the damaged regions overlaying the actual defect location. Accompanying details, such as defect type, estimated sizes, inspection date, and prior inspection annotations are also displayed. This information can be saved on the reconstructed 3D map, allowing inspectors to revisit sites, reposition their MR headsets, and review annotations from past sessions during future inspections [30].

Wang et al. [26] introduced a novel Immersive Virtual Reality framework, designed with a specific emphasis on enhancing user experience during remote infrastructure inspections for data visualization and decision-making. Damage identification within the framework utilized 3D exclamation marks strategically placed over affected areas, color-coded (green, yellow, and red) to denote severity. Testing the developed IVR prototype revealed its effectiveness in identifying damage during remote bridge inspections, showcasing acceptable usability. Table 1 summarizes the related studies that have used MR.

The literature review demonstrates the potential of Mixed Reality (MR) and Virtual Reality (VR) in integration with Building Information Modeling (BIM) to improve visualization and information management during bridge inspections and maintenance processes. Existing research often lacks a standardized methodology that allows for the efficient exchange of data between platforms, ensuring interoperability and accuracy of information throughout the lifecycle of the infrastructure. Therefore, this research aims to address these gaps by proposing an integrated MR and BIM model that provides a continuous and validated workflow in a real case study. This approach improves the accuracy of damage location, optimizes communication between maintenance teams, and enriches the documentation of inspection and repair processes, contributing to more efficient and collaborative bridge maintenance management.

Table 1. Comparative summary table of the studies analyzed.

Ref.	Approach	Devices used	Inspection	Purpose	Results and observations	Challenges
[24]	MR and VR prototypes	Tablet	On-site	Digital support for on-site bridge inspectors using BIM data	Emphasis on BIM data integration, online collaboration, and efficient damage visualization	Lack of BIM data for existing bridges, user interface design, and adoption of norms for public tender
[25]	Mixed Reality (MR)-based Digital Twin Model (DTM)	Microsoft HoloLens 2	In the office	Enhancing visualization of semantic information within a Bridge Maintenance System (BMS)	The goal is to improve the interaction between engineers and the maintenance database	Potential enhancements in visualizing and integrating maintenance data
[13]	BIM-based MR Application and "HoloBridge" Framework	Microsoft HoloLens	Remotely from office	Develop a BIM-based mixed reality (MR) application to enhance and facilitate the process of bridge inspection and maintenance works remotely from office	Real-time monitoring, updating, and informed decision-making about inspection and maintenance progress. Damage mapping algorithm for assessing progression	Workflow complexities during BIM modeling and application development
[27]	Holographic Inspection Method	Microsoft HoloLens 2 and Tublebot2	Inspection results on-site	Real-time interaction with the damage detection process, providing quantitative damage information	Accurate estimation of spalling damage extent with less than 10% error. Enhanced precision, real-time analysis, and immersive data visualization	Limitations in field of view and gesture input system for smart glasses
[30]	Human-Machine Collaborative Inspection (HMCI)	Microsoft HoloLens 2, robotic data collection platform	Real-time inspection on-site	Collaboration through MR and robotic data collection platforms for efficient visual inspections	Efficient collaboration among inspectors through MR and robotic data collection. Enhanced precision, real-time analysis, and immersive data visualization	Complex workflow involving data collection, transmission, and integration with MR
[26]	Immersive Virtual Reality (IVR) framework	IVR prototype	Remote inspections	Enhancing user experience (UX) during remote infrastructure inspections	Effective identification of damage during remote bridge inspections. Acceptable usability	Device compatibility and potential issues related to remote data visualization

3. Methodology

This research proposes a study combining mixed reality with inspection procedures and the development of parametric objects for identifying, describing, and localizing damage to the structure. Figure 1 illustrates the structure of the proposed methodology.

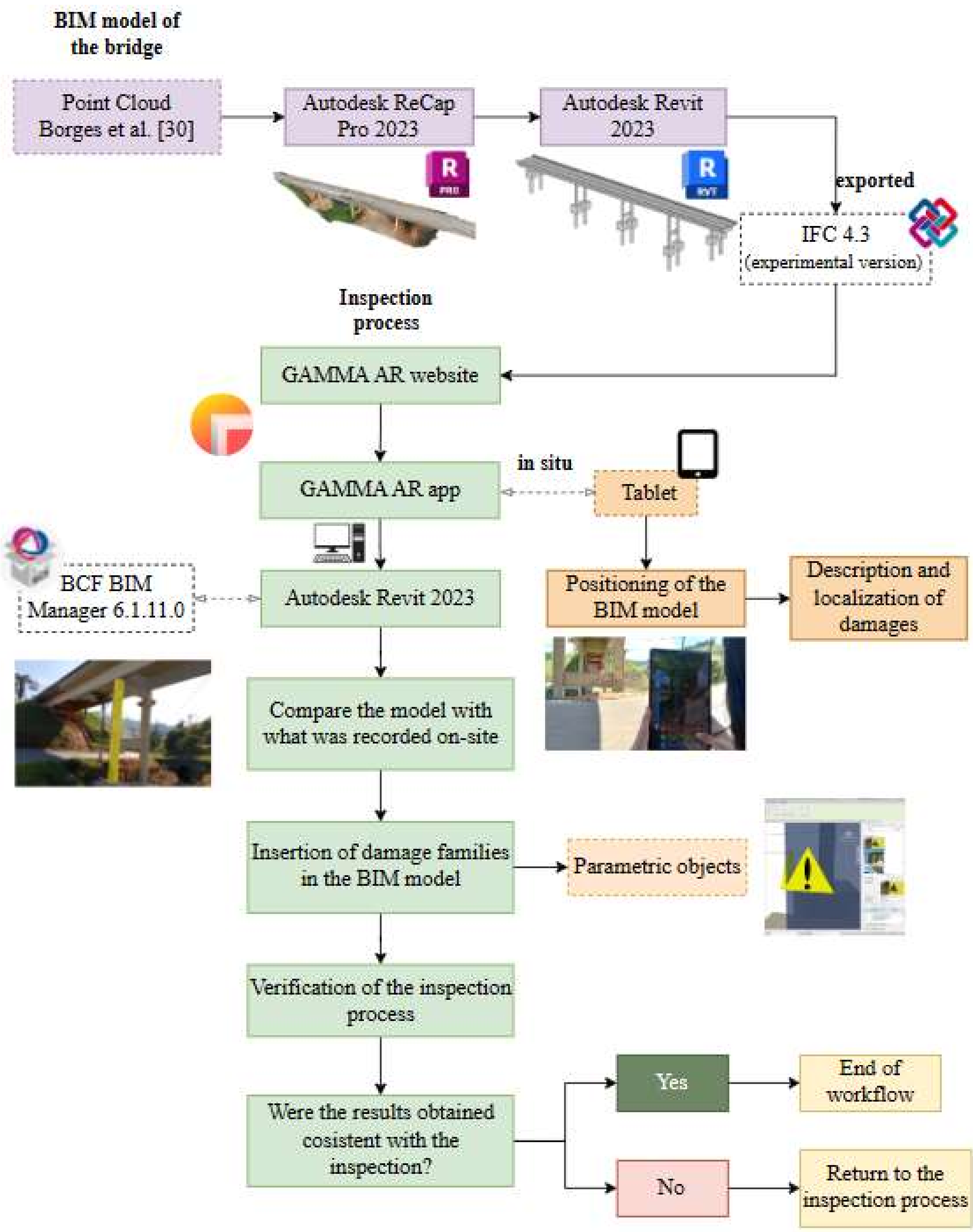


Figure 1. Flowchart of the proposed methodology.

3.1 Research workflow

The inspection methodology proposed in this study was applied to the Coimbra I Viaduct, situated in the city of Coimbra, in the state of Minas Gerais, Brazil, at km 640 of BR 120. This viaduct was designed with cast-in-situ reinforced concrete, featuring a deck supported on two girders. It comprises four lines of columns and a direct support line on the foundation blocks. This structure was previously studied and modeled by Borges et al. [31] with the aid of a point cloud generated with a DKI Matrice 300 RTK drone. There was a lack of information in some of the areas surveyed, especially at the ends of the viaduct. Thus, attempts were made to improve the outline of the structure by meshing the point cloud using interpolation. However, Revit presented some input problems. As a result, filters were applied in CloudCompare v2.13 alpha, a free, open-source program specializing in point cloud processing, which removed some of the disturbances on the bridge deck caused by vehicles passing by at the time of the survey. The modeling process for the viaduct began by delimiting the region of interest, and the point cloud underwent cleaning using Autodesk ReCap Pro 2023 (Figure 2). Autodesk Revit 2023 was used to model the viaduct's structural elements. The final model is depicted in Figure 3(a), with an overlay of the point cloud shown in Figure 3(b) to facilitate an approximate evaluation of the model against the existing structure.

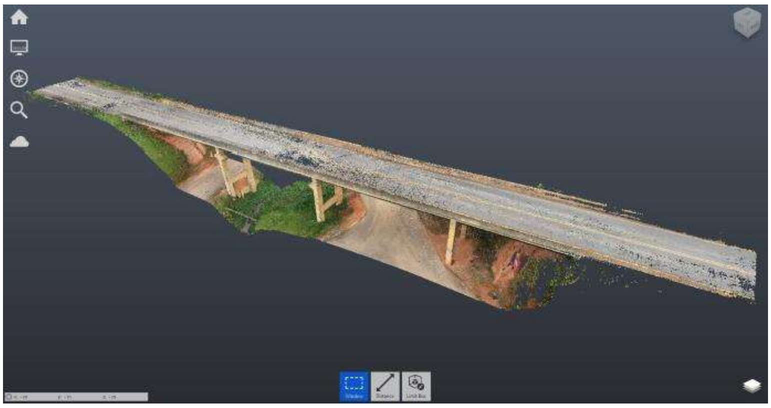
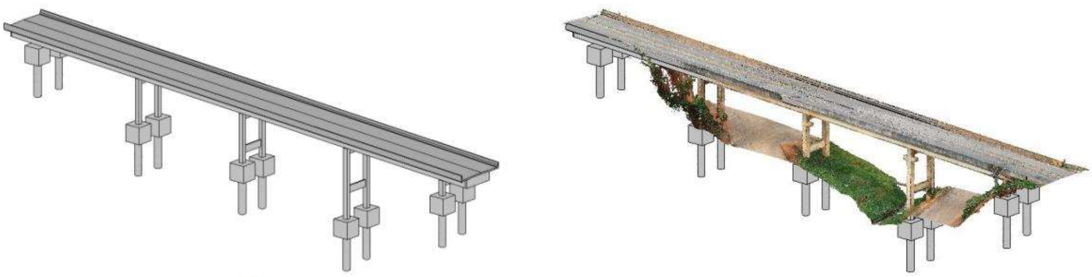


Figure 2. Point cloud filtered and delimited in ReCap [31].



(a) (b)

Figure 3. (a) proposed bridge model; (b) overlay of the model with the point cloud [31].

For implementing Mixed Reality (MR), the GAMMA AR software was selected for its prominent features, including Simultaneous Localization and Mapping (SLAM) technology, compatibility with iPhones or smartphones, and lower cost compared to alternatives, as indicated in studies by Vilela [32]. GAMMA AR operates with a BIM Collaboration Format (BCF) extension for recording notes, audio, and photos. The software maintains a website where collected information is registered and stored in a database, organized by record dates, 3D model elements, and the nature of the information (messages, audio, and photos). It is noteworthy that while GAMMA AR was chosen for its specific features, alternative software capable of exporting IFC files for BIM modeling and importing IFC and BCF for MR could be considered.

Utilizing the Revit software framework, a BIM model incorporating essential geometric and non-geometric bridge information was developed. Subsequently, the model was exported to an exchangeable 3D format, specifically IFC (experimental version 4.3.1.0, in Revit), for import into the GAMMA AR website (version 3.1.1). This approach facilitated access to the project in the library by inspectors through the GAMMA AR app on a smartphone or tablet. A tablet enables shared experiences, fostering collaboration among multiple users [33,34].

The combined use of MR with the actual bridge model during the on-site inspection assists the inspector in identifying and reporting damage to the structure and possible discrepancies with the BIM model. Consequently, the collected information is documented by the site inspector through the application and made accessible on the GAMMA AR website. In this investigation, the inspection data in BCF format (version 3.0) was downloaded and imported into the BCF Manager. Subsequently, leveraging the integration with Revit through the BCF BIM Manager 6.1.11.0 plugin from BCF Collab, comparisons were made between the reported information in situ and the BIM model, allowing for necessary modifications. A detailed explanation is provided in Chapter 4.3.

3.2 Creation of Families of Damage

Parametric objects were generated to characterize and identify damage, along with their corresponding geometric parameters and locations on bridge elements. Within Revit, these are recognized as parametric families, serving to represent pathological manifestations identified during the inspection. Based on insights from prior research by Martins et al. [35], a list of the most common and impactful damages in reinforced concrete bridges was compiled and parameterized (Table 2). To visualize these damages on the BIM model, a generic volumetric object (3D) was modeled, starting with a generic model face-based family template (Figure 4). This template facilitates the localization, identification, and storage of pertinent information for each identified pathological manifestation within the model.

Table 2. Recurrent damage in reinforced concrete bridges.

Damage	**Unit**
Efflorescence	m^2
Crack	m
Concrete spalling	m^2
Water leakage	m^2
Damp patches	m^2
Concrete delamination	m^2
Honeycomb	m^2
Uncoated reinforcement	m^2

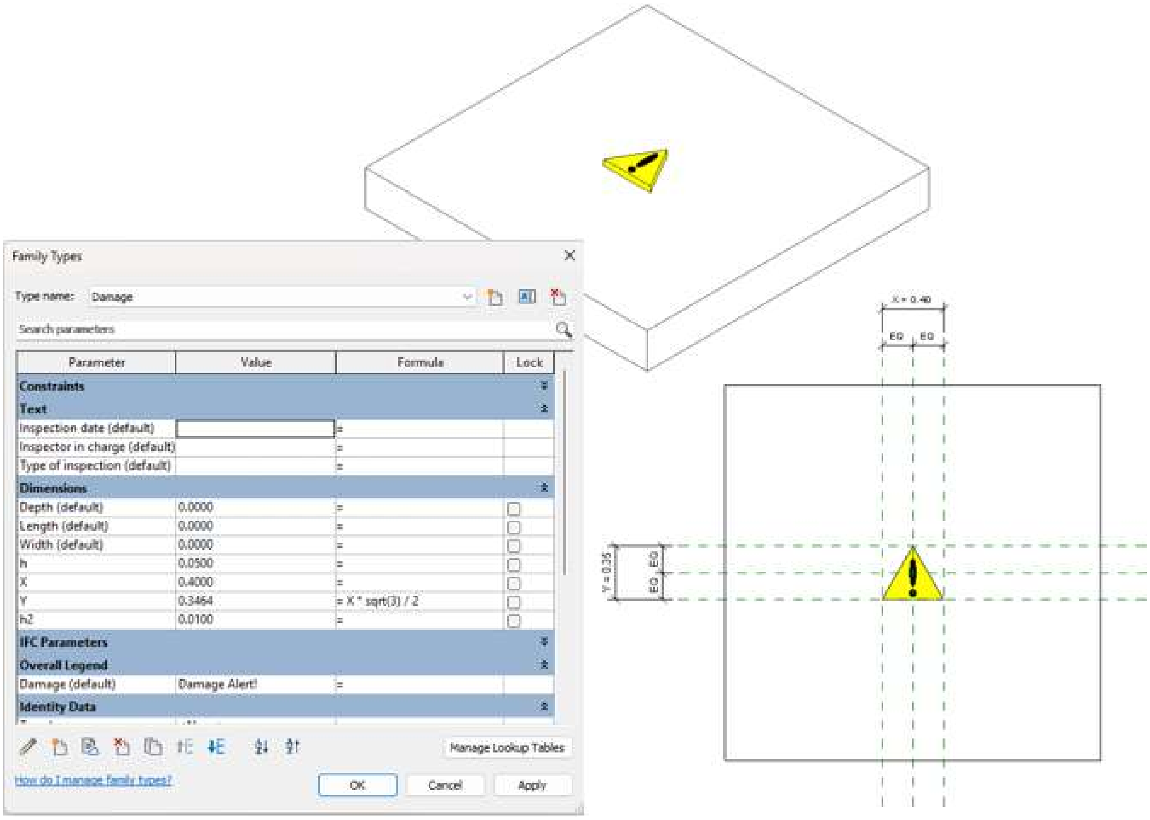


Figure 4. Generic representation for damage with associated parameters.

For precise characterization of each damage during the inspection, input parameters were defined to encompass crucial information within the family structure in Revit. Shared parameters were established to capture inspection and damage identification details (Figure 5). This solution was adopted to streamline the process of inserting parameters into families, facilitating comprehensive documentation of inspection findings and damage specifics.

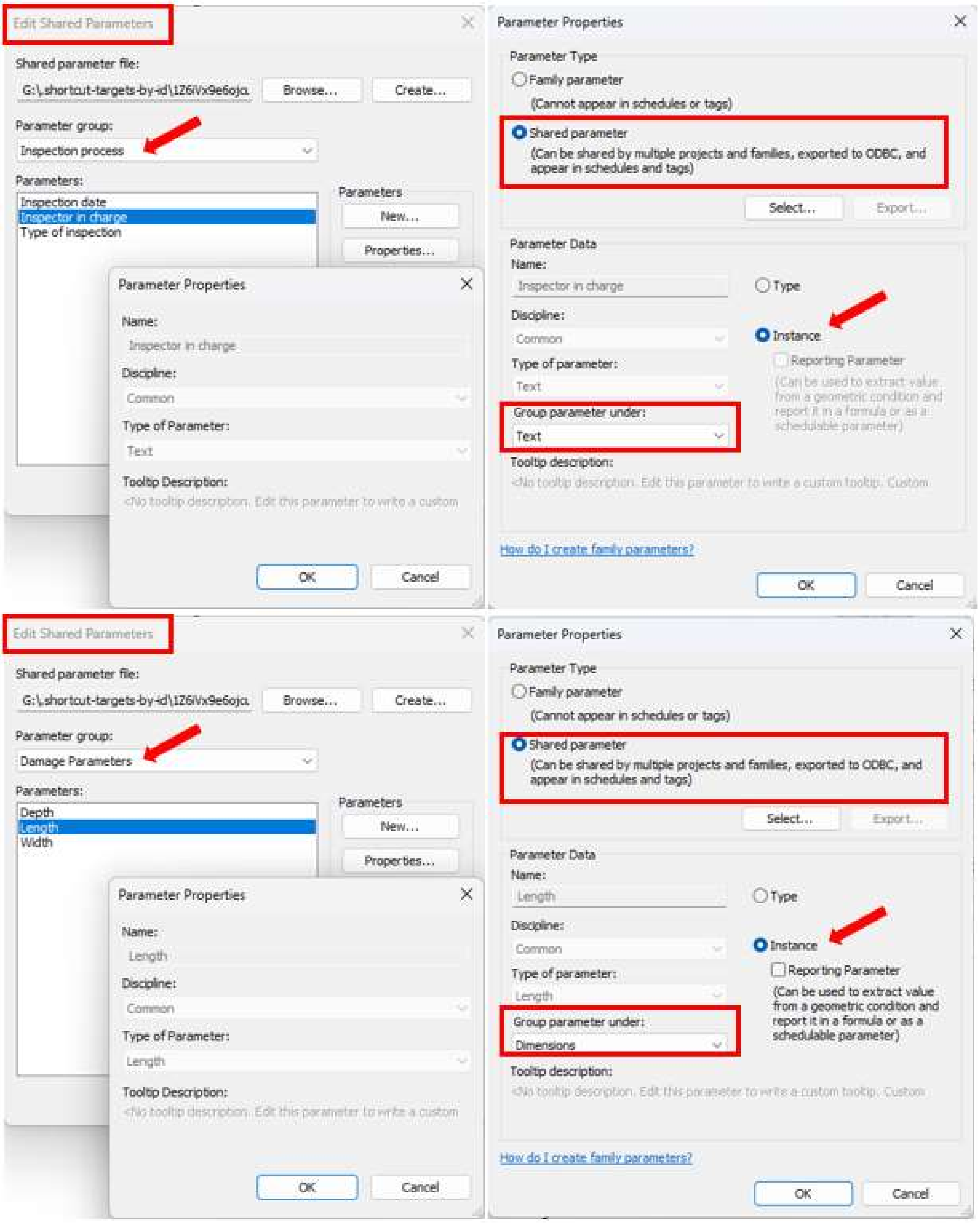


Figure 5. Creation of shared parameters to the inspection process and damage on Revit.

Shared parameters are configuration settings that can be utilized in multiple families or projects. It is important to note that information defined in one family or project using a shared parameter doesn't automatically carry over to another family or project utilizing the same shared parameter. While certain parameter categories may repeat for various damages, the values of all parameters can vary based on the specific damage. To capture inspection details, specific parameters were established, including the inspection date, the responsible inspector, and the type of inspection being conducted. Additionally, to effectively characterize damage, dimensional parameters (length, width, and depth) were defined, accounting for the unique configuration of each pathological manifestation. Figure 6 provides an example of a parameterized family for the "Crack" damage type, highlighting the shared parameters created.

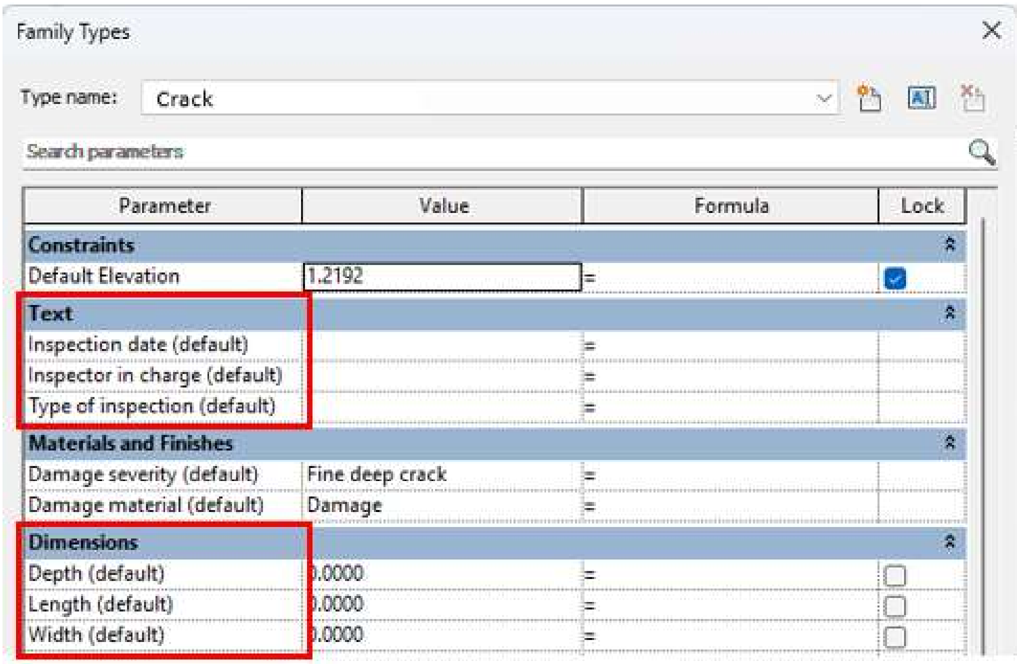


Figure 6. Shared parameters inserted on family type “Crack”.

4. Case study

The subject of the case study is the Coimbra I Viaduct, constructed in 1985. This viaduct features reinforced concrete beams and is cast in place, spanning a length of 100 meters with four spans, as illustrated in Figure 7. This viaduct is part of the Brazilian *SGO (Sistema de Gerenciamento de Obras de Arte Especiais)*, developed by *DNIT (Departamento Nacional de Infraestrutura de Transportes)*. Figure 8 presents the workflow of the proposed methodology applied in the Coimbra I Viaduct.

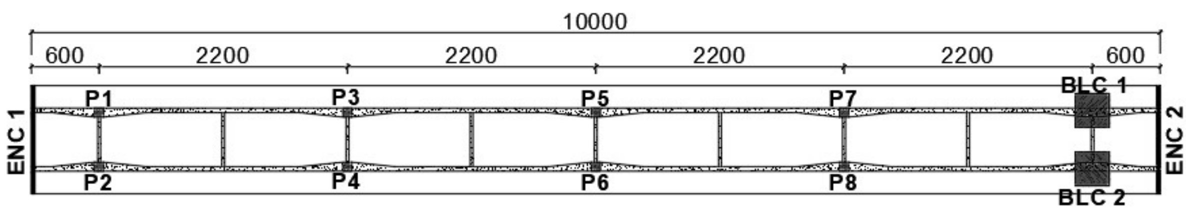


Figure 7. Longitudinal layout of the viaduct.

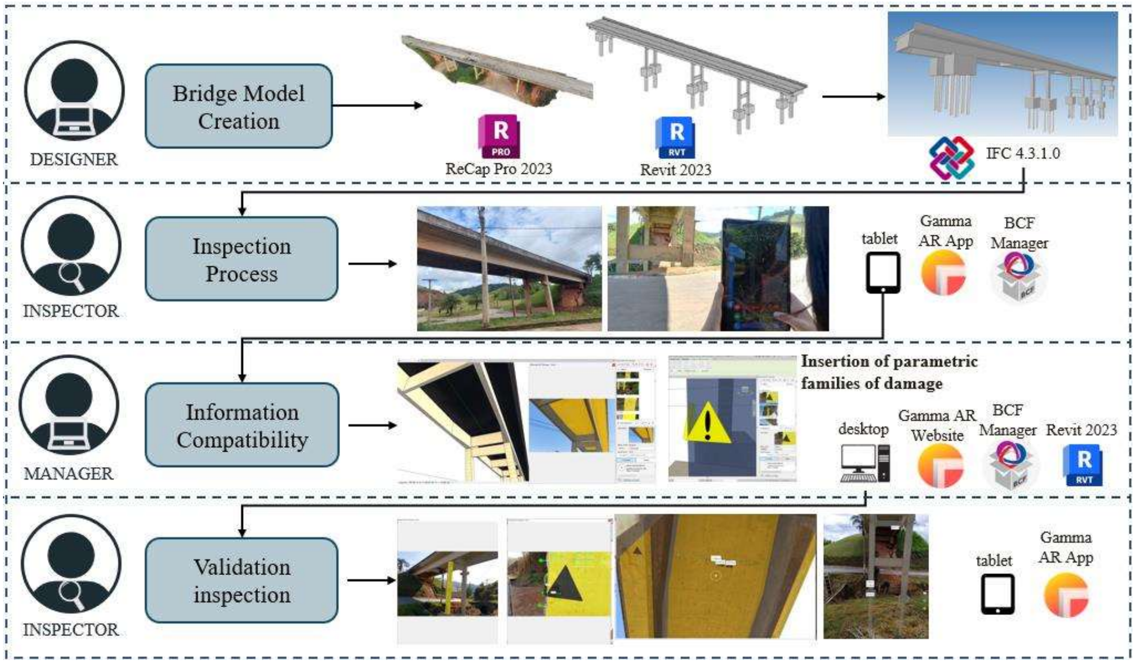


Figure 8. Workflow of the methodology applied in the case study.

4.1 BIM model tracking and positioning (1st inspection)

Initially, the BIM model of the viaduct was exported from Revit using the experimental version of IFC 4.3.1.0 and then imported into the GAMMA AR website. The IFC file export and import process in the AR software depends on an internet connection and takes place quickly. Once the IFC file has been imported into GAMMA AR, an internet connection is no longer necessary to access it. Upon launching the GAMMA AR app in the field, the bridge model was loaded and prepared for positioning.

The positioning process of the BIM model in the GAMMA AR software involves several steps to ensure the correct overlap between the virtual model and the actual environment. First, it is necessary to select the project in the application, followed by choosing the specific floor or level of the structural model (such as the foundation or pillar level). In this case study, the pillar level was selected, with Pillar P8 (Figure 7) chosen as the reference element for alignment.

For model alignment, a markerless alignment method was used, which relies on the natural visual features of the bridge to facilitate location. During the research, the only option available in the software was two-point alignment, but in version 6.0.8, updated on August 12, 2024, GAMMA AR also offers QR code positioning.

Choosing the two-point alignment method, as used in the case study, involved the following steps:

1. **Selecting the Reference Element:** A structural element is chosen to serve as a reference for positioning. In this study, the app was configured to select pillars, and Pillar P8 was chosen as the reference point.
2. **Defining a Corner and Direction:** After selecting Pillar P8, one of its corners and a specific direction were chosen to draw a reference vector.
3. **Creating a Plane and Vector:** The final step involves making a plane by moving the mobile device (tablet). The tablet sensors capture the position and orientation in space, allowing a reference vector to be drawn from the initial point (selected corner). This vector helps insert the virtual model of the structure into the actual environment in an aligned manner.

After the initial positioning of the virtual model, meticulous adjustments are made to improve the overlap between the virtual model and the actual environment. These adjustments allow changes to the x, y, and z coordinates as needed (Figure 9), ensuring the precision of the alignment and the correct visualization of the BIM model integrated into the physical environment.

Figure 9. Positioning the BIM model on the physical structure.

During this process, continuous analysis is carried out to ensure the accuracy of the positioning. Additional challenges are faced in open environments, where factors such as sunlight can interfere with positioning accuracy. This methodology, although complex, provides a solid basis for the effective integration of virtual models into real environments, promoting significant advances in the application of Augmented Reality in various areas of interest.

4.2 Damage observation and description (1st inspection)

The field inspectors observed and recognized the damage during their on-site assessment, aided by a Samsung Tablet S7 with an MR technology system that helped in documenting and detailing these observations by overlaying the virtual model of the bridge over the physical structure in the field. Other MR devices could be employed to apply the methodology developed in this study, such as smart glasses like the Apple Vision Pro, Hololens, Quest 3, and Quest Pro. The choice of tablet was motivated mainly by the economic issue and practicality in the field with interaction between different inspectors.

In the GAMMA AR app, inspectors can document the damage comprehensively, including additional details such as photographs, text descriptions, and status updates. The description section allows to provide specific information about the damage, including the precise location of the bridge's structural components. This collaborative approach, which combines real-world inspection with digital tools, increases the accuracy and efficiency of damage documentation and analysis.

The inspection data is automatically transmitted from the GAMMA AR app to the company portal, necessitating internet connectivity on the tablet. Users can access the inspection data and export the file in BCF format within the GAMMA AR website. BCF notes within the file can be interpreted by BIM software. To enable Revit to read the BCF file, the inclusion of the BCF Managers plugin (version 6.2.19.0) from the BIM Collab company was essential. This is crucial because REVIT is software in its native format that does not inherently interpret BCF files.

It is important to emphasize that this first inspection could be carried out automatically with the help of new technologies, such as Unmanned Aerial Vehicles (UAVs) and Terrestrial Laser Scanner (TLS) with AI processing capabilities. A literature review developed and recently published by the authors Martins et al. [6] addresses the use of these technologies in the inspection and damage detection process. In this way, the inspector would be essential to process the BIM model with the damage detected in the field in an automated way.

4.3 Comparison of the BIM model with BCF notes

The Revit and the BIM Collab BCF Managers facilitated a thorough comparison of images and notes generated during the inspection in situ with the BIM model (Figure 10). The plugin provides functions that significantly streamline this process. Among these tools is "Camera positioning," which precisely places viewpoints on the model corresponding to the reported damages. It automatically adjusts for discrepancies in coordinate systems, such as topographic survey points in Revit. Furthermore, the plugin allows zooming in on the reported images, enhancing the analysis and evaluation of the damages.

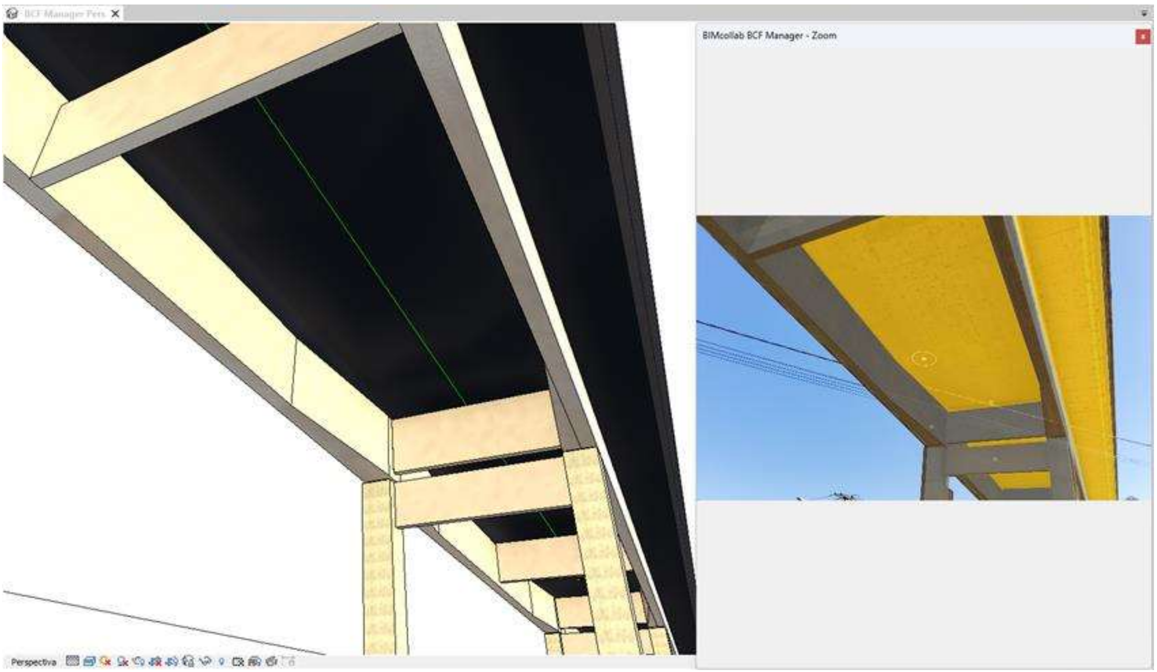


Figure 10. Reading of the BCF file in the BIM software.

Damage was reported and localized using photos and descriptive texts during the first inspection in situ, with the help of the GAMMA AR App. In the office, the manager imports the file generated in the field into Revit and works with the BIM Collab BCF Manager tool to help insert the parametric families corresponding to each specific damage. This is done by importing the damage families created, with the shared parameters, into the BIM model. With each damaged photo taken, it is possible to use the "Camera positioning" tool to locate the same region in the BIM model, so the parametric families are inserted over the damage located in the element. The information on each damage that was filled in during the inspection in text format will help to fill in the parameters for each parametric damage family.

Once all the damage observed in the structure has been positioned, the Revit IFC file is exported and imported back into the GAMMA AR website for a follow-up inspection. This inspection involved verifying the placement of the damages, and precise measurements were taken to accurately assess the extent of the damages.

4.4 Position analysis and damage measurement (2nd inspection)

A second bridge inspection was undertaken to evaluate the damage placement and to test the application's measurement tool. Initially, the virtual model must be aligned with the physical structure, repeating the tracking and alignment processes carried out during the first inspection. Figure 11 illustrates the outcome of this procedure. At this stage, the virtual model that is overlaid on the physical model shows the parametric damage families positioned according to what was reported in the first inspection.

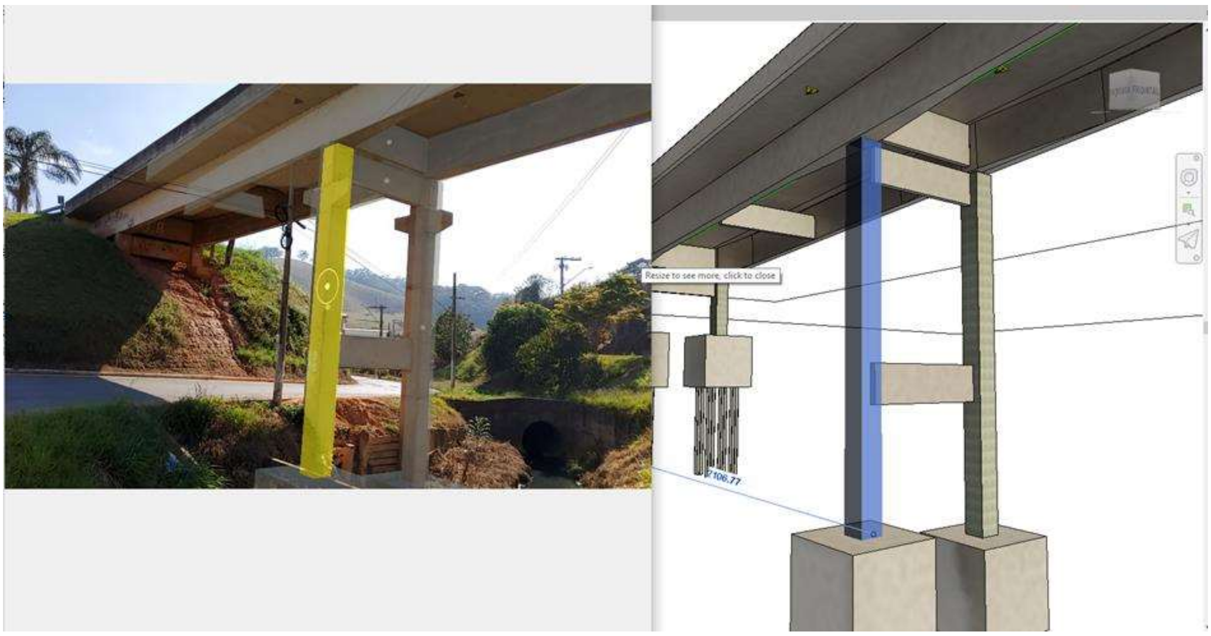


Figure 11. Final positioning of the AR and the real structure.

Data on the identified damages were collected using the GAMMA AR App "measure" tool, capturing their width and length. This tool in the AR application allows users to measure the BIM model overlaid on the physical structure, which enables inspectors to measure the actual damage to the bridge using the BIM model with the damage families inserted as a reference.

Damage measurements in the field are an essential part of the inspection process since these damage measurements will guide the decision-making process for the maintenance, repair, or reinforcement of a structure, significantly impacting the budget. As the damage families have specific geometry parameters, it is possible to input these measured values for each damage into the BIM model.

Some examples of damage measurement using the GAMMA AR App tool are shown in Figure 12 and Figure 13. Figure 12 depicts the results of measuring the " Concrete spalling " damage at P8. Other damages, such as "efflorescence" and "crack," were also measured (Figure 13). Furthermore, the positioning of the damages inserted on-site was verified during this assessment. This "measure" tool proved to be practical and very useful for measuring damage in hard-to-reach places, as in the case of the crack on the underside of the slab (Figure 13).

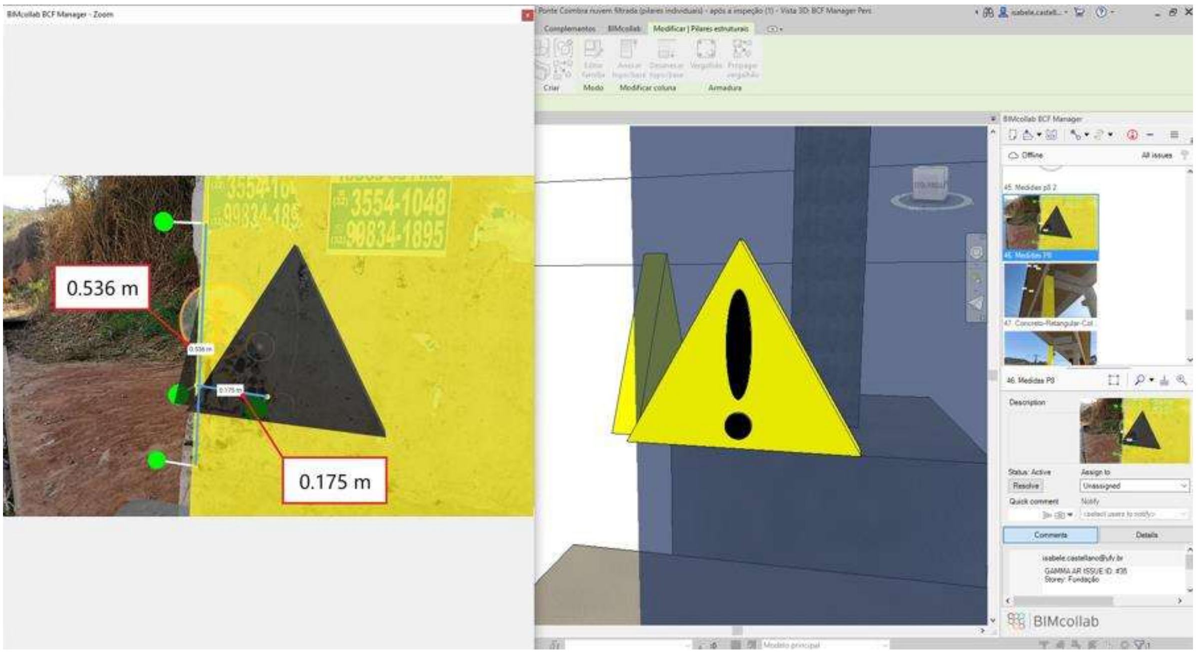


Figure 12. Concrete spalling measurements at P8.

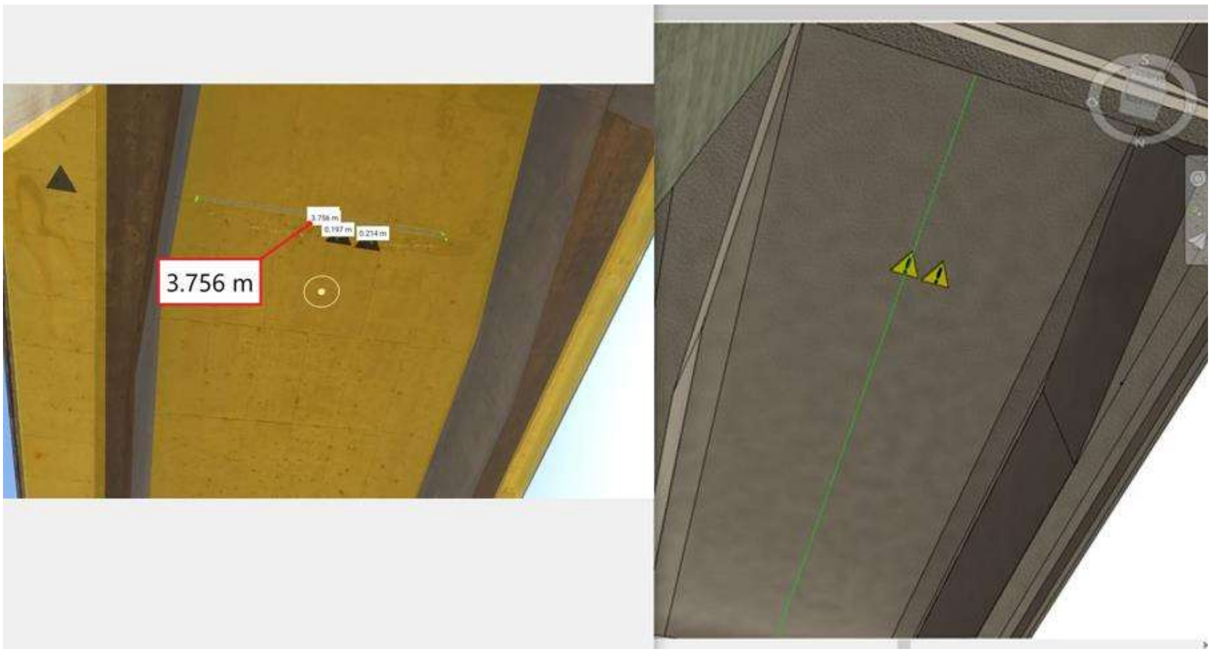


Figure 13. Efflorescence and crack measurements at the bridge slab.

5. Discussion and considerations

5.1 Considerations on Viability

Bridge as-built modeling from the point cloud in a BIM interface: Building the 3D bridge model using the proposed method involves specific UAVs with 3D scanners and BIM modeling software. This stage demands expensive equipment and specialized knowledge and is time-consuming due to the detailed processes required for data collection, model creation, and refinement. In contrast, traditional methods use manual measurements, photographs, and 2D drawings. These methods are less expensive and moderately time-consuming but lack the precision and detail of 3D models. It is important to note that accurate BIM models cannot be considered optional in a BIM-based bridge management system. Additionally, the model itself is not part of the inspection method but serves as the documentation of the bridge, provided once and used throughout the bridge's lifespan.

Virtual and Physical Model Alignment: The proposed methodology uses advanced 3D modeling software and tablets to align the virtual model with the physical structure on-site. This stage requires proficiency with the technology and a moderate amount of time due to the initial setup, calibration, and necessary adjustments. In contrast, the traditional method relies on manual measurements and written reports, so this stage is not applicable. However, it is important to consider that the traditional method is less accurate and comprehensive. Additionally, this stage ensures the accuracy and time savings of the following stages.

Inspection: Inspectors using the proposed methodology utilize tablets with specialized augmented reality software to navigate the BIM model, document findings, and verify data in real-time. This approach involves a moderate investment in equipment, software, and proficiency with the technology. Traditional methods can involve smartphones, cameras, 2D drawings, clipboards with paper and pen, and measurement tools. These low-cost methods require a significant amount of time, making the process less standardized and efficient, labor-intensive, and unsafe.

Check and report: The proposed methodology uses AR software and a tablet to check and report the damage in situ and BIM software and a notebook to align and verify the damage, leading to moderate costs and low time commitment. This stage ensures that all identified damages are accurately documented and aligned within the model. The traditional method, which uses visual inspections, photographs, manual notes, and drawings, is low-cost but takes a long time and is more prone to errors and omissions.

Results verification: Results verification using the proposed methodology involves AR software, a BIM model, and a tablet, resulting in moderate costs and low time. This automated and precise process contrasts with the traditional method of manual report reviews, which, although low in cost, requires a significant amount of time and can be less reliable.

Cost-Benefit Analysis: While the proposed methodology involves moderate to high costs and time investments for certain stages, the enhanced accuracy and depth of the information obtained allow for more efficient resource management. This, in turn, enables better-informed decision-making and more effective interventions, resulting in medium-to-long-term cost savings and improved structural safety. Additionally, the traditional methodology lacks the utilization of the BIM model of the bridge as a centralized repository of information. Instead, information is scattered across different media, making it difficult to analyze the structure as a whole. It is also important to note that consistent and accurate information is crucial for implementing current and future data-based and AI-assisted technologies in managing infrastructure assets. Table 3 summarises the qualitative comparative analysis between the proposed and traditional methodologies.

Table 3. Qualitative comparative analysis between the proposed and traditional methodologies

Item	Proposed	Traditional	Comments
Investment in equipment and software	High	Low	- The proposed methodology involves high initial investment but offers financial returns over the medium to long term from savings generated. - Traditional methodology requires lower initial investment but may incur higher ongoing operational costs.
Training and expertise required	Moderate	High	- Inspectors in traditional methods currently hold significant responsibility and exercise high-level decision-making on-site. - Requires professional expertise and higher education. - Assisted technologies in the proposed methodology require proficiency but entail less on-site decision-making.
As-built model cost	Moderate-to-High	Low	- The proposed methodology requires UAVs, 3D scanners, and BIM modeling software. - Traditional methodology uses manual measurement and 2D models.
Time required in as-built model	Moderate-to-High	Moderate	- The proposed methodology requires time to obtain the BIM model using the point cloud and modeling software. - Traditional methodology involves structuring 2D drawings based on field measurements.
Time required in routine inspection	Moderate-to-low	High	- Reduced need for field professionals to move and access various parts of the structure using tablets and AR software. - Uses parametric models for damage assessment and standardized forms for data collection. - All tools consolidated into a single device in the proposed methodology. - Traditional methods involve smartphones, cameras, 2D drawings, written reports, and various tools to measure and access the bridge elements.
Time required in reporting and documentation	Low	Moderate-to-high	- Data is automatically stored in the model. - Uses parametric models for damage and repair. - Standardized forms streamline the process. - Traditional methods require manual data entry and compilation.
Time required for review and validation	Moderate	Moderate	- Inspection data verification and parametric family insertion directly into the BIM model. - Data is centralized, enabling documentation throughout the structure's lifecycle. - Traditional methods involve manual verification and decentralized data storage.

5.2 Methodology Strengths

This study demonstrates Mixed Reality (MR) technologies with Building Information Modeling (BIM) to enhance traditional bridge inspection techniques and improve information flow in Bridge Maintenance Management. The key strengths of this approach are:

- **Integration of damage data into BIM:** The methodology outlines a streamlined process for incorporating damage information directly into the post-inspection BIM model. This ensures that structural data is accurately represented within the digital model, aiding professionals in efficient data management.
- **Localization of damage**: A standout feature is the ability to accurately input the geometric parameters of damage into the BIM model. Using the GAMMA AR application, damage identified in the field is precisely recorded and integrated into Revit models, ensuring alignment with the inspection data and improving the reliability of the digital representation.
- **Enhanced lifecycle documentation:** The methodology strengthens bridge maintenance by documenting damage throughout the bridge's lifecycle within the Industry Foundation Classes (IFC) framework. This consolidated approach improves data storage, accessibility, and the planning of maintenance activities.
- **Improved assessment of hard-to-reach damages:** The methodology also addresses the challenge of inspecting difficult-to-access areas by providing effective tools for damage measurement, thereby increasing the accuracy and thoroughness of bridge inspections.

5.3 Research Challenges and Limitations

During the inspections, several challenges and limitations were identified in the field:

- **Model tracking and positioning:** One of the main challenges was accurately tracking and positioning the model, hindered by the lack of a depth sensor in the tablet used. Incorporating mixed reality glasses could potentially resolve this issue by improving model placement precision.
- **Sunlight exposure**: Excessive sunlight made it difficult to view the tablet screen outdoors. Despite this, all structural damage was effectively reported, and the data was collected efficiently.
- **Uneven terrain**: The bridge's location on uneven terrain presented challenges in tracking a stable plane for model positioning. Addressing this issue may require

implementing advanced tracking mechanisms or alternative positioning techniques to ensure accurate model alignment.

- **Technological limitations**: The technology employed for tracking and positioning, mainly through the camera on devices lacking a Time-of-Flight (ToF) sensor, faced considerable hindrances. Future advancements in sensor technology or the adoption of alternative tracking methods may be necessary to mitigate these limitations effectively.
- **Dependence on a single Case Study:** A limitation of this study is its reliance on a single case study, which constrains the generalization of the results. The findings should be considered preliminary, with the understanding that future studies involving a set of bridges are planned to validate the methodology more broadly.
- **Early Stage of BIM with BMS:** It is important to note that the integration of BIM with Bridge Management Systems (BMS) is still in its early developmental stages. Continuous technological advancements and research are needed before these integrated practices become standard in daily operations, highlighting the need for ongoing innovation in bridge maintenance management.

Addressing these challenges and limitations, it is intended to provide insights into areas for improvement and future research directions in the integration of MR technologies and BIM methodology for enhanced bridge maintenance management.

5.4 Improvements

To augment the inspection's precision, strategies should be formulated to refine the positioning of the BIM model. Inaccuracies in positioning can result in inconsistencies and uncertainties regarding families of damage. Some improvements could be implemented for greater accuracy in the MR inspection method:

- **Development of the GAMMA AR "Description" Tab:** Further development of the "Description" tab within the GAMMA AR application could be beneficial. This enhancement would allow for the inclusion of additional information required for the family of damage parameters and the inspection procedure. By expanding the capabilities of this tab, inspectors can provide more comprehensive data related to identified damages, facilitating a more detailed analysis and assessment.
- **Increased Level of Detail (LoD) in the BIM Model:** Enhancing the level of detail (LoD) in the BIM model would significantly improve the inspection process. While

reinforcements were not modeled in the current project, their inclusion would enable inspectors to analyze their condition and identify any associated damages accurately. By incorporating reinforcements into the BIM model, inspectors gain access to crucial information for assessing structural integrity and identifying potential issues, thereby enhancing the overall accuracy of inspections.

By implementing these improvements, the MR inspection method can be enhanced to achieve greater accuracy and reliability. These enhancements would not only address current limitations but also pave the way for more comprehensive and effective bridge maintenance management strategies in the future.

Including concrete reinforcement data in the model could be a possibility to improve the analysis of the risks that the structure is facing and determine the necessary measures for structural reinforcement. This inclusion would provide insights into the size and significance of the reinforcement. Chi et al. [42] propose the creation of a method that uses laser scanning associated with augmented reality to check the execution of rebars. In this study, the positions and shapes of the reinforcement are analyzed to detect incompatibilities concerning the structural design. The results obtained confirmed that the method was effective in detecting and correcting non-conformities in the positions of steel bars, regardless of their type, shape, or complexity. In addition, it promotes accurate inspection of steel bar dimensions and intuitive visualization, contributing to effective quality control of steel bars.

Mixed Reality (MR) enables inspectors to overlay the BIM model with real images of the concrete structure, providing additional information such as dimensions, coverings, reinforcement shapes, spacing, and possible discrepancies with the structural design. Furthermore, this technology allows the responsible engineer to make real-time annotations, which can be shared with project stakeholders afterward.

6. Conclusions

This paper explored the integration of MR technologies and BIM with inspection techniques to enhance bridge maintenance management. The methodology involved utilizing MR for real-time inspection alongside BIM parametric damage models, enabling the classification, localization, and sharing of information on pathological manifestations in the structure. The approach was tested on-site at the existing viaduct Coimbra I in MG, Brazil. The key conclusions are as follows:

- Mixed reality (MR) inspection represents a significant evolution over conventional visual inspection to assess the condition of bridges. While the conventional approach is manual, subjective, and has limitations when it comes to documenting and sharing information with the structure's database, MR inspection uses advanced technologies such as (BIM) and technological devices to streamline the process and improve accuracy and data documentation. This transition to digital methods offers operational efficiency and significant improvements in the bridge's safety, reliability, and maintenance management.
- MR-aided inspection is feasible with current technology, employing well-established and available computational and interface tools. This facilitates information exchange with a small investment in development, training, and acquisitions.
- The case study successfully demonstrated the feasibility of integrating MR inspection with a BIM model using proposed parametric damage families. It proved to be precise and effective in exchanging information, paving the way for integration with a BIM-based BMS. Tablets, with their practicality, cost-effectiveness, and accessibility, provide a more intuitive and collaborative tool for field inspections.
- This methodology offers several strengths, including the insertion of damage information into the BIM model, the precise localization and integration of damage data, the improved documentation of damage tracking throughout the bridge's life cycle, and the facilitation of damage measurement in hard-to-reach areas. These strengths contribute to more comprehensive and accurate bridge inspections, empowering professionals with efficient tools for planning and executing maintenance while ensuring the overall integrity of the inspection process.
- Similar to other techniques involving BIM models, modeling existing bridges is a resource-intensive task, both in terms of time and cost. Nevertheless, it is a necessary step for implementing a full BIM-based BMS that supports MR-aided inspection methods.
- Limitations related to internet signal availability and the need for adaptations of current tools and technologies for on-site inspection were observed. Addressing these issues is essential for broader and more precise applications. Additionally, typical challenges of conventional visual inspection, such as access to hard-to-reach sites, remain relevant.

The demonstrated approach highlights the potential for implementing a streamlined and cost-effective MR-based inspection routine. However, its effectiveness depends on ongoing advancements in establishing a BIM-based BMS, especially in creating models for existing bridges. This proves challenging for agencies with limited budgets and extensive infrastructure networks. Nevertheless, the method can serve as a supplementary and supportable approach within a versatile BMS capable of integrating diverse input methods into universal and integrated databases.

It is worth acknowledging that this study is based on a single case involving the Coimbra I viaduct. While the results are promising and illustrate the potential of integrating MR with BIM for bridge inspection, they are specific to this context and may not be directly generalizable to all structures or environments. Future research should aim to apply this methodology to a range of case studies, encompassing different bridge types and varied environmental conditions, to validate the findings and assess the scalability and adaptability of the approach. Expanding the scope would help further confirm the benefits and address the limitations identified in this initial study.

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CHAPTER VI

Final consideration

Abstract

This chapter presents the conclusions of the research, highlighting its contributions to bridge damage management. The study developed a methodology for damage information modeling (DIM) integrated with Building Information Modeling (BIM), allowing for greater standardization and interoperability in structural management. In addition, immersive technologies were explored to optimize damage inspection and documentation.

1. General conclusions

This research proposed an innovative approach to bridge damage management by integrating Damage Information Modeling (DIM) with Building Information Modeling (BIM) and exploring the use of Mixed Reality (MR) for inspection and documentation. From the inspection and damage identification phase to the parameterization and structuring of information in digital models, this study proposed solutions to improve the efficiency and accuracy of bridge management systems. In addition, it investigated the application of immersive technologies such as Mixed Reality (MR) to optimize the documentation and visualization of damage, facilitating decision-making and making maintenance processes more efficient.

The results demonstrate significant contributions to the literature and practice of bridge management. The main contribution of this study was the development of a structured methodology for damage modeling, promoting standardization and interoperability in the flow of information within BIM-based systems. BIM and DIM integration allowed the creation of detailed digital representations of damage, enabling more accurate and accessible recording. In addition, the research presented a parametric model for preliminary maintenance estimates, helping to plan interventions and allocate resources efficiently. Another significant advance was the application of immersive technologies to inspecting and documenting damage, demonstrating their viability in supporting structural analysis in complex environments.

In conclusion, this research contributes significantly to the advancement of digitalization in bridge management, offering innovative solutions that integrate parametric modeling, maintenance estimates, and immersive technologies. BIM and DIM, combined with MR, represent a breakthrough regarding how structural information is collected, analyzed, and used to support decision-making. By modernizing inspection and maintenance processes, these approaches contribute to greater efficiency, sustainability, and safety in infrastructure management. The findings of this study pave the way for further research and encourage the adoption of digital methodologies, driving innovation in bridge maintenance and the management of critical infrastructure.

2. Unprecedented Research

This thesis presents unprecedented contributions to the modernization of bridge maintenance management, addressing critical challenges related to the modeling and damage information integration into Bridge Management Systems (BMS). The innovative nature of this research can be seen on several fronts, as described below.

a) **Structured Methodology for Damage Information Modeling (DIM)** – A systematic approach to standardizing, tracing, and ensuring inspection and maintenance interoperability data.
b) **Parametric Model for Maintenance Estimation** – An innovative preliminary cost model and service estimation in reinforced concrete bridges, optimizing financial and operational resource management.
c) **Immersive Technologies for Inspection and Documentation** – Mixed Reality (MR) and BIM integration enhances visualization and recording of structural anomalies, improving assessment accuracy and reducing subjectivity in visual inspections.
d) **Holistic Approach to Bridge Management** – Unlike previous studies that focused on isolated aspects, this research covers the entire process, from damage identification to BIM integration, improving data-driven decision-making and stakeholder communication.
e) **Technological Convergence for Infrastructure Modernization** – BIM, DIM, and MR integration marks a breakthrough in digitalizing data, automating processes, and enhancing bridge maintenance efficiency.

3. Proposals for future works

The advancements introduced in this research open avenues for further exploration and refinement:

- Enhancing the parametric maintenance estimation model by incorporating additional factors such as material durability, environmental conditions, and intervention history to improve cost and service forecasting accuracy. Machine learning techniques could enhance predictive capabilities, enabling automated and dynamic decision-making.
- Automating inspection and damage modeling using artificial intelligence (AI) and deep learning. Computer vision and neural networks could enable automatic damage detection, reducing subjectivity and increasing efficiency. Integrating these technologies with BIM and DIM would facilitate real-time decision-making and continuously updated digital models.
- Standardizing Mixed Reality (MR) use in bridge inspections, developing methodologies, operational guidelines, and cost-benefit analyses to accelerate its adoption in infrastructure management.
- Improving interoperability between modeling and management platforms, developing

solutions such as plug-ins or APIs to enhance data exchange between BIM, DIM, and other management systems, and ensuring seamless integration across different tools and stakeholders.

By addressing these challenges, future research can drive the digital transformation of bridge management. Advancements in automation, predictive modeling, and standardization will significantly improve inspection, maintenance, and planning processes, promoting efficiency, precision, and sustainability in infrastructure management.