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AI-based deterioration index model for bridge management systems with limited database

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Doctor Scientiae

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CHRISTIAN ALEXANDRE FEITOSA DE SOUZA

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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*.

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ABSTRACT

SOUZA, Christian Alexandre Feitosa de, D.Sc., Universidade Federal de Viçosa, March, 2025. **AI-based deterioration index model for bridge management systems with limited database**. Adviser: Jose Maria Franco de Carvalho. Co-advisers: Diogo Silva de Oliveira, Jose Carlos Lopes Ribeiro and José António Silva de Carvalho Campos e Matos.

This thesis proposes methods for managing bridges, with a focus on predicting deterioration and defining deterioration indices for prioritizing interventions and inspections. The research combines traditional and advanced approaches, including probabilistic methods based on Markov matrices and artificial neural networks to predict the evolution of the condition of bridges over time. In addition, an inspection methodology adapted to the Brazilian context is presented, integrating international best practices. The developed models were validated with real and simulated data, allowing the evaluation of different deterioration scenarios depending on the environment and the Average Daily Traffic (ADT). Finally, the thesis proposes a bridge deterioration index to help prioritize interventions and plan inspections, contributing to optimize the efficient management of road infrastructure.

Keywords: Bridges; Forecasting; Inspection; Management; Intervention; Deterioration

RESUMO

SOUZA, Christian Alexandre Feitosa de, D.Sc., Universidade Federal de Viçosa, março de 2025. **Modelo de índice de deterioração baseado em IA para sistemas de gerenciamento de pontes com banco de dados limitado**. Orientador: Jose Maria Franco de Carvalho. Coorientadores: Diogo Silva de Oliveira, Jose Carlos Lopes Ribeiro e José António Silva de Carvalho Campos e Matos.

A presente tese propõe metodologias para a gestão de pontes, com foco na previsão da deterioração e na definição de índices de deterioração para priorização de intervenções e inspeções. A pesquisa combina abordagens tradicionais e avançadas, incluindo métodos probabilísticos baseados em matrizes de Markov e redes neurais artificiais para prever a evolução do estado de condição das pontes ao longo do tempo. Além disso, é apresentada uma metodologia de inspeção adaptada ao contexto brasileiro, integrando as melhores práticas internacionais. Os modelos desenvolvidos foram validados com dados reais e simulados, permitindo avaliar diferentes cenários de deterioração em função do ambiente e do volume médio diário de tráfego (VMD). Por fim, a tese propõe um índice de deterioração de pontes para auxiliar na priorização de intervenções e no planejamento de inspeção, contribuindo para a otimização da gestão eficiente da infraestrutura viária.

Palavras-chave: Pontes; Previsão; Inspeção; Gestão; Intervenção; Deterioração

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SUMMARY

CHAPTER I

General Introduction

Abstract

This chapter introduces the study, presenting its general and specific objectives. Additionally, it outlines the structure of the thesis, highlighting its key aspects to enhance readability and understanding. It also explores the synergy among the articles that comprise the thesis, emphasizing the connections between the topics addressed.

1. INTRODUCTION

The efficient maintenance and management of bridges has a fundamental role to play in ensuring the safety and structural integrity of vital infrastructures worldwide. The progressive deterioration of bridges is an ongoing challenge faced by engineers, government authorities and infrastructure management professionals. To tackle this complex and vital issue, this compilation of articles aims to offer a comprehensive and integrated approach that covers from inspection to models and indices that support data-driven decision making.

1.1. Objectives

The general objective of this thesis is to develop comprehensive bridge management methodologies that integrate everything from the inspection stage to the prediction of deterioration and the definition of indices for intervention prioritization and inspection scheduling. These methodologies aim to provide effective decision support tools that contribute to a more complete and efficient management of road infrastructure.
Accordingly, the following specific objectives have been defined:

- Conducting a robust literature review across all articles included in this research, providing a solid theoretical foundation for discussions, methodological developments, and the contextualization of findings within the broader scientific and technical landscape.
- Developing an inspection methodology that adapts best practices and protocols adopted by various countries to the specific conditions, regulations, and challenges of the Brazilian infrastructure context, ensuring a more structured and standardized approach to bridge inspections.
- Creating predictive models for bridge deterioration, utilizing methods probabilistic and artificial intelligence, with data-driven techniques to estimate the progression of structural degradation over time. These models will serve as essential tools for bridge management in Brazil, enabling proactive maintenance strategies and minimizing risks associated with structural failures.
- Designing a bridge deterioration index, capable of classifying structures based on their urgency for intervention. This index will assist in prioritizing maintenance actions, optimizing resource allocation, and improving the planning of inspection schedules to enhance the overall safety and longevity of the bridge network.

By integrating these elements, this thesis aims to contribute to the advancement of bridge management practices, supporting more data-driven, strategic, and effective decision-making processes in the field of road infrastructure maintenance.

1.2. Thesis Structure

This thesis has been structured as a compilation of articles, as permitted by the Federal University of Viçosa. As such, the research is presented through four main articles, which make up chapters II to V, addressing different aspects of bridge management. The thesis also includes two additional chapters: an introductory chapter and a concluding chapter. Complementing the main study, six additional articles on relevant and related topics expand the knowledge base developed, incorporated as appendices, reinforcing the robustness and comprehensiveness of the work.

Chapter I introduces the study, detailing its general and specific objectives. In addition to providing an overview of the research, this chapter describes the structure of the thesis, highlighting its main aspects to make it easier for the reader to understand. It also explores the relationships between the articles that make up the thesis, highlighting the connection between the topics covered and the methodological coherence adopted throughout the research.

Chapter II begins with a comprehensive literature review of bridge management systems implemented worldwide, with an emphasis on their inspection methods. Based on the analysis of these methods, the second part of the chapter proposes a methodology adapted to the Brazilian context, integrating the most relevant aspects of the existing approaches to establish a model more suited to national conditions.

Chapter III deals with the development and validation of probabilistic models based on Markov matrices to predict the deterioration of bridges in Brazil. Using a set of real inspection data from 885 bridges and generating additional information through deterministic models, specific models were developed for different environmental conditions (aggressive and non-aggressive) and different ranges of average daily traffic (ADT above and below 4,000 vehicles).

Chapter IV explores the use of artificial intelligence (AI) to predict bridge deterioration in scenarios with limited data. By integrating real inspection data with simulated data, this chapter demonstrates that artificial neural networks outperform conventional methods, such as deterministic and probabilistic models, in terms of accuracy and applicability.

Chapter V proposes a bridge deterioration index as a tool to support road infrastructure management. First, a review of current practices is presented, including inspection, structural assessment, prediction models, safety, and prioritization. Next, the index methodology is developed, which classifies bridges into different priority levels, allowing for a structured identification of those that require the most urgent intervention. In addition, the index helps to develop a strategic inspection plan based on this classification.

Finally, Chapter VI presents the final conclusions of the thesis, summarizing the main findings and contributions of the study. In addition to highlighting the implications and practical applications of the developed methodologies, the limitations of the research are discussed and directions for future studies are proposed. This chapter emphasizes the importance of continued research in bridge deterioration prediction and management and suggests possible improvements and methodological extensions to further strengthen the field.

1.3. Article Synergy

All the articles that make up this thesis are interrelated, either directly, by serving as a methodological basis for other studies, or indirectly, by complementing discussions and strengthening arguments. This connection between chapters and appendices strengthens the coherence of the work and highlights the gradual construction of knowledge throughout the research.

The first article (Chapter II) discusses bridge inspection methodologies based on internationally adopted practices and adapted to the Brazilian reality. This chapter has a number of indirect links with the conference papers in Appendices A, C and E, which have provided a practical basis for bridge inspection in Brazil. These studies helped the author to understand the shortcomings of the methods currently used and to develop a more efficient approach. Appendix A contains a comparative study of bridge evaluation methods through the routine inspection of three bridges in the state of Rio Grande do Norte. This study identified weaknesses and limitations in the inspection methodology developed by the *"Departamento Nacional de Infraestrutura de Transportes"* (DNIT) and provided valuable insights for its improvement. Similarly, Appendix C presents a study conducted in the State of Ceará, in which two bridges were inspected. This study revealed deficiencies in the formulation of effective strategies for structural interventions, and highlighted aspects to be improved in the inspection methodology. Finally, Appendix E focuses on special inspections, applying this type of evaluation to four bridges located in the states of Rio Grande do Norte and Paraíba. The research provided a more detailed understanding of this specific type of inspection and its relevance to the monitoring of structural deterioration.

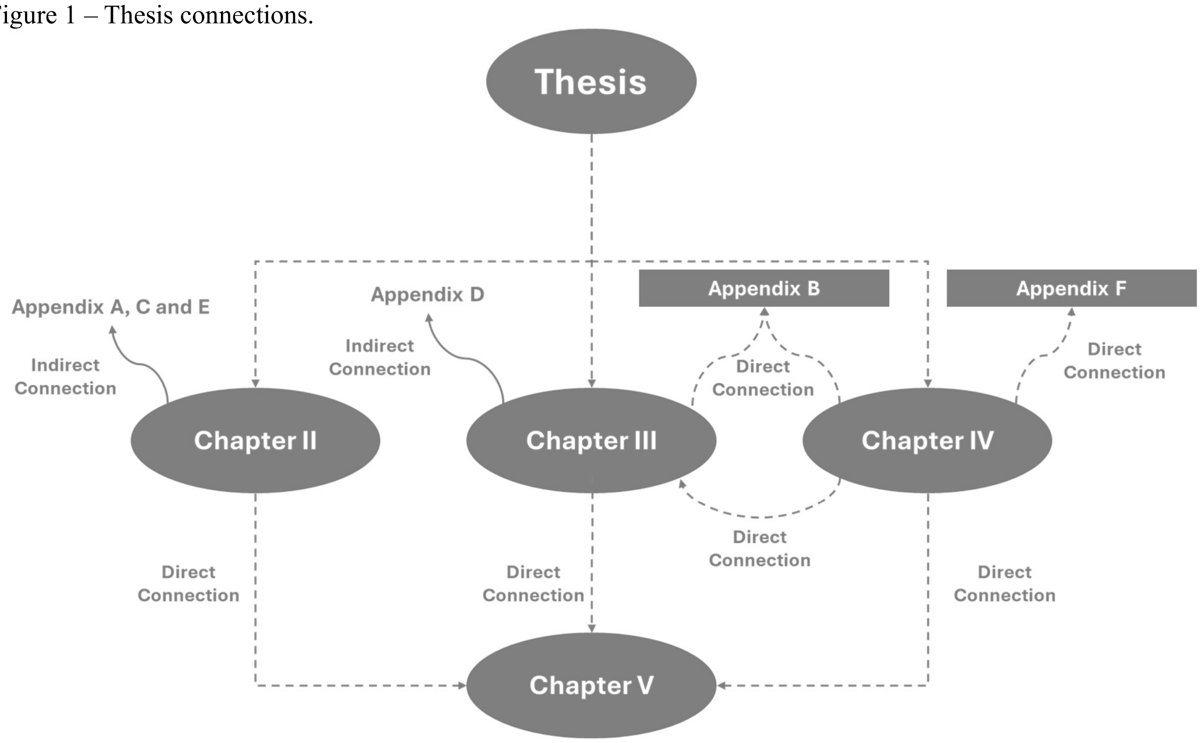
The second article (Chapter III) deals with the development of bridge deterioration prediction models using probabilistic methods, specifically Markov matrices. This study is directly related to the article in Appendix B and indirectly related to Appendix D. Chapter III itself highlighted the lack of data needed to formulate more robust prediction models. In this sense, Appendix B played a fundamental role, using data from the "*Sistema de Gerenciamento de Obras*" (SGO) to develop deterministic models for predicting bridge deterioration based on third-order polynomial regression. These models were essential for simulating the data needed to develop the probabilistic model in Chapter III. Appendix D presents a comprehensive review of bridge deterioration prediction models used in management systems around the world, providing an overview of the subject and reinforcing the indirect relationship to Chapter III.

The third article (Chapter IV) uses neural networks to develop models for predicting bridge deterioration, especially in scenarios where data is scarce. This chapter is directly related to Chapter III, Appendix B, and Appendix F. The link with Chapter III and Appendix B is due to the process of simulating inspection data, which is essential for developing models based on artificial intelligence in the Brazilian context. While Appendix B generated simulated data from deterministic models to feed the probabilistic modeling of Chapter III, the latter in turn used probabilistic models to simulate data that enabled the training of the neural networks described in Chapter IV. Appendix F was also directly related to this chapter, as it introduced an algorithm for estimating the year of construction of the bridges. This method made it possible to expand the dataset by simulating the year of construction of various bridges, thus making a significant contribution to the database used in neural network modeling.

Finally, the fourth article (Chapter V) presents the development of a bridge deterioration index aimed at prioritizing interventions and planning inspections. This study is directly related to the previous three chapters (Chapters II, III and IV). The relationship with Chapter II is because the developed inspection methodology is used to define strategies for planning bridge inspections. Chapter III is fundamental for the construction of the deterioration index, since the probabilistic prediction models provide essential coefficients for the classification of the intervention priority. Finally, Chapter IV also plays an important role as neural network models are used to predict the structural condition of bridges over time. In this way, the deterioration index can be calculated dynamically, making it possible to define priorities over the years and optimize the planning of inspections and maintenance.

In this way, the thesis is structured in a logical sequence, as summarized in Figure 1, where each article contributes to the advancement of the research. This integrated approach strengthens the robustness of the results and reinforces the practical applicability of the studies developed.

Figure 1 – Thesis connections.



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CHAPTER II

Bridge inspection methods worldwide: Proposed Integrated Approach for Brazilian Bridges

Abstract

Proper management and inspection are essential to ensure the safety and structural integrity of bridges. In this paper, bridge management systems implemented around the world have been studied with a focus on their inspection methods. Based on the results, the authors propose a methodology that integrates the most relevant aspects of many existing approaches, targeting a Brazilian context. It covers six types of inspections, including three levels of depth and an emergency inspection. The aim is to obtain a methodology that can be adapted to the specificities and local conditions of Brazilian bridges. The three levels of inspection depth allow for a comprehensive analysis, from a basic to a detailed assessment, ensuring an accurate understanding of the condition of the bridges.

Keywords: Inspection; Bridge Management System; Assessment; Bridge; Infrastructure.

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2. BRIDGE INSPECTION METHODS WORLDWIDE: PROPOSED INTEGRATED APPROACH FOR BRAZILIAN BRIDGES

2.1. Introduction

Bridges are essential to transportation infrastructure, providing connectivity and safety. However, they are exposed to environmental factors and dynamic loads, leading to deterioration over time. Ensuring their safety and structural integrity requires a systematic management and inspection approach (Figueiredo; Manuel; Marques, 2013). Various management systems have been developed and implemented worldwide to support bridge monitoring and maintenance. These systems offer guidelines and recommended practices for inspection, assessment, and management, aiding in early damage detection and corrective actions.

The Silver Bridge collapse in the United States in 1967, which caused 46 casualties, prompted the prioritization and implementation of bridge management systems. In response, the US Department of Transportation and the American Association of State Highway and Transportation Officials (AASHTO) established bridge inspection standards in 1971 and created a national database (Mark Hurt; Steven Schrock, 2016).

Despite these advancements, similar tragedies still occur, causing financial losses and significant losses of life. Table 1 lists collapses that have had severe consequences for affected communities. These failures resulted from inefficient management and could have been prevented with an effective management framework.

Table 1 – Bridge collapses are caused by inefficient bridge management.

Year	Country	Bridge	Deaths	Reason
1994	South Korea	Seongsu	39	Inefficient checkups, and repairs
2001	Portugal	Hintze Ribeiro	59	Pillar foundation compromised
2007	USA	I-35W	13	Poor maintenance
2008	China	Dumu Reservoir	3	Poor maintenance
2016	India	Savitri River	28	Degraded condition.
2018	Italy	Morandi	43	Corrosion and poor maintenance
2019	China	Nanfang'ao	6	Corrosion and poor maintenance
2024	Brasil	Juscelino Kubitsche	6	Poor maintenance

Sources: (Huo *et al.*, 2023; Kim; Sohn, 2018; Lauris; Reis, 2024; Mendonça; Brito; Costa, 2016; Rajendran, 2019; Witcher, 2007; Xu *et al.*, 2016).

Cervantes et al. (2024) illustrate the concerns, reporting that in Ecuador, 50% of bridge collapses were linked to management deficiencies, with 12.5% directly caused by poor maintenance. Notably, 91.7% of the collapsed bridges were still in service, highlighting the need for proper care.

Based on a comprehensive bibliographic and analytical review, this article proposes a bridge inspection program that integrates the best features of various management systems implemented worldwide. The resulting methodology offers a flexible and adaptive approach for Brazilian bridges, combining key elements of existing systems into an integrated framework. The proposed program aims to provide a comprehensive and accurate assessment of bridge conditions, supporting efficient resource management and decision-making based on reliable information.

2.2. Methodology

The bibliometric review was based on a search conducted in the Scopus database in August 2024, using the term "Bridge Management System" in "Titles, Abstracts, and Keywords." Only documents in English from 2001 to 2023 were considered, resulting in 751 documents. VOSViewer, Bibliometrix, and Scopus tools were used for analysis.

The StArt software was used for refining the search, selecting studies related to Bridge Management Systems (BMS) and inspection programs from the 14 most contributing countries identified in the bibliometric analysis.

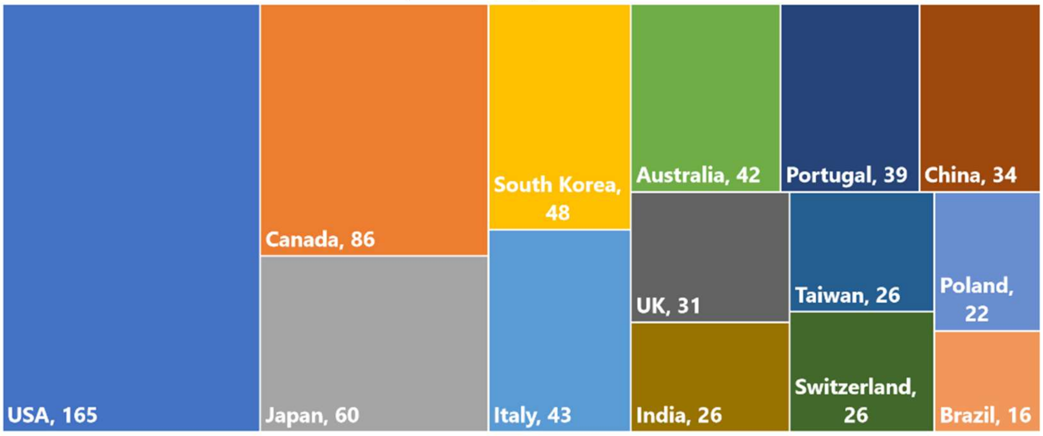
Additionally, inspection manuals, data from Ministries of Transportation, books, reports, and relevant articles were included, resulting in 55 documents for the analysis.

After a deep review of the documents and the selected BMS, a unified inspection program was proposed, focusing on levels, types, and frequency of inspections.

2.3. Bibliometric review

Figure 2 depicts a tree map of the 14 most collaborative countries in this field, considering only those with at least 16 publications. It highlights the USA's strong influence, reflecting their high publication volume and extensive connections, driven in part by its early leadership in this research area.

Figure 2 – The most collaborative countries by scientific production in the field.



Source: Author.

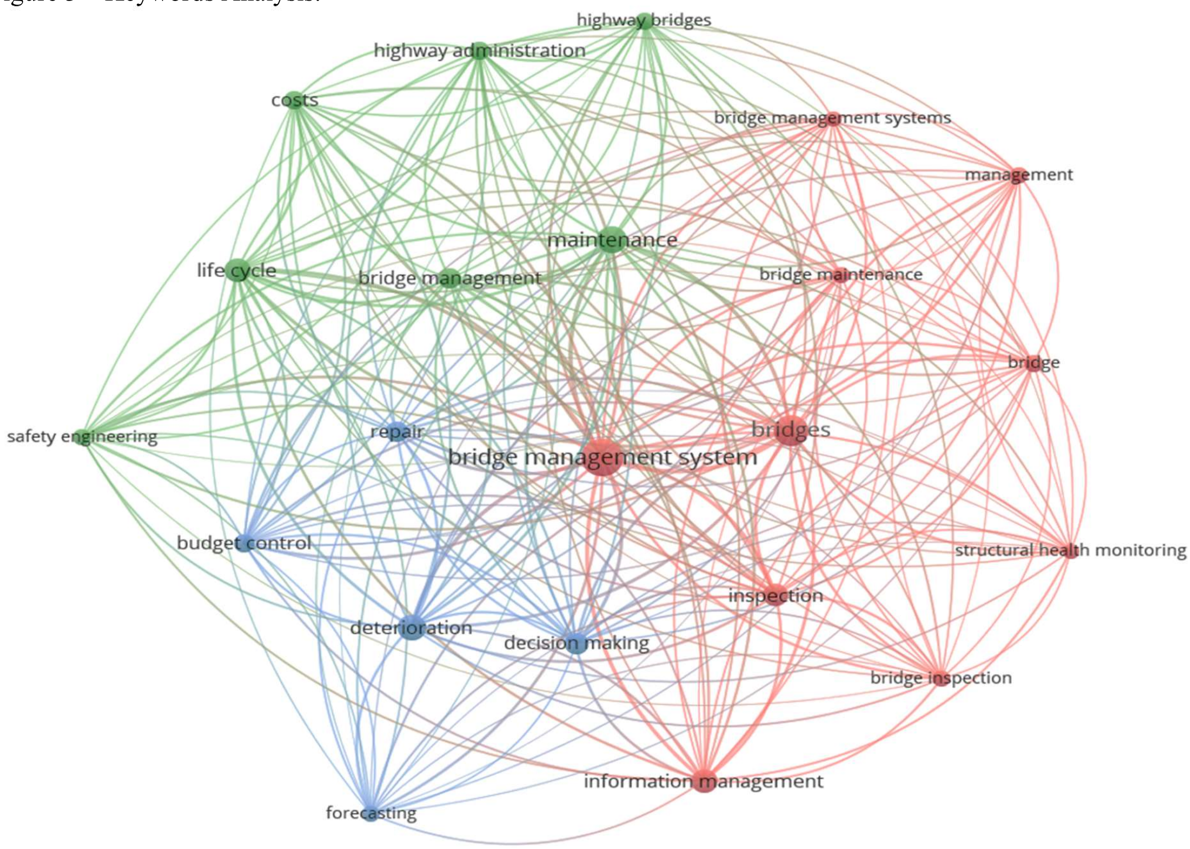
Keywords related to inspection and monitoring are among the most prominent (Figure 3). The word cloud is organized into three clusters, each representing key themes in bridge management research.

The red cluster includes terms like "bridge," "management," "inspection," and "structural health monitoring," emphasizing bridge monitoring and the role of advanced technologies in structural assessment.

The green cluster features words such as "maintenance," "highway bridges," and "life cycle," highlighting lifecycle management and the importance of preventive maintenance to optimize resources and extend bridge lifespan.

The blue cluster contains terms like "deterioration," "forecasting," and "budget control," focusing on deterioration prediction and budget-based decision-making to support efficient financial planning and long-term infrastructure sustainability.

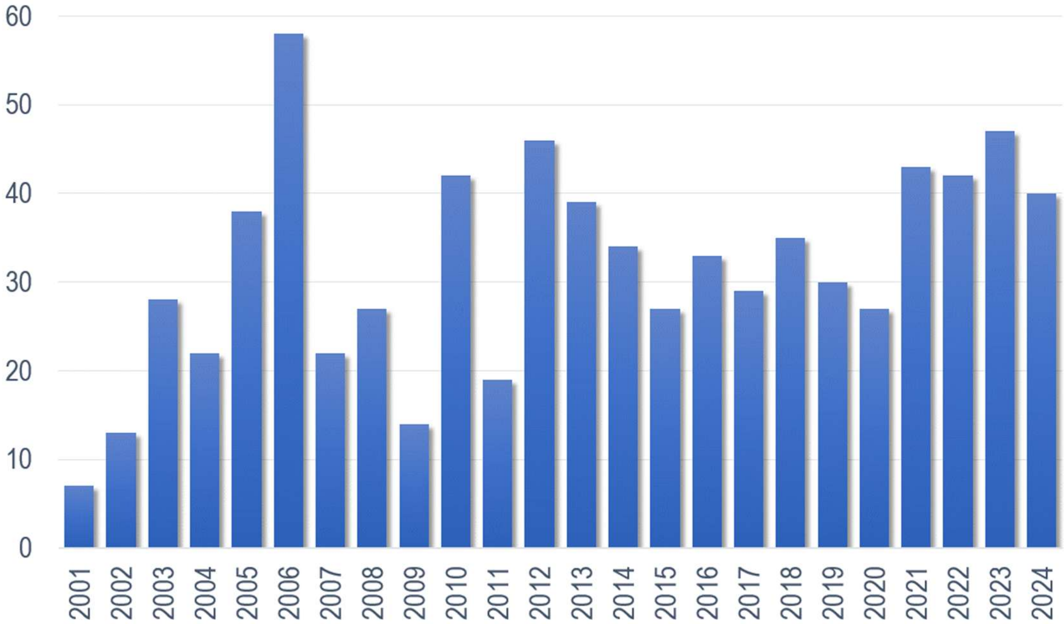
Figure 3 – Keywords Analysis.



Source: Author.

Research on bridge management systems grew significantly in the early 21st century, largely because many systems were developed during the 1990s and 2000s (Adey; Klatter; Thompson, 2014). Although the number of publications has since stabilized, the topic remains relevant globally. Figure 4 shows the number of papers published each year.

Figure 4 – Number of documents by year.



Source: Author.

The peak in 2006 is linked to the 3rd International Conference on Bridge Maintenance, Safety, and Management (IABMAS), which generated 34 publications on BMS, the highest in this century. The biennial IABMAS congress has also contributed to publication spikes in even-numbered years, including 2006, 2010, and 2012.The top four journals in bridge management are Structure and Infrastructure Engineering, Transportation Research, Journal of Bridge Engineering, and Journal of Infrastructure Systems. These journals are leading sources in the field, covering research on bridges and transportation infrastructure.

2.4. Bridge management systems in the world

The performance, safety, and functionality of a bridge depend on how interventions are planned and executed. Bridge management optimizes these actions to enhance performance while minimizing risk, supporting investment decisions (Oliveira, 2019). A BMS consists of three main components: database, data analysis, and decision support. The database includes bridge inventory, inspections, cost data, and maintenance records (Fontes *et al.*, 2014). These inputs enable efficient data analysis, where systems prioritize key factors such as deterioration prediction and cost models (Adey; Klatter; Thompson, 2014; Almeida, 2013). Decision support then uses this analysis to guide actions based on technical assessments.

With advances in computing, BMSs have transitioned from paper-based to digital systems, improving information processing. In 1980, North Carolina and other U.S. states began using BMSs (Mark Hurt; Steven Schrock, 2016). Research and investments in BMSs have since expanded globally, leading to the development of various systems. Table 2 presents 14 BMSs from different countries, detailing their establishment years and the number of structures they manage.

Table 2 – Information about Bridge management systems analyzed.

Country/Bridge Management System	Inspection Levels	First Version	Nº of bridges[a]
Australia/ NSW	4	1996	6143
Brazil / SGO	5	1994	6833
Canada / OBMS	1	2002	5400
China / CBMS	3	1992	658100
India / UBMS	3	2015	169758
Italy / APTBMS	2	2004	1953
Japan / RPIBMS	1	2006	5018
Poland / SMOK	5	1997	33250
Portugal / GOA	2	1999	16000
South Korea / KRMBS	4	2005	6192
Switzerland / KUBA	1	1989	31313
Taiwan / TBMS	3	1999	27895
United Kingdom / SMIS	6	1999	16000
United States of America / AASHTOWare	8	1992	750908

[a]The number of structures managed in each system may be out of date, since this information was obtained through the references cited in the last column.

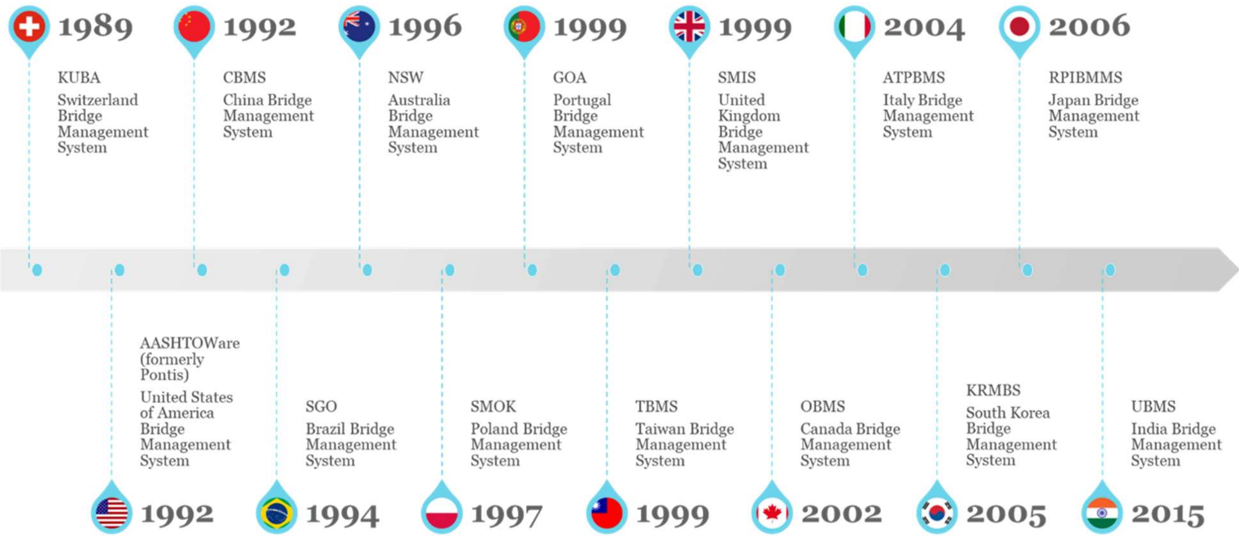
Sources: (AASHTO, 2016; AASHTOWare Bridge Management, 2021; Adey; Klatter; Thompson, 2014; Chattopadhyay; Raman, 2013; Dai *et al.*, 2014; DNIT, 2023; FHWA, 2012; Fontes *et al.*, 2014; Habeenzu *et al.*, 2021; Hammad *et al.*, 2007; Highways Agency, 2007; Hsien-Ke *et al.*, 2017; Jeong *et al.*, 2018; Joshi; Joshi, 2016; Joshi; Raju, 2018; Joshi, 2022; Maharajpur, 1997; Melhem; Caprani; Ng, 2018; Mendonça *et al.*, 2006; Mendonça; Brito, 2014; Ministry of Land Infrastructure and Transport, 2012; Ministry of Transport of the people's Republic of China, 2011; Ministry of Transportation Ontario, 2008; MOTC, 2015; Saback *et al.*, 2021; Souza *et al.*, 2022; Task Group GOA, 2007; Thompson, 2004; Traffic Authority of NSW, 2007).

The first system developed and implemented was KUBA, the Swiss Bridge Management System, in 1989. Shortly after, in 1992, the U.S. implemented Pontis, now known as AASHTOWare, and China developed and implemented the Chinese Bridge Management System (CBMS). Figure 5 shows a timeline of the selected management systems.

The two largest BMSs are AASHTOWare, with 750,908 structures, and CBMS, with 658,100 structures. In third place is UBMS, with a significantly smaller number of 169,758 structures. The large size of their countries and extensive road networks partly explains these figures. Among the 14 countries analyzed, the five with the largest road networks are the U.S. (6.59 million km), India (4.77 million km), China (4.70 million km), Brazil (2.00 million km), and Japan (1.22 million km).

In Brazil, the main management system oversees 6,833 structures, which does not reflect the actual size of the country's road network, the 4th largest in the world. This discrepancy arises because road management and maintenance are often outsourced through concessions. For instance, the privately-operated *Sistema de Gestão de Ativos (SGA)*, managed by the MRS company, oversees 631 structures (Masini *et al.*, 2021).

Figure 5 – Timeline of implementation of the selected management systems.



Source: Table 2.

In Brazil, most highways are managed by state governments rather than the federal government, with each state's Department of Highways and Roads overseeing bridges. However, there is no unified or efficient system at the state level. The country is estimated to have around 137,000 bridges, but only 6,833 are managed by the federal agency (Silva; Almeida De Melo, 2021). This is surprising, given Brazil's success in creating unified systems in other sectors. For example, the Unified Health System (*Sistema Único de Saúde* - SUS) is globally recognized for its broad coverage and near-universal access to healthcare services, involving all levels of government and both private and public networks.

Despite its large size and diversity, Brazil has a cultural inclination toward unified systems that promote governance and data management efficiency. Therefore, it seems likely that Brazil will eventually develop and implement a universal BMS. Supporting this view, most U.S. states have adopted the AASHTOWare BMS, with 41 out of 50 asset management agencies in the U.S. using it in 2021 (AASHTOWare Bridge Management, 2021). Other countries also give autonomy to their state or regional transportation departments to either adopt existing BMS or develop their own. Notable examples include Canada, where each of the ten provinces uses a different system, and Australia, which has 50,000 road bridges divided into nine regions, each with its own BMS (Hammad *et al.*, 2007; Melhem; Caprani; Ng, 2018).

In contrast to most countries, China uses a management system (CBMS) that covers most of its structures, operating in a unified manner with a single national methodology for inspection and evaluation (Dai *et al.*, 2014). While a unified BMS can be beneficial for standardizing data, methodologies, and large-scale statistical coverage, as well as supporting national-level decisions, it also has drawbacks. These include the generalization of methodologies, which may overlook important regional, political, and financial differences, and potentially complicating information processing.

There is no one-size-fits-all approach to managing a country's infrastructure. However, considering both the advantages and disadvantages, a unified system holds significant potential for efficient management. Its success depends on flexibility and the ability to effectively address local specifics. While this can make data collection and processing more complex, it can also influence decision-making (Thompson, 2004; Wu *et al.*, 2021). A unified system is generally more advantageous and simpler in countries with smaller road networks, such as Portugal and South Korea. In these countries, there are fewer regional differences, and standardized methodologies can be more easily applied and representative (Mendonça *et al.*, 2006; Mendonça; Brito, 2014; Ministry of Land Infrastructure and Transport, 2012).

In contrast, countries with larger road networks and more research in the field often have decentralized management, granting autonomy to state transportation departments. This decentralization is necessary due to regional, political, and financial differences. In the U.S., although each state manages its assets independently, most use AASHTOWare. The U.S. also has a unified database, the National Bridge Inventory (NBI), which provides an overview of the country's infrastructure. This demonstrates that efficient management can be achieved with a widely used BMS, while still respecting regional specificities and decentralizing management for better data processing and decision support (AASHTOWare Bridge Management, 2021).

Brazil is an example of the challenges involved. Many Brazilian assets are not covered by an efficient system due to the costs and effort required to develop and maintain a functioning BMS (Souza, C. *et al.*, 2024). However, such an effort is feasible at the national level with significant government investment, including research and technological development, particularly in data science. Unifying data, methodologies, and systems would enhance safety and cost-efficiency in management and maintenance, supported by ongoing research and continuous improvements.

2.5. Inspection of the bridge management system

Three systems OBMS (Canada), RPIBMS (Japan), and KUBA (Switzerland) use only one level of inspection (Adey; Klatter; Thompson, 2014). OBMS requires a Detailed Visual Inspection every two years, or sooner in emergencies. (Adey; Klatter; Thompson, 2014; Ministry of Transportation Ontario, 2008). KUBA and RPIBMS perform a principal or routine inspection every five years (Saback *et al.*, 2021).

Portugal and Italy (GOA and ATPBMS) use two inspection levels: routine and principal. In Portugal, routine inspections are every 12 to 15 months, while in Italy, they are annual. Principal inspections are conducted every three to six years in Portugal and every three years in Italy (Adey; Klatter; Thompson, 2014; Mendonça; Brito, 2014). Three systems use three levels of inspection. Three systems use three levels of inspection. Details on these BMSs are provided in Table 3.

Table 3 – BMS with three levels of inspection.

BMS	**Description**		
	1º Level	**2º Level**	**3º Level**
CBMS	Routine inspection: monthly visual observation of the bridge's structural elements.	Periodic inspection: carried out every three years, it uses visual equipment to assess the bridge's condition.	Special Inspection: The inspections are more detailed and depend on the structure.
UBMS	Routine Inspection: This consists of a broad general visual inspection once a year.	Detailed inspection: thorough examination of all bridge components and superstructure, with equipment and prepared checklist (five years).	Special inspection: performed on specific bridges for extraordinary reasons, such as accidents, natural disasters, old bridges, or bridges in need of major repairs
TBMS	Daily Patrol: whereby two inspectors drive over a bridge to check for defects (Regularly).	Regular inspection: to examine the overall condition of the bridge, visual inspection only, and essential tools. (Two years).	Damage inspection: unscheduled assessment of structural damage caused by extraordinary events (as needed).

Summary description, for more details, see the manual or standard.
Sources: (Dai *et al.*, 2014; Hsien-Ke *et al.*, 2017; Joshi; Joshi, 2016; Joshi; Raju, 2018; Joshi, 2022; Maharajpur, 1997; Ministry of Transport of the people's Republic of China, 2011; MOTC, 2015).

NSW and KRMBS adopt four levels of inspection. In NSW, a fourth level evaluates the structure's load capacity, including a load test when necessary (Melhem; Caprani; Ng, 2018). KRMBS in South Korea adds an In-depth Safety Inspection to the three levels of Routine, offering more detail. The frequency of these inspections' ranges from four to six years, depending on the structure's condition (Jeong *et al.*, 2018). Two methodologies use five levels of inspection. One is the SMOK system, as shown in Table 4. The other, used by SGO, includes cadastral, routine, intermediate, special, and extraordinary inspections (DNIT, 2010), detailed in Table 5.

Table 4 – Inspection methodology adopted in Poland.

Inspection	**Description**
Current	Visual inspection is carried out during periodic patrols (at least twice a year) to record and assess defects that affect traffic safety.
Basic	An annual visual inspection with simple equipment assesses the structure's condition and determines what maintenance or rehabilitation is needed for safe operation.
Extended	Every five years, an inspection with specialized equipment bridge's technical condition, safe operation, and maintenance and rehabilitation needs.
During basic	The team of experts performs a comprehensive inspection of all structural components, including basic measurements and tests, to assess and document the technical condition of the object (as needed).
During extended	The expert performs an advanced inspection based on specialized tests and theoretical analysis to assess the technical condition of the structure (as needed).

Source: (Bien; Juzawa, 2016).

Table 5 – Inspection methodology adopted in Brazil.

Inspection	Description	Frequency
Cadastral	Inspection is carried out immediately after its conclusion, installation, or when it is integrated into the BMS.	Performed when bridge's configuration is changed (rehabilitation).
Routine	The Routine Inspections are periodic. In these inspections, the evolution of failures and new defects and occurrences are detected and registered.	Two years
Special	Special Inspections are detailed visual inspections, commanded by a senior inspector. It may also be necessary to complement the conventional observations and measurements including deflections and deformations.	From five to eight years. Anticipated in cases of structures with poor condition.
Extraordinary	The extraordinary inspection must be presented in a specific report, identifying the anomalies, including mapping, photographic documentation, and recommended therapy.	Perform when there is a need for a deep evaluation of an element or after accidents or nature events
Intermediate	Inspection is recommended to monitor a suspected or already detected deficiency	When recommended by previous inspections.

Source: (DNIT, 2010, 2024a).

Finally, two methodologies use more than five levels of inspection. The methodology used in SMIS has six levels of inspection, as shown in Table 6 (Habeenzu *et al.*, 2021). AASHTOWare has eight levels of inspection, as presented in Table 7.

Table 6 – Inspection in the UK.

Inspection	Description
Safety	A cursory inspection is carried out from a slow-moving vehicle (usually).
General	Visual inspection from the ground level. Report on the physical condition of all structural elements visible from the ground level (two years).
Principal	Close visual examination, within touching distance of the entire bridge, utilizing, as necessary, suitable inspection techniques (six years).
Special	Detailed investigation of areas of concern or following significant events (as needed).
Assessment	An inspection is undertaken to provide the information required to undertake a structural assessment (as needed).
Acceptance	A formal mechanism for exchanging. Information before the changeover of responsibility (as needed).

Source: (Habeenzu *et al.*, 2021).

Table 7 – Inspection levels prescribed by the AASHTOWare BMS.

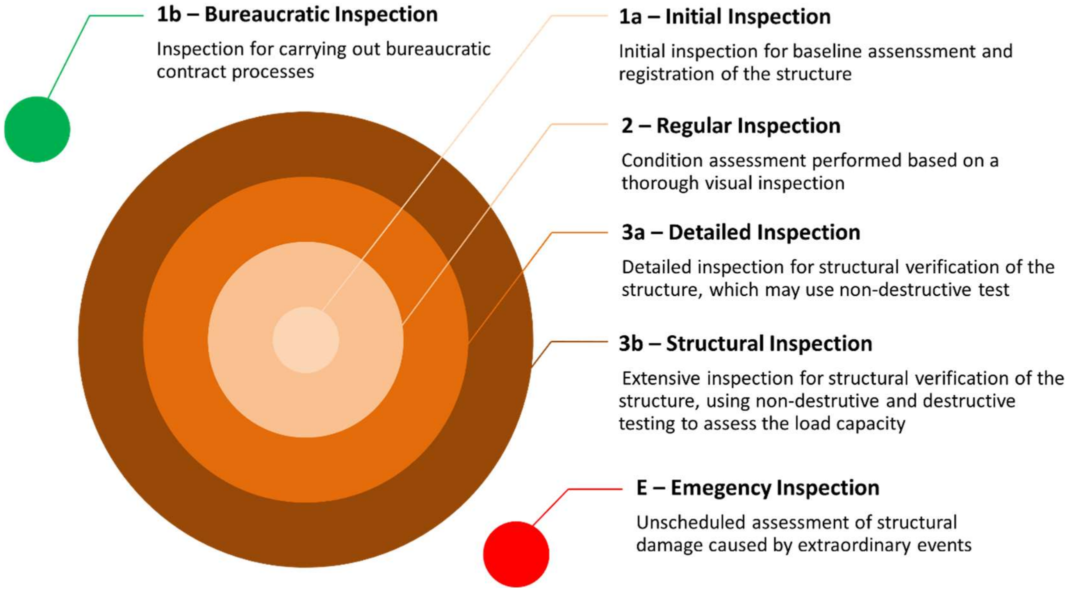
Inspection	Description
Initial	First inspection of a bridge as it becomes a part of the bridge inventory to determine baseline structural conditions.
Routine	Regularly scheduled inspection consisting of observations and/or measurements needed to determine the physical and functional condition of the bridge (two years).
Damage	Unscheduled inspection to assess structural damage resulting from environmental factors or human actions (as needed).
In-depth	A close-up inspection investigates deficiencies not detected during Routine Inspection (as needed).
Special	An inspection scheduled at the discretion of the bridge owner is used to monitor a particular known defect or suspected deficiency (as needed).
Underwater	Inspection of the underwater portion of a bridge substructure and the surrounding channel (five years).
Hands-on	Inspection within arm's length of the component. Inspection uses visual techniques that may be supplemented by non-destructive tests (as needed).
Fracture – Critical Member	A hands-on inspection of a fracture-critical member or components that may include visual and other non-destructive evaluation (two years).

Source: (AASHTO, 2016).

2.6. Proposed inspection methodology

This article proposes depth scales with varying levels of detail. These scales include three inspection depths, subdivided into "a" and "b", plus an emergency inspection for extraordinary cases. Figure 6 shows the inspection levels, from least to most detailed (smallest to largest circle). Emergency and bureaucratic inspections are outside the circle, depending on the situation. Emergency inspections may range from superficial to structural, while bureaucratic ones are based on contractual terms and regulations. Based on inspection level ranges from the studied approaches and the proposed inspection depths, the frequencies are outlined in Table 8.

Figure 6 – Conceptual schema of the proposed inspection methodologies.



Source: Author.

Table 8 – Frequency of the proposed inspection depths.

Depth	Inspection	Frequency*
1a	Initial	1st inspection or when the structural configuration changes
1b	Bureaucratic	As needed
2	Regular	2 years
3a	Detailed	6 years
3b	Structural	As needed
E	Emergency	As needed

*If there is more than one inspection in the same period, perform the most thorough inspection.
Source: Author.

As shown in Figure 6, the inspections performed on the bridges have different levels of detail, with the more detailed inspections providing a greater amount of information and technical analysis. Table 9 lists the data to be collected for each inspection type, including general bridge information and specific details based on inspection depth. For example, data from the initial inspection and the building information model (BIM) should be updated for later inspections. Additionally, existing damage must be cataloged and photographed, and the bridge's condition must be assessed.

The mandatory use of BIM in all inspections aligns with Decree No. 10.306, dated April 2, 2020, from the Presidency of the Republic of Brazil. This decree regulates BIM use for engineering works and services contracted by federal public administration bodies, in line with the National Strategy for the Dissemination of Building Information Modeling (BIM BR Strategy) (Presidência da República do Brasil, 2020). In addition to fulfilling legal requirements, BIM is widely recognized in academic and professional circles as an essential tool, used in various software and civil engineering applications for its ability to integrate information and optimize processes (Bradley *et al.*, 2016; Isailović; Petronijević; Hajdin, 2019). Level 3 inspections involve more detailed analyses of specific aspects of the bridge, including underwater inspection, non-destructive testing, structural safety assessment, load capacity verification, and the development of computer models for structural analysis. While non-destructive testing and structural safety analysis are common to both detailed and structural inspections, activities like destructive testing, failure probability assessment, intervention project development, and cost estimation are exclusive to structural inspections.

Table 9 – Information on each type of inspection.

Information	**1a**	**1b[1]**	**2**	**3a**	**3b**	**E**
Data collection and/or updating	X	X	X	X	X	X
Contract requirements[1]	X	X				
Photographing and categorizing all damage	X	X	X	X	X	X
Condition State	X	X	X	X	X	X
BIM model	X	X	X	X	X	X
Intervention recommendations (if necessary)	X	X	X	X	X	X
Underwater inspection				X	X	X[2]
Non-destructive tests				X	X	X[2]
Structural Safety				X	X	X[2]
Load capacity				X	X	X[2]
Computational models for structural assessment				X	X	X[2]
Semi-destructive and destructive tests					X	X[2]
Failure probability					X	X[2]
Structure rehabilitation/ reinforcement project					X	X[2]
Cost of rehabilitating/reinforcing the structure					X	X[2]

[1] It depends on the contract terms and requirements between the infrastructure owner and the contractor.
[2] The depth of the inspection and the amount of information will depend on the emergency that prompted the inspection and the damage to the bridge.
Source: Author.

For emergency inspections, the depth and amount of information gathered depend on the emergency that triggered the inspection and the severity of the damage. In bureaucratic inspections, the information collected is determined by the contract terms, which can also influence the level of detail, and the analyses performed.

2.6.1. First depth (1a – Initial Inspection and 1b – Bureaucratic Inspection)

The first level of inspection addresses both the construction phase and the bridge's lifespan. It involves registering the bridge, evaluating its initial condition, and updating records for structural changes, previous inspections, and contractual responsibilities. This level also facilitates the exchange of information in case of a responsibility transfer.

The information collected is divided into two categories: indispensable (for a basic condition assessment) and preferred (enhancing the analysis). Table 10 lists the recommended data to be recorded. This inspection depth includes two types:

1a – Initial Inspection: After the bridge's completion or modification, data on design, location, records, and contractual information is collected and analyzed to ensure compliance with specifications and identify potential issues.

1b – Bureaucratic Inspection: Conducted before, during, and after responsibility transfer to ensure the accuracy of inspection data and compliance with contractual terms, confirming the work aligns with contract specifications and the bridge is safe for use.

Three BMS use the first inspection level: SGO, SMIS, and AASHTOWare. SMIS is the only system using level 1b. Though some BMS don't include the first level, it remains crucial for registration and bureaucratic security in bridge management.

Table 10 – Recommended information for this level of inspection.

Recommended information for this level of inspection[1]	
Registration data	Bridge name and code
Bridge features	Type of transposition; construction system; typology; material; vehicle design; year built; Average Daily Traffic; environment class; length; width; number of spans; and among other information
Elements	All elements with code, name and quantity of each
Special aspects	All special aspects with code, name and observations
Functional Deficiencies	All functional deficiencies with code, name and observations
Location	Highway; km; section; state; altitude; latitude; longitude; and among other information
Responsible	Responsible agency/company; administration type; builder; contract data; and among other information
History of responsible agencies/companies	Agency/ company; period of operation; and among other information
Project data	Original project; BIM project; BIM software project; BIM model design engineer; intervention project; and among other information
Material characteristics	Mechanical characteristics and details of the materials used
Tests available	All tests available
Inspection data	Inspection specifications: equipment required; inspection history; and inspection planning
Structural assessment	Assessment history; non-destructive and destructive testing; structural safety; load capacity; computer model; probability of failure; structural health monitoring; and among other information
Intervention data	Intervention history; intervention project; intervention budget; and among other information
Cadastral images	Cadastral images of the bridge and all its elements, including image mapping
BIM model	Computer model file in BIM software
Additional information	Additional information not mentioned above

[1]If it is possible to obtain the information.

Source: Author.

2.6.2. Second depth (2 – Regular Inspection)

The second level of inspection focuses on monitoring the bridge's condition through visual assessment of damage, which is recorded in a database. This regular inspection helps detect potential failures early and guides preventive actions. Inspectors check for cracks, corrosion, deformations, and other deterioration signs. The goal is to ensure safety, extend the bridge's lifespan, and recommend repairs or maintenance. Regular inspections are typically conducted every one to two years.

Canada, Japan, and Switzerland exclude the second level, instead performing more detailed inspections (3a-equivalent) at intervals of two years in Canada, and five years in Japan and Switzerland. Canada's methods prioritize safety, while Japan and Switzerland require stricter quality control due to longer intervals, which may be challenging in regions with fewer resources.

2.6.3. Third depth (3a – Detailed Inspection and 3b – Structural Inspection)

The third level of inspection provides a detailed analysis of the bridge structure, using advanced techniques like visual and underwater inspections, non-destructive and destructive testing, and computer models to assess structural safety, load capacity, and failure risks. This thorough evaluation helps identify potential issues before they become significant, enabling informed decisions on repairs or interventions to extend the bridge's lifespan. This inspection is divided into two types:

3a – Detailed Inspection: Performed every six years, this inspection builds on regular inspection procedures, using non-destructive testing and computer models to analyze the bridge's internal and structural condition. The results allow for precise recommendations for intervention.

3b – Structural Inspection: Conducted when necessary or requested, this inspection includes all aspects of a detailed inspection, adding destructive tests and failure probability analysis. It is used to prepare intervention projects with cost estimates.

Most systems, except TBMS, use a 3a inspection, typically every five years due to its higher cost. Structural inspections (3b) are addressed in four systems: SMOK, AASTHOWare, NSW, and KRMBS, and are performed only when necessary. Despite the higher cost, structural inspections can reduce overall intervention costs, as demonstrated by Bjerrum et al. (2008), that showed, in some instances, significantly decreased intervention costs[1].

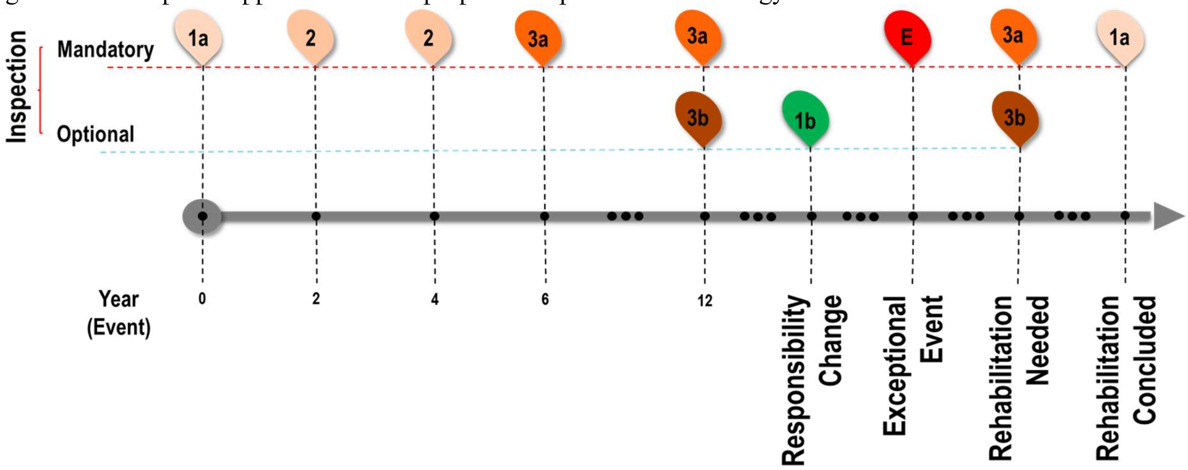
2.6.4. Emergency inspection (E)

Emergency inspections are conducted in response to exceptional events, such as accidents, natural disasters, or damage from environmental or human factors, that may threaten the integrity of the bridge. These inspections focus on identifying and documenting anomalies, with photographic evidence and detailed reports that include recommendations for repairs and maintenance to ensure safety.

Typically unscheduled, the emergency inspection aims to quickly assess damage and implement preventive measures. The depth of the inspection varies depending on the nature of the event. While some countries may not have a designated inspection for such cases, the structure's integrity is always evaluated. Including an emergency inspection in the methodology ensures formal preparation and provides legal security.

Figure 7 illustrates the application of the proposed inspection methodology in a timeline.

Figure 7 – Example of application of the proposed inspection methodology in a timeline.



Source: Author.

2.6.5. Discussions

The Initial Inspection, the first level, aims to improve control over information collection, enhance security, and ensure infrastructure regulation. While similar to the Cadastral Inspection described in DNIT-PRO Standard 10 (2024) (DNIT, 2024a), the proposal broadens the scope by requiring more data and the use of BIM models, as per Decree No. 10.306. This expansion is especially relevant in Brazil, where data quality and availability have long been challenges,

[1]More than $30 million on 11 bridges studied.

as shown by Souza et al. (Souza, C. *et al.*, 2024; Souza *et al.*, 2025b). Their studies highlight issues like missing or inconsistent data, such as the lack of construction year records for 41.70% of bridges and inconsistencies in SGO records Souza et al. (2025a). Such gaps stress the need for a robust methodology to improve data collection and registration.

Brazil has around 137,000 bridges, but only 6,833 are directly managed by DNIT (Silva; Almeida De Melo, 2021). The majority fall under other public agencies or private entities. In this context, both the initial and bureaucratic inspections are crucial: the initial inspection is key for registering bridges in systems like SGO, while the bureaucratic inspection ensures compliance with contractual terms and security during responsibility transfers.

The second level, regular inspection, is widely used globally and is also applied in Brazil as per DNIT-PRO Standard 10 (2024) (DNIT, 2024a). This inspection method, which has proven effective, aligns closely with existing practices.

The third level includes more detailed inspections, such as Detailed Inspection (3a), widely accepted across methodologies and effective for identifying issues not visible in regular inspections. This is covered in DNIT-PRO Standard 10 (2024) (DNIT, 2024a) as Special Inspection. However, the standard lacks specific execution guidelines, a gap the proposed program addresses with detailed instructions. Structural inspection, though costlier and more specialized, is used only, when necessary, for critical cases requiring in-depth analysis. Studies have shown that detailed information from such inspections reduces long-term costs and enhances intervention safety (Bjerrum *et al.*, 2008). Given the need for specialized teams and equipment, Structural Inspection can be considered optional.

Lastly, emergency inspections are flexible and swift, responding to exceptional events such as natural disasters or accidents. These inspections have fewer bureaucratic requirements and are adaptable to the specific needs of each case, allowing for varying levels of inspection based on the severity and urgency.

2.7. Conclusions

Based on a bibliometric review, the United States and Canada are the leading countries in publishing research on Bridge Management Systems in the 21st century. Their prominence in this field can be attributed to their pioneering role, geographic proximity, extensive road networks, and significant financial development.

The review analyzed 14 Bridge Management Systems from 14 countries, focusing on the year of the first version, the number of structures monitored, and the adopted inspection methodologies. Most systems were developed between the last decade of the 20th century and the first decade of the 21st century, driven by both technological advancements and the need for efficient management. It was found that management strategies vary by country, with some employing unified systems and others decentralizing management with regional autonomy. The choice of strategy often depends on the country's research development and the size of its road network. Generally, countries with large road networks and strong research development tend to favor decentralized management, while those with smaller networks or limited research may opt for unified systems.

The number of structures in each Bridge Management System is typically linked to the size of the country's road network. Countries with extensive networks usually manage a larger number of bridges, but in decentralized systems, responsibility may be divided among multiple bodies. For example, Brazil, with the fourth largest highway network globally, has around 137,000 bridges. However, only 6,833 are monitored by its main Bridge Management System (SGO), with others managed by concessions or regionally, often lacking centralized data. This gap highlights the need for further investment in bridge management research and development.

Regarding inspection programs, 14 approaches were analyzed, leading to the development of a proposal of a comprehensive inspection system classified into three levels of depth and including six inspection types. The inspections range from basic to advanced, covering bureaucratic issues to emergency situations. The proposed methodology integrates the best aspects of existing systems, adapting them to Brazilian conditions. It includes initial and cadastral inspections for data collection and regulatory compliance, as well as periodic, detailed, and structural inspections that incorporate advanced techniques such as non-destructive testing, computer modeling, and structural safety analysis.

In summary, the bibliometric review highlights the importance of efficient bridge inspection and management. The proposed program, based on existing models, offers a flexible solution tailored to Brazilian needs, aiming to enhance the safety and integrity of vital transportation infrastructures.

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CHAPTER III

Probabilistic bridge deterioration prediction models based on Markov matrices using real and simulated data from deterministic models

Abstract

This study uses real and simulated information from 885 bridges in Brazil. A total of 2,655 available inspection data were collected from the database, and 37,170 additional data were simulated from deterministic deterioration prediction models developed in previous studies. The probabilistic Markov matrices-based models obtained include one covering all the bridges, specific models for non-aggressive and aggressive environments, and models for Average Daily Traffic (ADT) of less than and more than 4,000. Validation showed good metrics, with a coefficient of determination of 0.6268, a mean absolute error and mean squared error below 0.5, and an accuracy of 66.25%. Finally, these tools enable more accurate forecasting, and a better understanding of the risks associated with the deterioration of structures for safe and cost-effective bridge management.

Keywords: Bridge; Deterioration Prediction Model; Bridge Management System; Deterministic Model; Probabilistic Model.

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3. PROBABILISTIC BRIDGE DETERIORATION PREDICTION MODELS BASED ON MARKOV MATRICES USING REAL AND SIMULATED DATA FROM DETERMINISTIC MODELS

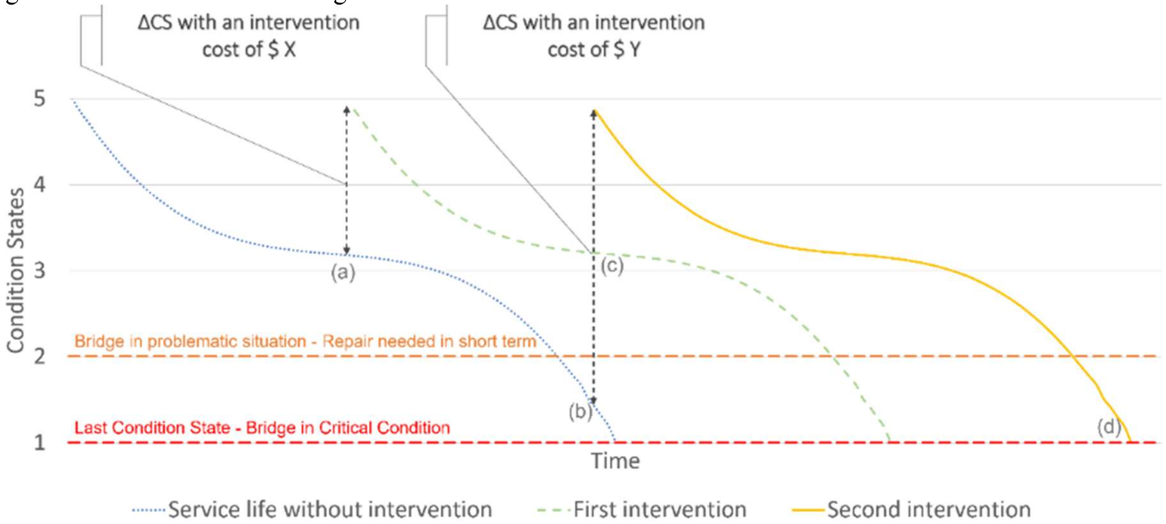
3.1. Introduction

Bridges are essential pieces of a country's infrastructure, acting as connections and support for highways, railways, waterways, fluid transport pipelines, and structures for pedestrian crossing. Whether from an economic point of view, since a large part of the inputs produced is transported by these routes, mainly highways and railroads, or from a social point of view, since today's society heavily depends on cars and public transport for its daily journey.

Brazil’s highway network is responsible for 64.9% of goods movement and more than 90% of passenger transportation, according to CNT (CNT, 2021). Trece (2020) reveals that Brazil's highway network indirectly influences up to 29% of the country's Gross Domestic Product (GDP). These data show the significant relevance of bridges as crucial elements of infrastructure, providing both economic and social benefits to the country. Therefore, it is essential to invest in the construction and maintenance of these structures to promote sustainable development and improve the population's quality of life. To ensure the adequate performance of these infrastructures, it is necessary to invest throughout their lifetime in maintenance, reinforcement, rehabilitation, and other measures. In Europe, bridges represent approximately 2% of the road network length yet corresponding to about 20% to 30% of the total life-cycle cost (Woodward, 2001). In Portugal, this proportion has also been confirmed. In 2006, 75 of the 250 million Euros allocated to the road network budget were invested in bridge maintenance (Poças, 2009). Likewise, in 2012, *“Estradas de Portugal”* directed 30% of its investments to the repair and rehabilitation of bridges. (Horta; Lopes, 2012).

Implementing a deterioration prediction model in a bridge management system is fundamental to optimizing the decision-making process of the administration offices responsible for investing in these structures; this is evidenced by the fact that 80% of BMS use such degradation prediction models in their systems (Adey; Klatter; Thompson, 2014). For example, considering a deterministic deterioration curve with condition states (CS) ranging from 1 to 5 (5 being the perfect state and 1 being the worst state), as illustrated in Figure 8, a bridge without interventions has a specific lifespan. The bridge lifetime is extended by performing an $ X intervention at point (a), where the condition state is not so bad. Then, by performing another intervention of similar cost at point (c), according to the new deterioration curve, the bridge reaches point (d), always maintaining good performance, with a total intervention cost close to \$2X, disregarding economic factors external to the bridge. On the other hand, assuming that the intervention is performed only at point (b), when the bridge is in a problematic or critical condition, requiring immediate or short-term intervention, the intervention cost will be \$ Y to achieve the same service life (d). However, following Sitter's law (Sitter, 1984), the longer the start of maintenance and rehabilitation actions is delayed, the more laborious and costlier the intervention will be. This increase follows a geometric progression of ratio five, related to the design, execution, preventive maintenance, and corrective maintenance stages. In other words, the cost of the intervention of \$ Y may become equal to or greater than \$ 5X.

Figure 8 – Performance of a bridge submitted to interventions over time.



Source: Author.

Consequently, efficient and cost-effective management demands knowledge of the evolution of bridge performance over a given period. It makes it possible to anticipate needs that may arise and to plan more adequately the interventions to be carried out in the medium or long term. In a study conducted on a bridge in New York, Xu; Azhari (2022) utilized a deterioration prediction model to formulate a risk-based bridge management approach. The outcomes showcased significantly lower annual and overall costs compared to conventional management methods (29% lower total costs than the benchmark policy), thereby substantiating the efficacy of a model-driven bridge management strategy.

Developing techniques and methods to predict bridge deterioration is an area of study that dates to the last century. Over the years, significant progress has been made in this field, with the implementation of these techniques in various bridge management systems worldwide; a more in-depth discussion of the techniques will be covered in section 3.3 of this article. However, research and advances in this area have been limited in Brazil. This study focuses on the Brazilian context and reveals that few developments and models are available, with several limitations in their practical application. Attention is drawn to the "*Sistema de Gerenciamento de Obras de Arte (SGO)"*, developed by the "*Departamento Nacional de Infraestrutura e Transporte (DNIT)"*, which is the main bridge management system in Brazil. This system has no specific method to predict bridge deterioration, further highlighting the lack of research and studies in this area in Brazil.

Therefore, this study stands out for pioneering and innovating, filling this gap, and providing data to subsidize implementation in the Brazilian context. This paper aims to develop deterioration prediction models based on probabilistic methods, using Markov chains. The study also proposes a solution for the lack of data for applying a probabilistic model by complimenting the real inspection data available with simulated data from deterministic dedicated models. The application study comprised 885 existing bridges in Brazil from different regions.

3.2. State of the art

To perform the bibliometric review, the authors used the Scopus database platform. The search was carried out in June 2024, using the search string "bridge AND deterioration OR degradation AND prediction OR forecasting" in "Titles, Abstracts, and Keywords". Only journal articles in English published in the last ten complete years (2013-2023) were considered. Filtering the subject areas not related to the objective of this work, a total of 410 documents were found and analyzed. VOSViewer and the Scopus platform tools were used in the analysis.

Research in the domain of bridge deterioration prediction shows an exponential increase, with a slight decrease in 2019, with its peak in 2023, accounting for 74 articles. This scenario emphasizes the prediction of bridge deterioration as a trending topic, gaining relevance in the academic context.

When analyzing the geographical distribution of academic production, it is evident that China and the United States play a dominant role in this area, accounting for 141 and 117 articles, respectively. This scenario can be attributed to the large road network of these countries, which naturally encompasses a greater number of bridges, as well as to their economic wealth and the central role they play in the development of research in various spheres at the global level. It is important to note that the United States has the largest road network on the planet, with 6.59 million kilometers, followed by China, with 4.77 million (Statista Search Department, 2018). As a result, their bridge management systems are the largest in the world, with ASSHTOWare (in the USA) covering 750,908 structures and CBMS (in China) covering 658,100 structures (Adey; Klatter; Thompson, 2014; Dai *et al.*, 2014).

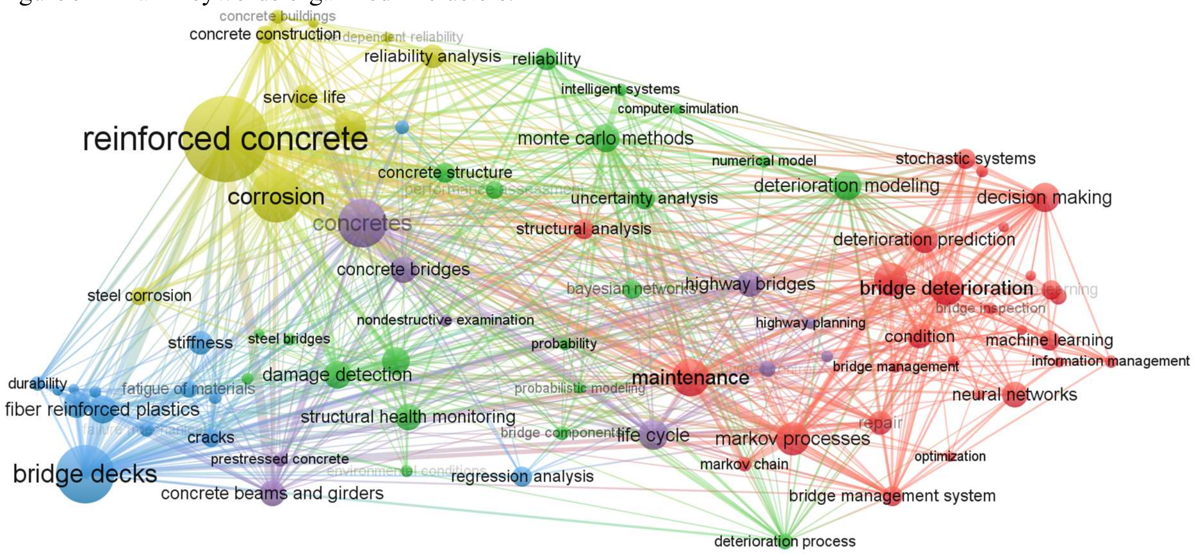
Within the scope of this investigation, Brazil has a modest academic production in the field, placed in the 26th position, with only three documents identified. Vieira et al. (2018) address the premature corrosion of concrete structures due to the ingress of chloride ions. Their study presents a model to estimate the service life of these structures, validated with real data on chloride concentration in a bridge in Brazil. Santos et al. (2022) address the importance of bridges for the transportation system and propose predictive models calibrated with Brazilian data to improve the prediction of bridge deterioration, considering factors such as age and location. The models suggest more efficient inspection frequencies, highlighting the influence of exposure and location on bridge degradation. This can contribute to more reliable decisions in bridge management, aiming to improve their safety and durability. Furtado; Ribeiro (2023) present a model for predicting the deterioration of in-service railway bridges, with high effectiveness for different materials (concrete and steel). The model is based on inventory data of bridge inspections in Brazil and contributes to optimizing maintenance strategies over time, improving the durability and efficiency of bridges.

It is noticeable that the first advances in the field of bridge deterioration prediction in the Brazilian scenario emerged from 2017 onwards, indicating that this is a recent research area that demands further investigations to deepen the knowledge of the Brazilian scenario with its specificities. Given Brazil's relatively recent entry into this domain, it becomes crucial to foster additional research and studies to grasp the specific characteristics of Brazilian bridges, their maintenance needs, and the most appropriate approaches for deterioration prediction within the local context. This implies considering technical, economic, and environmental factors, ensuring that deterioration prediction strategies are in tune with the country's conditions and circumstances. It is important to say that Brazil, as an emerging country, faces development challenges that can hold valuable lessons and serve as case studies for countries at a similar stage of economic, social, and academic development.

By addressing such challenges, research conducted in Brazil can serve as guidance for policy and strategy development in other emerging nations, allowing them to foresee and address future dilemmas concerning the maintenance and conservation of their bridges. Furthermore, by considering the peculiarities of the Brazilian scenario, such as its vast territorial extension and climatic and geographical diversity, it becomes feasible to formulate specific strategies and technologies that can be applied in analogous situations in other developing countries. This approach contributes to stronger international collaboration and a collective approach in the search for effective solutions to shared challenges.

The keywords co-occurrences were examined, excluding those used in the search, and limiting their minimum occurrence to 10. Five distinct clusters were identified and shown in different colors in Figure 9. The first and largest cluster, shown in red, has "maintenance" as the most important keyword. This cluster includes topics such as bridge deterioration, inspection, decision-making, and Markov chain and processes. The second cluster, shown in green, has "deterioration modeling" as the most significant keyword and includes topics like damage detection, structural health monitoring, Monte Carlo methods, uncertainty analysis, and the finite element method. The third cluster, shown in blue, has "bridge decks" as the strongest keyword and includes topics like fiber-reinforced plastics, reinforcement, cracks, stiffness, fatigue, and durability. The fourth cluster, shown in yellow, is led by "reinforced concrete" and includes topics such as corrosion, chlorine compounds, service life, reliability analysis, and steel corrosion. Finally, the fifth cluster, shown in purple, is led by "concretes" and includes topics like concrete bridges, concrete beams and girders, highway bridges, life cycle, budget control, and nondestructive examination. It is worth noting the significant presence of Markov processes in the red cluster, which emerges as an important topic in the field of bridge deterioration prediction.

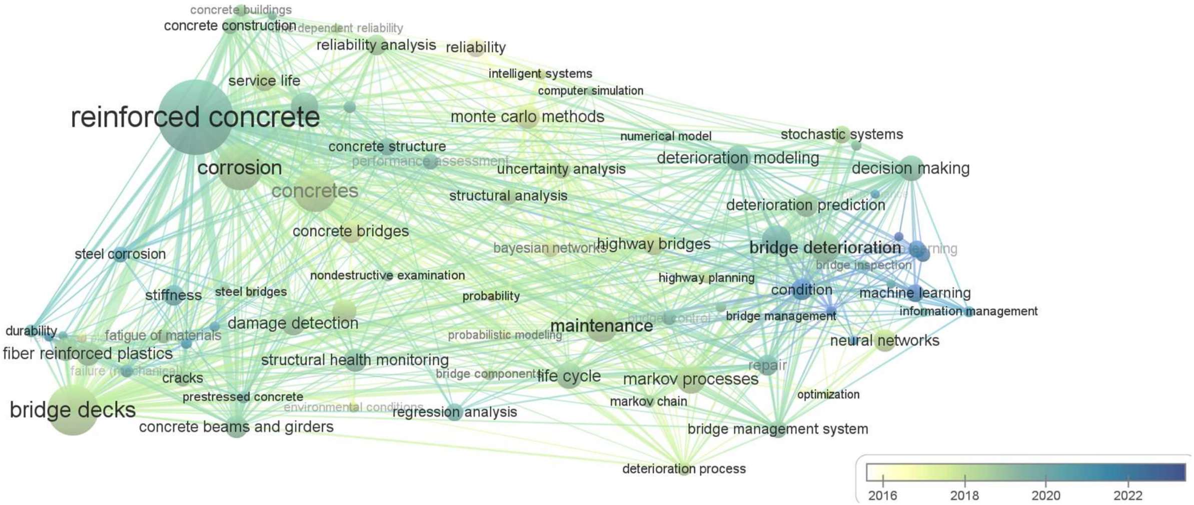
Figure 9 – Main keywords organized in clusters.



Source: Author.

To identify the predominant trends, the authors highlighted the main emerging keywords, categorizing them by color based on their recent thematic associations. The analysis was performed using 410 selected articles published between 2013 and 2023. In the color scheme used, yellow-to-white indicates topics with an average number of publications before 2018, while blue denotes themes that were more prominent after 2021. The trending topic analysis is summarized in Figure 10.

Figure 10 – Evolution of the occurrence of keywords over the last five years (timeframe legend starts from 2016 for better visualization, emphasizing the most recent topics).



Source: Author.

The most recent publications, along with several other areas, show a strong connection with artificial intelligence, specifically machine learning. Significant emerging topics include information management, deep learning, condition-based maintenance, and long and short-term memory, all of which are linked to cluster one, which includes Markov processes. Themes related to durability and mechanical performance (cluster three), such as steel corrosion, stiffness, and fatigue, have also shown relevance. Although regression analyses, previously not evident in Figure 9, were introduced, this topic has remained stagnant around 2020 and has not been addressed in the last two years. On the other hand, Markov processes maintain a steady level of academic interest and remain a relevant topic today.

Predicting the deterioration of bridges has proven to be a relevant topic, garnering increasing interest in recent years. This highlights a growing emphasis on effective and accurate methods for safe and cost-effective management practices and tools. This interest includes emerging technologies based on information and artificial intelligence-related techniques aimed at predicting deterioration within a management framework focused on making faster and more comprehensive and precise data-supported decisions. The international interest in this topic is evidenced by the number of publications from prominent and wealthy countries. Brazil, as one of the world's top 10 largest economies with a vast and expanding road network, must address these concerns seriously and invest in scientific development tailored to its specific challenges. This effort can also contribute to advancing technologies applicable to other developing countries with similar characteristics. Finally, in this context, Markov processes remain a relevant and applicable approach, especially in transitional contexts where data volumes may still be insufficient for implementing more exigent data-driven approaches.

3.3. Deterioration prediction models

The adequate performance of a bridge during its lifetime, ensuring a satisfactory level of safety and functionality, depends fundamentally on how the interventions are carried out (Oliveira, 2019). The ability to predict the deterioration process of a bridge over time plays a crucial role in managing these structures, as it allows knowledge about the evolution of the bridge's performance in each period (Souza *et al.*, 2023). It makes it possible to anticipate future needs and to plan interventions more efficiently in the medium or long term. However, due to several factors that influence bridge degradation and the heterogeneity of these structures, predicting their deterioration is a challenging task.

A study conducted by Miao (2021), using artificial intelligence, investigated several potential factors and their degree of influence on bridge deterioration to predict this process. Among the 12 parameters analyzed, six factors that accelerated deterioration were identified. These factors are bridge service time, carbon dioxide concentration, chloride ion concentration, traffic volume, snow accumulation, and the lowest recorded temperature. All the factors identified by Miao are directly related to the location of the bridges and the environmental conditions, which makes each model representative only for the set of structures for which it was developed. In other words, a model created for one country is unlikely to be efficient when applied in another due to their different conditions. In some cases, differences in the conditions under which bridges are in a country require the development of several deterioration prediction models. For example, in Canada, the GNWT bridge management system has developed a probabilistic bridge prediction model to consider the specific conditions of the Arctic region. However, this model becomes impractical to be used in other systems in Canada, such as OBMS, QBMS, PEI BMS, and EBMS, which have different climatic and environmental conditions (Adey; Klatter; Thompson, 2014). Therefore, it is essential to adapt bridge deterioration prediction models according to the particularities of each region and its specific conditions to ensure accurate and valuable results for proper management and maintenance.

According to an IABMAS report covering an overview of 25 bridge management systems (Adey; Klatter; Thompson, 2014), about 80% of these systems use some deterioration prediction model. This statistic demonstrates the significant relevance of these models and highlights the importance of their inclusion in bridge management systems. They can be classified into physical, deterministic, and probabilistic models. This classification allows a comprehensive approach to bridge deterioration prediction, using different methods and approaches to better understand and anticipate the degradation process of the structures. Other methods have been developed and validated but have not been implemented yet in bridge management systems (Santamaria; Fernandes; Matos, 2019), which include Reliability-based models, Artificial Intelligence models, Bayesian network models, and Petri-Nets models. It is important to note the significant advance of artificial intelligence in various areas today. This suggests that this technology has great potential to be explored and implemented in bridge management systems soon (Althaqafi; Chou, 2022).

3.3.1. Physical models

Physical models have been developed to represent the degradation processes associated with these infrastructures, which relate a physical and/or chemical interaction between materials and specific environmental conditions, as discussed by several authors (Papadakis, 2013; Santamaria; Fernandes; Matos, 2019; Zambon *et al.*, 2019). The main models are chloride corrosion and carbonation, as these are the leading causes of degradation in bridges (fib Bulletin 59, 2011; Papadakis, 2013; Souza, 2019; Zambon *et al.*, 2018).

Many models are available to predict the service life of reinforced concrete structures considering chloride depassivation of reinforcement. Most of these models assume that the process is governed by diffusion (Andrade; Possan; Dal Molin DCC, 2019). In addition, some physical models not implemented in the management systems studied can be explored based on previous works (Silvestro; Andrade; Dal Molin, 2019; Vieira *et al.*, 2018; Zambon *et al.*, 2018). The main bridge management system in which physical deterioration models are considered is the Bauwerk Management System (GBMS), used in Germany (Adey; Klatter; Thompson, 2014).

3.3.2. Deterministic models

Deterministic models focus on relating the inventory records on the state condition of bridges to their lifetime, considering various factors that influence degradation. There are three main types of deterministic methods used for the development of these deterioration prediction models (García-Sánchez, 2016; Morcous; Hatami, 2011; Moscoso, 2017; Souza *et al.*, 2023), they are:

- Extrapolation Curve Adjustments: In this method, extrapolation curves are used to relate the current condition state of bridges to the remaining service life. Based on the past inspection records, mathematical adjustments are performed to estimate the future condition state.

- Regressions: In this method, regression techniques are applied to establish relationships between predictor variables (such as bridge age, environmental conditions, and traffic, among others) and the condition state of the bridge. Based on these relationships, it is possible to make predictions.
- Linear method: Involves linear equations that relate the condition state with relevant independent variables. These equations are constructed based on past inspection records and allow estimating the future condition state of bridges.

These deterministic methods are used to develop deterioration prediction models that allow estimating the future state of bridges based on past information and factors that influence the degradation of these structures. The most developed deterministic models today are regressions, comprising linear or non-linear, in which an attempt is established to an empirical relationship between one or more variables, one dependent on the remaining, and the other independent variables if they exist (Souza *et al.*, 2023).

Several authors have been engaged in developing deterministic models through regressions to assess bridge deterioration. For example, (Kim; Gucunski; Dinh, 2019) used a sigmoid function in conjunction with non-destructive evaluation data to assess the deterioration of a bridge deck. In turn, (Jeong *et al.*, 2017) created a nonlinear regression model to determine the expected service life of a bridge. Researchers such as (Tolliver; Lu, 2012) opted to use polynomial regressions, while. (Lu; Wang; Tolliver, 2019) used ordinal logistic regression to develop their respective bridge deterioration prediction models. One of the main BMS that uses a deterministic method for deterioration prediction is the KRMBS from South Korea (Adey; Klatter; Thompson, 2014).

The deterministic model used in the methodology of this current paper was proposed by (Souza *et al.*, 2023), who analyzed 6833 bridges registered in the SGO of the DNIT (Brazil). Five deterioration prediction models were developed using 2655 inspection data from 885 selected bridges. These models were divided into two categories of environmental aggressiveness and two groups of Average Daily Traffic (ADT), besides a global model encompassing all bridges. The construction of the models involved using a third-order polynomial regression, both linear and nonlinear.

3.3.3. Artificial intelligence models

Artificial intelligence models employ inspection data and computational tools to identify relationships between the condition state of a bridge and the external and internal variables.

Through this approach, it is possible to make predictions regarding the deterioration of the bridge (Almeida, 2013; Santamaria; Fernandes; Matos, 2019). The main applications make use of different types of Artificial Neural Networks (ANN) and Case-based Reasoning (CBR)(Althaqafi; Chou, 2022; Carvalho *et al.*, 2019; Chen *et al.*, 2015; Srikanth; Arockiasamy, 2020). From a library of previous cases, the CBR technique seeks examples like the current problem to identify the best way to solve it (Carvalho *et al.*, 2019; Morcous; Rivard; Hanna, 2002). On the other hand, ANNs are computational models used to approximate unknown functions inspired by biological neural networks (Srikanth; Arockiasamy, 2020).

The Multi-Layer Perceptron (MLP) is widely adopted among the various types of ANN used. The MLP comprises three layers: an input layer containing only one set of neurons, one or more hidden layers (first hidden layer, second hidden layer, etc.), and an output layer with only one set of neurons. Each neuron in the hidden layers, except the input layer, uses a nonlinear activation function (Carvalho *et al.*, 2019; Srikanth; Arockiasamy, 2020). MLP employs a supervised learning technique called Back Propagation (BP) to train the neural network (Haykin, 2009; Winn, 2011). Using this technique, the net can learn from experience and later apply this knowledge to perform complex computations and find data values. Each processing unit in the net receives multiple inputs through weighted connections from neurons in the previous layer (Srikanth; Arockiasamy, 2020). MLP is a highly connected network composed of several simple linear or nonlinear processors distributed in parallel. To date, although it is a constantly growing area, no management system has implemented AI for deterioration. However, it is possible to find several models developed by various authors that address this issue (Althaqafi; Chou, 2022; Bu *et al.*, 2015; Chen *et al.*, 2015; Hasan, 2015; Huang, Y. H., 2010; Huang, Ying-Hua, 2010; Miao; Yokota; Zhang, 2022; Narasinghe; Karunananda; Dissanayake, 2006; Santos *et al.*, 2022; Winn, 2011).

3.3.4. Probabilistic models

The model used in this paper is based on a probabilistic method, which mainly employs Markov matrices. These matrices represent the probabilities of transitions between different levels of condition state, allowing to predict the evolution of the performance parameter over time. This model is commonly used in bridge management systems due to the ease of obtaining the necessary data to identify the transition probabilities between different performance levels (Almeida, 2013). The prediction of bridge deterioration using Markov matrices is performed using stochastic processes, in other words, random processes that describe the behavior of a system over time, based on probabilistic considerations. These processes are classified according to the condition state and time, and the time can be divided into discrete or continuous (Lotmis; Madanat, 2002; Mishalani; Madanat, 2002). The models based on Markov matrices have proven very efficient, leading several authors and BMS to use them as a basis for their deterioration models due to their ease of implementation and good results over time. Various countries use the Markov process in BMS, for example, the Ontario Bridge Management System (Canada), Quebec Bridge Management System (Canada), The Autonomous Province of Trento Bridge Management System (Italy), AASTHOWare (United States of America), among others (Adey; Klatter; Thompson, 2014).

Roelfstra et al. (2004), proposed to predict the condition state of reinforced concrete highway bridges using matrices calculated based on simulated data from a chloride-induced reinforcement corrosion model. These matrices were implemented in the KUBA bridge management system used in Switzerland. Considering five classification levels (ranging from 1, as good, to 5, as the alarming state), three different types of degradation were also established in the definition of the matrices: slow degradation (50% in the worst state in 200 years), medium degradation (50% in the worst state in 150 years), and rapid degradation (50% in the worst state in 100 years). Using a database of 850 steel and reinforced concrete bridges in New York State, Cesare et al. (1992) developed a deterioration model that resulted in Markov matrices related to the condition state evolution of various bridge types and their element. The model considered seven classification levels for the condition state, with 1 being the best and 7 the worst. The Markov matrices had dimensions 7x7, representing a discrete time interval of 1 year. The matrices developed by Cesare et al. (1992) cover the degradation of four bridge types, and a matrix encompassing all bridges. The model developed by Devaraj (2009) is proposed to predict deterioration based on inhomogeneous matrices, differentiated by three distinct groups of construction age, and used as information for calculating the matrices in a database with 4400 bridges from the North American State of Michigan. Like Cesare et al. (1992), Devaraj (2009) classifies the bridge condition into seven levels, originating 7x7 matrices. In addition to predicting the deterioration of the bridge, the model presents matrices for its three main components: the deck (including elements such as rails and expansion joints), superstructure (including the structural elements on the support), and substructure (columns, abutments, and foundations).

In Brazil, Oliveira (2019) analyzed 1707 bridges on 16 road sections, obtaining matrices for each section studied, following the classification adopted by NBR 9452 and DNIT, with condition states between 1 and 5. The matrices developed had dimensions 5x5. However, due to limited data, their models present some gaps in the matrices and are not representative at the national level, being quite specific for certain sections. Differently from Oliveira, Santos et al. (2022) adopted a broader approach, developing both a model based on Markov matrices and employing artificial intelligence techniques. Their analyses encompassed an extensive sample of 7754 bridges and more than 12,000 inspection datasets. This broader scope allowed their models to incorporate a diversity of factors, including material types, states of repair, geographic regions, bridge lengths, average daily traffic, distance from the coastline, and aggressive agent exposure zones.

These models were primarily aimed at optimizing inspection intervals in bridge management. Therefore, their deterioration curves were plotted from the state of perfect condition to the end of their service life, following an approach like the deterministic one. While this strategy has its advantages in certain contexts, it also has specific disadvantages for uses. Various authors also have developed other models, including (Calvert *et al.*, 2020; Jiang, 1990; Li; Sun; Ning, 2014; Manafpour *et al.*, 2018; Morcous; Lounis; Mirza, 2003; Orcesi; Cremona, 2009; Wellalage; Zhang; Dwight, 2015; Xu; Azhari, 2022; Zambon *et al.*, 2017). Table 11 summarizes the various works, their models, and the databases used.

Table 11 – Summary table of probabilistic models.

Authors	Models	Database
Jiang, 1990	Reinforced concrete and steel bridges	Database of 5700 bridges in the USA
Cesare et al., 1992	Four bridge typologies	Database of 850 bridges in the USA
Morcous et al., 2003	Four types of degradation in decks	9678 bridges in Quebec, Canada
Roelfstra et al., 2004	Three types of degradation	Simulated data from a chloride-induced corrosion model
Devaraj, 2009	Three groups of construction age	Database with 4400 bridges from Michigan, USA
Orcesu & Cremona, 2009	Concrete bridges	9000 bridges in France
L.Li et al., 2014	Three deterioration circumstances	Given the thousands of bridges in Shanghai between 2004 and 2013
Wellalage et al., 2015	Bridge elements	1000 Australian railway bridges over 15 years
Zambon et al., 2017	Reinforced concrete bridge decks	1100 bridges in Portugal
Manafpour et al., 2018	Reinforced concrete bridge decks	22000 bridges in Pennsylvania, USA
Oliveira, 2019	16 road sections	1707 bridges in Brazil
Calvert et al., 2020	Masonry railway bridges	9726 masonry railway bridges in UK
Xu & Azhari, 2022	Concrete Bridge's	Maximum likelihood estimation was used to obtain both the transition probabilities and the WPHM parameters based on NBI data
Santos et al., 2022	Material type; state; region; bridge length; ADTT; Coastline distance; and aggressive zones.	7754 bridges in Brazil

Sources: (Calvert *et al.*, 2020; Cesare *et al.*, 1992; Devaraj, 2009; Jiang, 1990; Li; Sun; Ning, 2014; Manafpour *et al.*, 2018; Morcous; Lounis; Mirza, 2003; Oliveira, 2019; Orcesi; Cremona, 2009; Roelfstra *et al.*, 2004; Santos *et al.*, 2022; Wellalage; Zhang; Dwight, 2015; Xu; Azhari, 2022; Zambon *et al.*, 2017).

3.4. Method

After previously analyzing 6833 bridges in the DNIT's *"Sistema de Gerenciamento de Obras de Arte (SGO)"*, filters were applied to obtain the necessary data to develop the deterioration prediction models. Reinforced or prestressed concrete bridges, with known age, without a state of condition improvement, without major rehabilitation, and with at least three inspection cycles were selected to compose the sample. Based on these filters, the authors identified 885 bridges, covering 2655 inspection data. Although a relatively large amount of information was obtained, generating a probabilistic model using the Markov matrix would not be sufficient. Therefore, the authors opted to develop and use deterministic deterioration prediction models based on third-order polynomial regression to complement the available data by including simulated data to supplement the missing series. The results of the deterministic method showed good representativeness according to the statistical metrics, which was satisfactory for the data simulation, as shown in Table 12. The statistical tests to assess the independence and identical distribution of the data variables were carried out in the previous work.

Table 12 – Statistical metrics of the simulated data.

Models/Statistic data	Coefficient of determination (r^2)	Mean Squared Error (MSE)
All Bridges model	0.9735	0.6104
Non-aggressive environment model	0.9542	0.6908
Aggressive environment model	0.9990	0.6854
ADT less than four thousand model	0.9746	0.5946
ADT larger than four thousand model	0.9749	0.5977

Source: (Souza *et al.*, 2023).

DNIT evaluation methodology uses condition states from 5 to 1, as described in Table 13. Note that condition state 5 is assigned only to bridges without defects (new bridges). Condition state 5 decreases to 4 in the first inspection cycle (after two years). This criterion was adopted in the simulation. The deterioration prediction results of the simulation were rounded to the closest integer on a scale of 1 to 5 to align with the DNIT method.

Table 13 – Condition state according to DNIT.

CS	Structural insufficiency	Conditions
5	There is no damage or structural insufficiency.	Excellent
4	There is some damage, but no signs of structural insufficiency.	Good
3	There is damage leading to structural failure, but no sign of the bridge being compromised.	Regular
2	There is damage causing significant structural weakness in the bridge, but no risk of structural collapse.	Poor
1	There is damage causing severe structural insufficiency and risk of structural collapse.	Critical

Source: (DNIT, 2010).

In the most favorable deterministic model, the time required for a bridge to reach the minimum condition state established by DNIT was 81 years. However, DNIT's specified time between inspections is two years. Therefore, the minimum condition state would be observed in year 82.

Thus, inspection data was simulated every two years for 82 years for the 885 bridges used in the study, comprising 41 cycles, and combining them with the existing inspection data previously compiled.

The characteristics related to environmental aggressiveness and average daily traffic volume were considered in the simulation, assigning a specific deterministic model for each bridge. In total, 37170 data were obtained, covering the period from 1950 to 2092. From such information, 7.14% (2655) corresponds to available inspection data, while 92.86% (34515) comprises simulated inspection data from the deterministic models. From the 885 bridges considered in the study, three classes of environmental aggressiveness were represented according to NBR 6118 (ABNT 2014) and two groups of Average Daily Traffic (ADT). In addition, the bridges were built from 1950 to 2014, presenting seven different types of structures (structural typology) and lengths ranging from 3 to 2830 meters. Table 14 summarizes the information, providing the respective percentages.

Table 14 – Bridge data.

Criteria	Data	Quantity	Percentage
Environmental aggressiveness class (NBR 6118)	Environmental aggressiveness class I	651	73.56 %
	Environmental aggressiveness class II	158	17.85 %
	Environmental aggressiveness class III	76	8.59 %
ADT	Less than four thousand	452	51.07 %
	Larger than four thousand	433	48.90 %
Year of bridge construction	Before 1983 (over 40 years)	618	69.83 %
	Between 1983 and 2003 (20 to 40 years)	170	19.21 %
	After 2003 (Under 20 years)	97	10.96 %
Type of structure (structural typology)	Reinforced concrete lower arch bridge	7	0.79%
	Reinforced concrete slab bridge	103	11.64%
	Prestressed concrete slab bridge	2	0.23%
	Reinforced concrete beam bridge	549	62.03%
	Prestressed concrete beam bridge	118	13.33%
	Reinforced concrete box beam bridge	55	6.21%
	Prestressed concrete box beam bridge	51	5.76%

Source: Author.

After obtaining the data, five models were developed in the probabilistic method based on the same models obtained in the deterministic one. These models included one Markov Matrix for all bridges, one for a non-aggressive environment, one for an aggressive environment, one for an ADT less than four thousand, and one for an ADT greater than four thousand. For the Markovian process, the discrete-time state-based method was considered the most promising approach due to the level of information available and the ease of development and implementation. The discrete time chosen was two years, following DNIT inspection cycles. All transition probabilities were calculated for each model to create the corresponding transition matrices. In addition, the condition states over 100 years were calculated for the deterioration curves. All these models, matrices, and curves are presented in section 3.5 of this document.

Finally, to validate the models, they were applied to a set of 274 bridges and 476 inspection data that were not used to build the models. These bridges were not included in the set of bridges used to build the models because they did not have 3 complete inspection cycles. The application of the models considered a simple rounding of the results since the bridges vary in CS in whole numbers. In addition, the application considered that the bridge started with its maximum SC in the year of construction and decreased over the years, following the deterioration curve of CS 5. This is due to the lack of data for a more detailed application.

3.5. Results and discussion

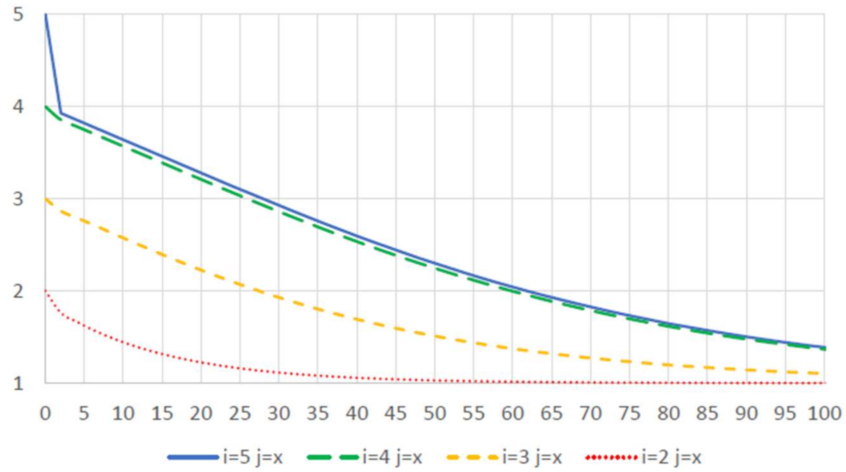
3.5.1. Models

The condition state scale ranges over five levels, so the matrices were 5x5. Over a discrete 2-year period, most observed transitions were of only one level, but there were rare instances of a two-level decrease. This two-level decrease has the highest probability of occurring in the aggressive environment model, with a chance of 1.32%, as observed in Figure 13, at the transition from condition state 5 to 3.

As mentioned, the matrices were developed to cover two environmental aggressiveness, two average vehicle volume groups, and one matrix representing all bridges. Figure 11 shows the matrix and deterioration curves applied to all bridges. Information regarding the two aggressiveness classes can be found in Figure 12 and Figure 13, while the two Average Vehicle Daily Traffic groups are detailed in Figure 14 and Figure 15; for all the graphs, the y-axis is the 5 condition states, and the x-axis is the years. Table 15 shows predicted transition years from condition state to condition state for each model and each deterioration curve.

Figure 11 – Deterioration curves and Markov matrix for the all-bridges model.

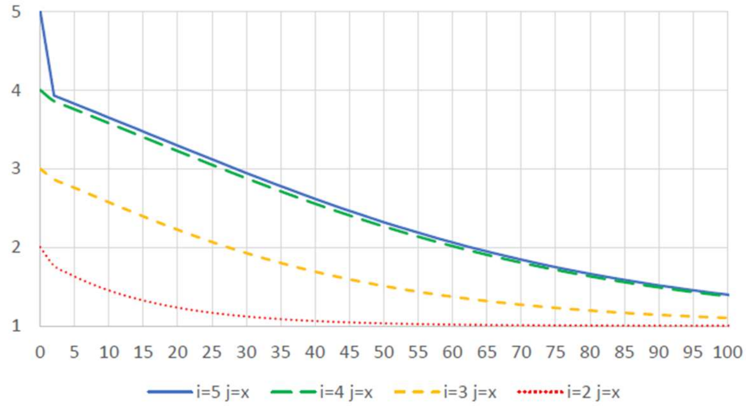
All bridges model				
0.0000	0.9977	0.0023	0.0000	0.0000
0.0000	0.9282	0.0713	0.0005	0.0000
0.0000	0.0000	0.9363	0.0622	0.0016
0.0000	0.0000	0.0000	0.8731	0.1269
0.0000	0.0000	0.0000	0.0000	1.0000



Source: Author.

Figure 12 – Non-aggressive and aggressive environment Model.

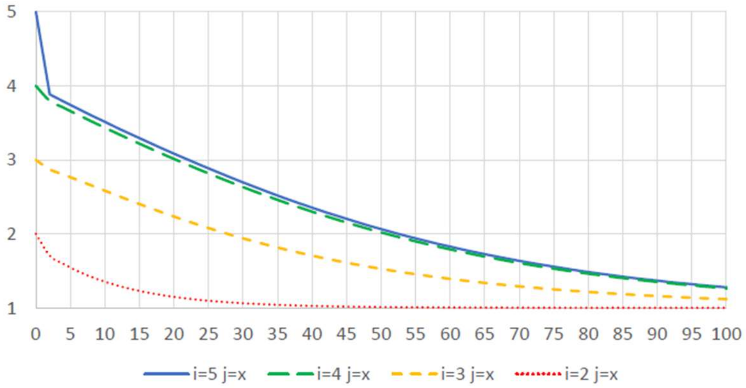
Non-aggressive environment model				
0.0000	0.9988	0.0012	0.0000	0.0000
0.0000	0.9299	0.0697	0.0003	0.0000
0.0000	0.0000	0.9357	0.0629	0.0014
0.0000	0.0000	0.0000	0.8754	0.1246
0.0000	0.0000	0.0000	0.0000	1.0000



Source: Author.

Figure 13 – Aggressive environment Model.

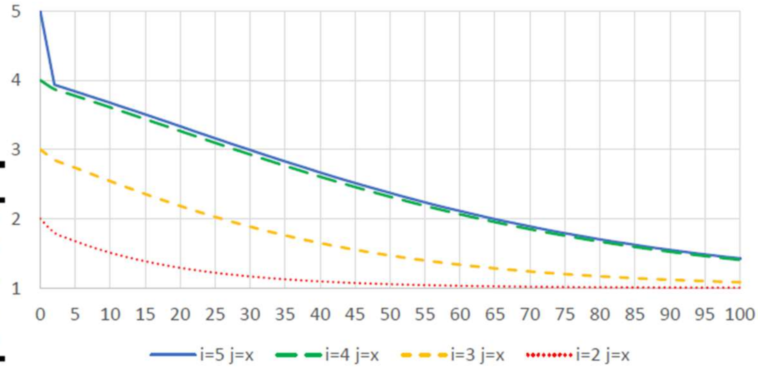
Aggressive environment model				
0.0000	0.9868	0.0132	0.0000	0.0000
0.0000	0.9013	0.0961	0.0026	0.0000
0.0000	0.0000	0.9417	0.0554	0.0030
0.0000	0.0000	0.0000	0.8407	0.1593
0.0000	0.0000	0.0000	0.0000	1.0000



Source: Author.

Figure 14 – ADT < 4,000 model.

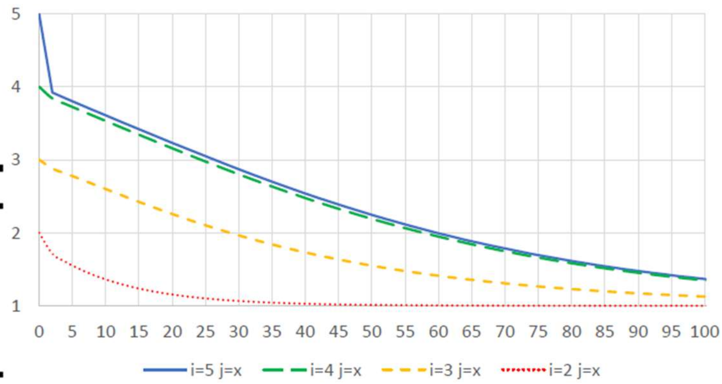
ADT < 4000 model				
0.0000	0.9977	0.0023	0.0000	0.0000
0.0000	0.9369	0.0628	0.0003	0.0000
0.0000	0.0000	0.9277	0.0708	0.0015
0.0000	0.0000	0.0000	0.8936	0.1064
0.0000	0.0000	0.0000	0.0000	1.0000



Source: Author.

Figure 15 – ADT > 4,000 model.

ADT > 4000 model				
0.0000	1.0000	0.0000	0.0000	0.0000
0.0000	0.9194	0.0802	0.0004	0.0000
0.0000	0.0000	0.9430	0.0556	0.0014
0.0000	0.0000	0.0000	0.8440	0.1560
0.0000	0.0000	0.0000	0.0000	1.0000



Source: Author.

Table 15 – Year of condition state transition and deterioration curves.

Start condition	Targeted condition	All Bridges	Non-aggressive environment	Aggressive environment	ADT < 4000	ADT > 4000
5	4	2 Years	2 Years	2 Years	2 Years	2 Years
	3	14 Years	16 Years	12 Years	16 Years	14 Years
	2	44 Years	44 Years	36 Years	46 Years	42 Years
	1	92 Years	92 Years	80 Years	94 Years	90 Years
4	3	12 Years	14 Years	10 Years	14 Years	12 Years
	2	42 Years	42 Years	34 Years	44 Years	40 Years
	1	90 Years	90 Years	78 Years	92 Years	88 Years
3	2	14 Years	12 Years	14 Years	12 Years	14 Years
	1	52 Years	52 Years	52 Years	48 Years	54 Years
2	1	10 Years	10 Years	6 Years	12 Years	8 Years

Source: Author.

In the curve with start condition 3, there is a differentiation of behavior compared to the other curves. In the ADT < 4000 model, the other curves (start conditions 5, 4, and 2) show a slower deterioration than other models due to the less aggressive environment and the lower load on the structure. However, faster decay occurs in the curve for start condition 3. This difference is justified in an article by Souza et al. (2023), who indicate the existence of subjectivity in the evaluation methodology adopted by DNIT. Another article by the same author Souza et al., (2022) demonstrates this subjectivity compared to other methodologies. This subjectivity results in a faster transition to condition 3 and a longer time of permanence in this condition state due to inspectors' cognitive factors, which influence the strategic decisions of inspectors

(Souza *et al.*, 2023). However, in the ADT < 4000 model, due to the slow deterioration of the bridge, this faster transition to condition state 3 and its staying longer is less evident. The deterioration curve behaves more linearly compared to the others. Therefore, when the bridge starts with condition state 3 in the ADT < 4000 model, it tends to stay less time in this condition. However, it takes longer to reach this initial level of deterioration.

Additionally, the models behaved as expected, showing the significant influence of the aggressive environment, as evidenced by several authors (Miao, 2021; Roelfstra *et al.*, 2004; Wang *et al.*, 2023). A bridge exposed to this environment, starting in the perfect state, decays to its most deteriorated state in only 80 years, while in the other models, this process occurs between 90 and 94 years, resulting in a minimum difference of 10 years in service life. Several authors attribute this acceleration in deterioration to the aggressive environment, highlighting the significant influence of chlorides, high relative humidity, and high rates of reinforcement corrosion (Andrade; Possan; Dal Molin DCC, 2019; CEB, 1992; Costa, 1997; fib Bulletin 59, 2011; Mehta, 1991; Miranda, 2006; Papadakis, 2013; Souza, 2019; Tang; Nilsson, 1996; Vishwanath; Banerjee, 2023).

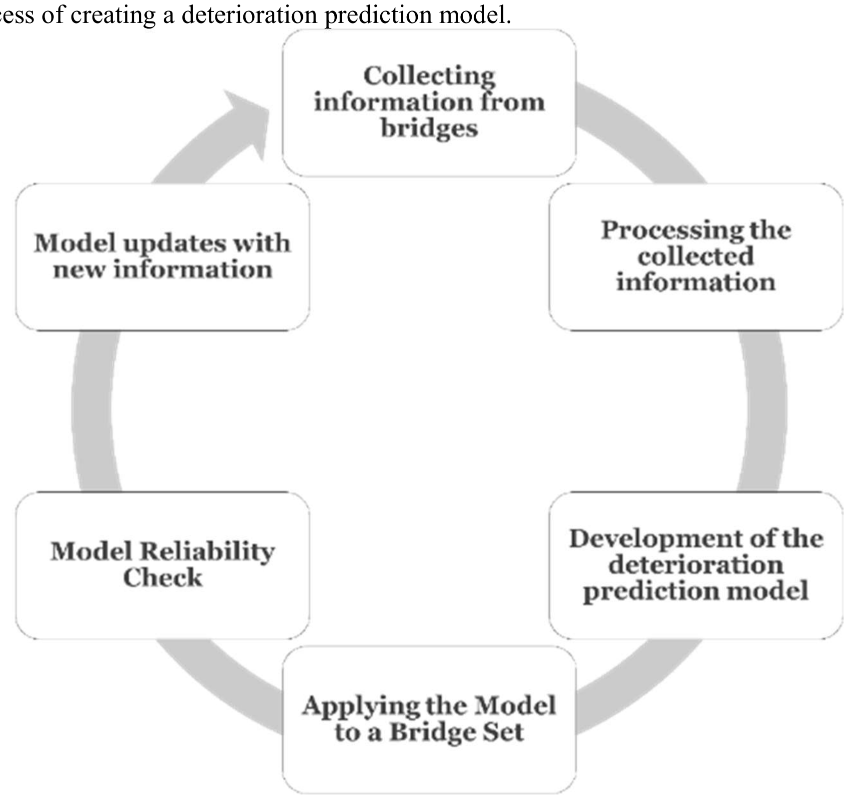
The ADT, a factor not considered by most other authors in their deterioration prediction models, has demonstrated its fundamental role in the deterioration timeline of bridges, as pointed out by Miao (2021a). Among the 12 factors analyzed, Miao highlighted the traffic volume as one of the key aspects that significantly influence degradation and deterioration prediction. By recognizing the importance of ADT in bridge deterioration, Miao's study brings valuable insights that can improve the accuracy and reliability of deterioration prediction models.

Of the models examined, only the one developed by Santos et al. incorporated ADT as a parameter. As a result, a more pronounced deterioration pattern associated with higher values of ADT was noted by (Santos *et al.*, 2022). The faster deterioration of the model with a higher ADT is notable compared to the model with a lower ADT, reaching a four-year difference in the deterioration curves. This is due to the assigned loads and frequency: the greater the number of vehicles, the greater the load transferred, the higher the frequency, and the greater the vibrations and fatigue in the structure (Souza *et al.*, 2023).

Another significant aspect of the ADT is the socioeconomic criteria attached to it, which, although not directly addressed in the models, has great relevance in the decision-making process. A practical example of the socioeconomic consequences of a bridge collapse with a high Average Daily Traffic was the negative impact on the local economy with the collapse of the I-35W bridge in June 2007, in Minnesota, USA. The economy of the State showed a loss of approximately 60 million dollars, in 2007 and 2008, in addition to an expense of 38 million dollars in compensation. It is estimated that the cost of building a new bridge was between $300 million and $ 350 million (Branco, 2013; Subramanian, 2008). A Minnesota Department of Transportation study showed that the daily cost for passengers to find a new way into downtown Minneapolis was approximately $400,000 (Subramanian, 2008).

Some essential steps must be followed to develop a deterioration prediction model regardless of the method. The first is collecting the relevant information, with the required amount of information varying depending on the selected method. Next, this data must be processed to be used effectively during the development. With the information adequately processed, the deterioration prediction model can be created. By applying this model to a set of bridges, it is possible to verify the reliability and uncertainty level of the proposed model. However, as time goes by, new information and advances arise, which may sometimes require an update or improvement of the model already developed. At this point, the cycle begins again with collecting this additional information. Figure 16 simplifies the cycle detailed above.

Figure 16 – Process of creating a deterioration prediction model.



Source: Author.

Based on the premise mentioned and the analysis of the methods discussed, and all the references mentioned in section 3, it is possible to perform a comparative evaluation of the criteria involved in the model creation process. Using a qualitative classification in five levels, where 5 is the best situation and 1 is the worst, a comparison of the methods regarding different criteria is presented in Table 16.

Table 16 – Comparison of deterioration prediction methods.

Criteria	Physical	Deterministic	Probabilistic	IA
Required Information	Very Low (5)	Low (4)	High (2)	Very High (1)
Information Processing	Very Easy (5)	Easy (4)	Easy (4)	Hard (2)
Model Development	Very Easy (5)	Easy (4)	Medium (3)	Hard (2)
Model Applicability	Very Bad (1)	Medium (3)	Good (4)	Very Good (5)
Model Reliability	Very Bad (1)	Bad (2)	Medium (3)	Good (4)
Model Updates	Very Bad (1)	Bad (2)	Medium (3)	Very Good (5)

Source: Author.

The most straightforward model to develop is the physical one since it depends not on the inspection data but on the chosen deterioration process. However, in many situations, several forms of deterioration occur synergistically on a bridge, which makes the physical model inapplicable in most cases. Furthermore, this model has a high level of uncertainty since it is directly related to a phenomenon and not to the inspection data. It means that possibilities for updating and improving the model are practically nil.

On the other hand, artificial intelligence-based models necessitate a substantial dataset and more computationally intensive procedures during their construction. (Miao; Yokota; Zhang, 2022) exemplifies this aspect in their predictive model for deterioration, where the model's performance is closely tied to the data quality for each factor. Insufficient or incomplete information for specific factors, or a lack of clarity in the inherent relationship between these factors and deterioration, can severely constrain the model's predictive capabilities or lead to its outright failure.

In the case of neural networks, for example, it is necessary to perform machine learning and constantly feed them with new information for continuous AI learning. However, once this process is completed, the model can be constantly updated, incorporating new information and considering various deterioration-related factors. It results in a model with good applicability and a high level of confidence, which gets better and better as more information is provided. In short, it is a model with constant updates and continuous improvement.

Between the methods mentioned, there are also deterministic and probabilistic methods, which seek to balance the difficulty of development with the quality of the model and the information. This study developed models using both cases, considering the volume of information available. By itself, this information would not be sufficient for developing a probabilistic model, which led to adopting a deterministic model. However, it was found that this model, although easier to develop in terms of processing and construction, was not as effective in terms of applicability and presented a higher level of uncertainty when complete information was unavailable.

An example of these limitations is the lack of information such as the year of construction. It affects the deterioration curve, established based on the bridge's age about the condition state. Furthermore, the way interventions are considered also influences this curve. For example, even if there is an increase in the condition state due to interventions, the bridge's age remains the same. These limitations compromise the accuracy of the deterministic model.

Another point to be considered is the low level of updates in the deterministic model. It follows a predefined regression and has no flexibility to incorporate new information or adjust to changes over time. This lack of adaptability restricts the model's ability to keep up to date and accurately reflect the reality of the bridge conditions.

On the other hand, while requiring a high level of information, the probabilistic model offers the ability to simulate this data through other models, as was done in this paper, using real available and simulated data from the previously developed deterministic model. An example is the models developed by many authors (Farrera, 2006; Morcous; Hatami, 2011; Reale, 2013; Roelfstra *et al.*, 2004), who used a physical corrosion-based model to create Markov matrices. In this way, the probabilistic model combines the ease of development of the other models, incorporating specific features and considering factors previously not considered.

Contrary to the deterministic model, the probabilistic model is independent of the year of construction and interventions. For each condition state, there is a deterioration curve as a function of time, not age, which makes the model more applicable and reliable. The more data available, the more factors can be considered, increasing the reliability of probabilistic models. However, it is important to note that updating these models is more complex than models based on artificial intelligence.

Santamaria Ariza et al. (2020) conducted a comparative analysis of various deterioration prediction methods and highlighted that ANN (Artificial Neural Network) models exhibited superior accuracy in forecasting bridge deck deterioration. In their study, they found that when compared to the Markov process, the ANN achieved a lower Mean Squared Error (MSE) of 0.2068 and a higher Accuracy factor of 1.3552, whereas the Markov process yielded values of 0.3336 and 2.3312, respectively. However, it should be noted that training the ANN involves a higher computational cost compared to other methods and demands a larger dataset, which could be considered a limitation.

To mitigate costs and address situations with limited data availability, a potential solution is the combined use of a probabilistic model with artificial intelligence for deterioration prediction, as discussed by Liu; Wang (2021). In addition to Liu & Wang, Li et al. (2023) introduce an innovative hybrid approach for predicting degradation, incorporating bias correction by merging insights from a physics-based stochastic degradation model with techniques derived from machine learning, reducing the mean square error of rebar degradation prediction by at least 27% under the proposed approach in comparison with only physics-based stochastic degradation model. This approach could offer an alternative to tackling data quantity and cost issues. Nevertheless, it is worth mentioning that this combined approach has not yet been widely explored in bridge deterioration prediction models.

3.5.2. Validation

To validate the bridge deterioration prediction models, 274 bridges were selected from five regions of Brazil that were not included in the model building because these bridges had a maximum of two inspection cycles. To predict the deterioration of the bridges, a simple rounding was assumed for the condition values, since they vary in whole numbers. In addition, it was assumed that the bridge started from its year of construction with the maximum CS and deteriorated over time due to the limited number of inspection cycles to obtain CS data. These inspection data varied between the years 2014 and 2020. The model was validated using several metrics, including coefficient of determination (R^2), mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), and hit rate, as shown in Table 17.

Table 17 – Model validation metrics.

Metrics	
Coefficient of determination (r^2)	0,6268
Mean Absolute Error (MAE)	0,3662
Mean Square Error (MSE)	0,4272
Root Mean Square Error (RMSE)	0,6536
Accuracy rate	66,25 %
Errors greater than 1	2,69 %
Errors where the model predicted a higher CS than the real one	26,03 %

Source: Author.

The results showed a coefficient of determination of 0.6268, indicating that the model reasonably represents the real data. In addition, the MAE of 0.3662, the MSE of 0.4272, and the RMSE of 0.6536, all less than one, indicate an acceptable accuracy of the model's predictions, considering that the state of health varies from one to one. The accuracy rate reached 66.25%, demonstrating the model's ability to correctly predict the condition of the bridges in about two-thirds of the observations. Of the errors, only 2.69% were errors greater than one, while 26.03% were considered bad errors, indicating that the predicted CS was better than the real one, which could compromise the structure's safety.

It is important to note that the models were applied in a situation different from reality, where in practice the deterioration analysis would consider the last transition of the bridge, instead of simply starting from its maximum condition state and deteriorating over time, as commonly observed in deterministic or physical models. For probabilistic models, the longer the interval between the year of analysis and the year of the last transition, the less accurate the results will be. However, even with an average analysis interval of 33 to 39 years with respect to the year of construction of the bridges, the models showed promising results, indicating a satisfactory ability to represent the real condition of the evaluated bridges.

3.6. Conclusions

Through a bibliometric and analytical approach, the authors offer a comprehensive view both nationally (Brazil) and internationally on bridge deterioration prediction. Although studies in this area date back to the last century, its contemporary relevance is undeniable, marked by exponential growth over the last ten years.

When investigating the keywords, the authors identified thematic clusters, with the red cluster being the most prominent in terms of quantity and frequency. It encompasses themes such as maintenance, inspection, repair, Markov processes, and decision-making, among others.

In the last five years, a predominant trend topic has been predicting deterioration using artificial intelligence, notably machine learning. There has also been a shift in emphasis from maintenance deterioration prediction towards decision making, and a stagnation of regression analysis. In addition, Markov processes continue to maintain their importance, with constant production, corroborating their relevance for bridge deterioration prediction.

In a Brazilian context, the academic production shows notable limitations, with only three documents identified in the bibliometric review. This gap indicates the need for further developments, as addressed in the article, which serves as a stimulus for future advances both in Brazil and in countries with similar economic, social, and academic circumstances.

In the analytical approach, four bridge deterioration prediction methods are analyzed, providing a brief review of their approaches and citing the main research that makes use of each one. Among these methods, Markov processes received particular emphasis, since they constitute the basis of the models developed in this paper.

Despite a small amount of information, it was possible to develop deterioration prediction models satisfactorily. It is due to the ease of developing deterministic models and the versatility of the probabilistic process, which allows the use of simulated data from other models combined with real inspection data. Thus, the probabilistic models for deterioration prediction were developed satisfactorily, incorporating characteristics that the deterministic model did not consider.

It is important to note that aspects observed in the deterministic models were incorporated into the current models described in this paper. These aspects include both expected influences, such as that of the aggressive environment on deterioration, and the influence of the Average Daily Traffic. In addition, aspects related to the subjectivity of the DNIT inspection methodology were also considered, as pointed out by (Miao, 2021; Souza *et al.*, 2022, 2023). It highlights the need for updates as new information is obtained to achieve a more reliable and trustworthy model.

It is important to note that each Markov matrix represents a particular group of bridges, and it is not possible to compare previously developed matrices, as each one represents a different reality. However, as the matrices described in this article highlight, corroborating the observations made by several authors (Miao, 2021; Roelfstra *et al.*, 2004; Wang *et al.*, 2023), the environmental condition is critical and should always be considered. Another point not commonly addressed before and revealed its importance is the consideration of the Average Daily Traffic.

When comparing the methods for developing deterioration prediction models, the probabilistic method is currently the most effective for balancing the difficulty of obtaining information, developing the model, and its reliability and applicability. However, a widely growing method is the use of models based on Artificial Intelligence, which currently faces as its main challenge the amount of information available and the processing of this data. However, it is important to highlight this subject as the object of future work and development, seeking increasingly reliable, applicable, and constantly updated models.

Finally, deterioration prediction is extremely important for bridge management, both in an international context (where several recognized bridge management systems have already addressed) and in the Brazilian context. Despite being well established worldwide, with models being developed since the 1990s, in Brazil, there are still few works in the area, which reveal the importance and contribution of this work. It demonstrates a viable reality in the Brazilian scenario, where the validation of the model proved effective in predicting the condition 66.25% of the time, allowing for more efficient planning and reallocation of financial and human resources in the decision-making process of a bridge management system.

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CHAPTER IV

Bridge deterioration prediction models using artificial intelligence in a missing data scenario

Abstract

Bridge infrastructure is crucial for global transportation, but its deterioration due to environmental factors and continuous use presents significant safety and maintenance challenges. This study introduces a methodology for predicting bridge deterioration using artificial intelligence (AI) in data-limited scenarios, integrating real inspection data with simulated data. Artificial Neural network models, particularly the Multi-Layer Perceptron, outperformed conventional methods such as deterministic and probabilistic models in terms of both accuracy and applicability. The methodology progressed from deterministic models based on third-order polynomial functions to probabilistic models using Markov matrices, ultimately culminating in neural networks. This approach overcame data limitations by combining real and simulated data, resulting in a comprehensive database. The AI models effectively captured complex interactions between key variables like bridge age, traffic volume, and environmental conditions, leading to more accurate predictions. Applied in both aggressive and non-aggressive environments, the AI models consistently outperformed traditional methods, achieving a coefficient of determination (R^2) of 0.84 and a mean absolute error (MAE) of 0.33 in non-aggressive environments, and an R^2 of 0.81 with an MAE of 0.34 in aggressive environments. Bridges in aggressive settings showed critical deterioration approximately 10 years earlier than those in non-aggressive environments. These results emphasize the potential of AI to enhance deterioration prediction, improving infrastructure management and maintenance.

Keywords: Missing Data; Artificial intelligence; Bridge Management; Infrastructure Management.

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4. BRIDGE DETERIORATION PREDICTION MODELS USING ARTIFICIAL INTELLIGENCE IN A MISSING DATA SCENARIO

4.1. Introduction

Bridges are vital components of a nation's infrastructure, providing essential connections and support for roads, railways, waterways, pipelines, and pedestrian crossings. Economically, their significance is evident, as a substantial portion of manufactured goods is transported along these routes, particularly by road and rail. Socially, they are equally important, as the daily mobility of modern society heavily relies on cars and public transportation.

The integration of deterioration prediction models into bridge management systems is fundamental for enhancing decision-making processes related to investments in these structures. Besides improving the safety of infrastructure, these models can significantly reduce intervention costs (Souza, C. *et al.*, 2024). This advantage is further underscored by the fact that 80% of bridge management systems (BMS) currently utilize deterioration prediction models in their operations (Adey; Klatter; Thompson, 2014).

However, the development of accurate deterioration models requires a large volume of inspection data. While countries like the United States benefit from comprehensive databases such as the National Bridge Inventory (NBI), countries like Brazil face a shortage of this critical data. In response, this study introduces a methodology to address this data gap by leveraging neural networks, specifically the Multilayer Perceptron (MLP), to create deterioration prediction models for reinforced concrete bridges. The models consist of five hidden layers, each containing 50 neurons with logistic activation. The study utilizes both real inspection data and simulated data from probabilistic models, encompassing 973 reinforced concrete bridges in Brazil and 108,003 inspection records. Each record includes the condition state of the bridge at the time of the inspection., constituting a significant advance and an unprecedented contribution. It is also worth noting that bridge deterioration models are highly dependent on the database and methodological framework adopted. Small changes in these elements result in models with different characteristics and specific applications. As an example, numerous studies use the North American database (NBI), each with different approaches and objectives - which shows that there is no single or universal model, but rather a field in constant development, where each solid methodological proposal represents a new contribution.

This article is structured into two main sections. The first part (Section 2) provides a literature review, beginning with the Brazilian context, highlighting the challenges in bridge maintenance and the current state of the national bridge inventory. It also reviews various approaches to bridge deterioration modeling, with an emphasis on methods based on artificial intelligence. This section identifies the main input parameters used in AI models and discusses the state-of-the-art techniques and gaps in current research. The second part (Section 3) introduces the proposed methodology, which includes strategies to overcome the challenge of data scarcity—one of the major obstacles in bridge deterioration modeling. It details the construction of predictive models using artificial neural networks, explains the dataset preprocessing steps, and presents the evaluation of the models' performance. This section also discusses the feature importance analysis, compares deterioration curves in aggressive and non-aggressive environments, and highlights the main findings and contributions of the study.

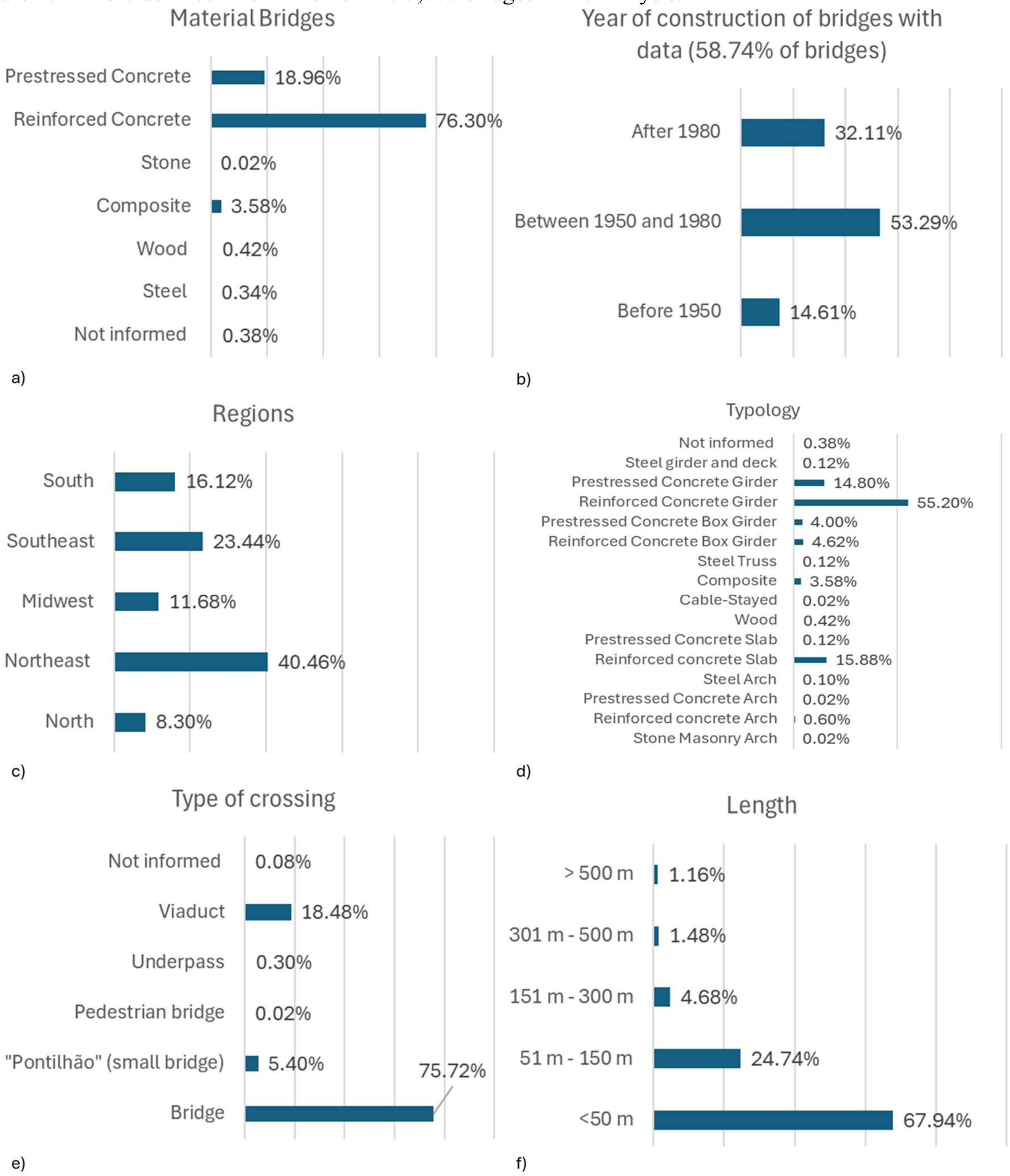
4.2. State of the art

4.2.1. Brazilian scenario

Brazil has approximately 137,000 bridges spread across its territory, but only a fraction of them, 6,833, are directly managed by the federal agency *"Departamento Nacional de Infraestrutura de Transporte"* (DNIT) (DNIT, 2023; Silva; Almeida De Melo, 2021). This disparity is because part of the road management and maintenance services have been outsourced through concessions, resulting in these infrastructures being managed by private companies. In addition, most highways in Brazil are under the jurisdiction of state governments, which means that the Departments of Roads and Highways of each state are responsible for managing the bridges in their regions. This administrative decentralization and the lack of a unified management system for bridges creates a significant gap in both the quantity and quality of information available about these infrastructures. Many Brazilian states still do not have an established bridge management system, which results in a lack of detailed and accurate information on the condition of bridges, making it difficult to implement preventive maintenance programs and make informed decisions.

The analysis carried out by the author of this study examined 5,000 of the 6,833 bridges managed by the DNIT, providing an even more partial view of the national scenario. Regarding the material used in the construction of the bridges, 95.26% of the structures analyzed were made of concrete, of which 76.30% were reinforced concrete and 18.96% were prestressed concrete. About the type of crossing, most of the infrastructures analyzed were bridges, representing 75.72% of the total, followed by viaducts with 18.48%. These two categories represent 91.2% of the structures studied. Figure 17 shows details of the five thousand bridges analyzed.

Figure 17 – More detailed information on the 5,000 bridges in the analysis.



Source: Author.

The analysis of the data revealed a recurring problem: absence, inconsistency or lack of information. One of the most critical aspects is the lack of records of the construction year for 41.70% of the bridges analyzed. This data is crucial for predicting the deterioration of structures over time. In addition, a study by Souza et al. (2025) showed that 9.18% of the bridges analyzed had inconsistencies in the data recorded in the Brazilian bridge management system, *"Sistema de Gestão de Obras"* (SGO).

Most bridges in Brazil have only three recorded inspection cycles, with a maximum of four cycles and a minimum of only one inspection. These inspection records vary between the years 2012 and 2021. Considering that most bridges were built before the 2000s (around 87.9%), and only 12.08% were built after the year 2000, many of these structures do not have a complete record of inspections throughout their useful life. This data gap becomes a significant obstacle to the development of reliable predictive models of bridge deterioration and compromises the ability to perform preventive maintenance effectively.

Given this lack of data quantity and quality, few bridge deterioration prediction models have been developed in Brazil. In the study by Souza et al. (2024), a bibliometric review identified only three documents related to the prediction of bridge deterioration in the country. Vieira et al. (2018) proposed a model to estimate the service life of concrete structures corroded by chloride ions, validated with data from a bridge in Brazil. Santos et al. (2022) developed both probabilistic and neural network prediction models to predict the deterioration of bridges, with the aim of optimizing inspections. Furtado; Ribeiro (2023) presented a model for predicting the deterioration of concrete and steel railroad bridges, using a semi-Markov process, based on inspection data in Brazil.

In addition to these, two other models were discussed by Souza et al. (2024). The first, developed by Oliveira (2019), used Markov matrices to predict deterioration on 16 stretches of highway in Brazil in his doctoral thesis. The second was developed by Souza et al. (2023), using a third-order polynomial function to create deterministic deterioration prediction models. The study by Souza et al. (2024) also developed probabilistic models for predicting bridge deterioration, using both real and simulated data. Table 18 summarizes all the prediction models mentioned, all models use the condition state as an input parameter.

Table 18 – Bridge deterioration prediction models developed in Brazil.

Authors	**Models**	**Method**	**Database**
Vieira et al. (2018)	Model to estimate the service life	Physical models (chloride corrosion)	One bridge
Oliveira (2019)	16 road sections	Probabilistic models (Markov process)	1707 bridges; 7374 transition data
Santos et al. (2022)	Material type; state; region; bridge length; ADTT; Coastline distance; and aggressive zones.	Probabilistic models (Markov process) and IA models (ANN)	7754 bridges; 12681 inspection data
Furtado & Ribeiro (2023)	One road section	Probabilistic models (Semi-Markov Process)	588 bridges; Inspection data between 2016 and 2020
Souza et al. (2023)	Five models considering ADT and environmental aggressiveness	Deterministic models (3ª order polynomial regression)	885 bridges; 2655 inspection data
Souza et al. (2024)	Five models considering ADT and environmental aggressiveness	Probabilistic models (Markov process)	885 bridges; 37170 inspection data

Sources: (Furtado; Ribeiro, 2023; Oliveira, 2019; Santos *et al.*, 2022; Souza, C. *et al.*, 2024; Souza *et al.*, 2023; Vieira *et al.*, 2018)

4.2.2. Bridge deterioration prediction models using AI

Artificial intelligence models use inspection data and computational tools to identify relationships between the condition of a bridge and the internal and external variables associated with it (Santamaria; Fernandes; Matos, 2019). This approach makes it possible to predict bridge deterioration.

Applications of machine learning and artificial intelligence in the context of bridges date back to the last century. Among the first examples was a knowledge-based decision system for assessing the corrosion of rebar (Nagaraja, 1997). Another pioneering case is an expert system developed for the classification of concrete bridges, which combined fuzzy inference with artificial neural networks (Kushida; Miyamoto; Kinoshita, 1997). Neural networks have also been used to analyze structural damage caused by corrosion (Furuta; Deguchi; Kushida, 1995), a topic that remains current and relevant, as evidenced by more recent studies (Calò *et al.*, 2025; Di Mucci *et al.*, 2024; Nettis *et al.*, 2024). Several other studies in the last century have already explored the use of artificial intelligence in this field, as illustrated by works such as (Hung; Kao; Lee, 2000; Kim; Yoon; Kim, 2000; Mukherjee; Deshpand; Anmala, 1996; Saito M; Fan, 2000).

However, it wasn't until 2003 that the first studies were published focusing specifically on predicting bridge deterioration using machine learning. Melhem et al. (2003) (Melhem; Cheng, 2003; Melhem *et al.*, 2003) conducted two important studies that marked the beginning of this line of research.

In the first study, Melhem; Cheng (2003) used instance-based learning (IBL), specifically the k-Nearest Neighbors (k-NN) algorithm, to predict the remaining useful life of bridge decks. The k-NN does not explicitly "learn" patterns, but stores training examples and uses this data to make predictions, classifying new examples based on the k nearest neighbors.

In the second study, Melhem et al. (2003) developed bridge deterioration models using decision trees combined with wrapper methods. Decision trees create a hierarchical structure to classify data based on specific attributes, while wrapper methods, such as bagging, boosting, and feature selection, are used to improve the performance of the algorithms by allowing additional operations, such as discretizing the data. The study analyzed 232 concrete bridge decks in Kansas (USA) and the best model had an accuracy rate of 75%, with tree sizes ranging from 3 to 40 and number of leaves ranging from 2 to 26.

Recently, the decision tree technique has been revisited in two important studies. Kong et al. (2023) applied Extreme Gradient Boosting (XGBoost), an advanced boosting technique, to investigate the factors affecting the condition of concrete and steel bridge decks and to improve deterioration prediction models. Using a database of 41,660 bridges in the United States, the best model developed achieved an accuracy rate of 84%, demonstrating the effectiveness of XGBoost for modeling structural deterioration on a large scale.

Similarly, Yang; Wang; Nassif (2024) used XGBoost to investigate how environmental factors affect the deterioration of reinforced concrete slabs, with a focus on improving the prediction of bridge deterioration. They analyzed a large dataset of 176,000 bridges in the United States and achieved a balanced accuracy of 0.704, highlighting the impact of environmental factors on deterioration and the robustness of XGBoost in modeling these effects.

While decision trees excel at understanding the factors that influence bridge deterioration, their application is geared toward data interpretation rather than accurate prediction. In contrast, neural networks have been widely used to create more robust predictive models. The main types of neural networks used to predict bridge deterioration include Artificial Neural Networks (ANNs); Recurrent Neural Networks (RNNs); and Convolutional Neural Networks (CNNs).

4.2.2.1. Neural network analysis of bridge deterioration prediction models

The first study using neural networks to develop bridge deterioration models was conducted by Huang (2010). Using the Backpropagation Multi-Layer Perceptron (BP-MLP classifier) and a database of 2,488 inspection records from 1,241 bridges in Wisconsin, USA, Huang developed a model that achieved an accuracy rate of 75.39% in the testing group. Since then, several other studies have been conducted. In addition, analysis of the structure of the neural networks reveals significant variability among the models, which is strongly influenced by the databases used. For example, with respect to the activation functions applied to ANNs, there is no dominant function, suggesting that the selection should be guided by the nature of the data and the behavior to be modeled. The same pattern of variability applies to the number of hidden layers and the number of neurons in each layer. This diversity reinforces the need for a customized approach when building neural networks to model bridge deterioration, considering the individuality of the problem and the data, which can directly affect the results obtained. In addition, analysis of the structure of the neural networks reveals significant variability among the models, which is strongly influenced by the databases used. For example, with respect to the activation functions applied to ANNs, there is no dominant function, suggesting that the selection should be guided by the nature of the data and the behavior to be modeled. The same pattern of variability applies to the number of hidden layers and the number of neurons in each layer. This diversity reinforces the need for a customized approach when building neural networks to model bridge deterioration, considering the individuality of the problem and the data, which can directly affect the results obtained. Table 19 provides an overview of the models developed using neural networks, detailing the method, structure, database, location, and evaluation metrics (results).

Table 19 – Bridge deterioration prediction models using neural networks.

Author	**Method and Structure**	**Database and Location**	**Evaluation metrics**
Huang (2010)	ANN (BP-MLP) with TanH, 5 hidden layers, 5 neurons each	1241 bridges, 2488 data, Wisconsin - USA	Accuracy classification rate 75.39% for test
Lee et al (2011)	ANN (TDNN)	350 bridges, 1050 data, Maryland - USA	Not detailed
Bu et al. (2012)	RNN (ENN)	94 bridges, 4115 data, Queensland - Australia	For steel, the method produces 55% reasonable patterns
Creary & Fang (2014)	ANN (MLP) with TanH, 2 hidden layers, and 42 neurons	7432 data, Connecticut - USA	Accuracy rate of 89.95 %
Santamaria et al. (2019)	ANN (MLP) with sigmoid activation, 3 hidden layers, 20 neurons each	766 bridges, ~14 data each, Rhode Island - USA	MSE = 0.2068; MAE=0.3154; Accuracy factor=1.3552
Srikanth & Arockiasamy (2020)	ANN (BP-MLP) with ReLU and TanH, 5 hidden layers and 64 neurons each	9398 data, Florida - USA	Accuracy classification rate 88% for test
Choi et al. (2020)	RNN (LSTM) with 11 hidden layers	Inspection data (1995-2017), Korea	Accuracy rate of 71.9%
Liu & Zhang (2020)	CNN with a mini-batch size of 1,024 and a moment coefficient of 0.95	6214 data, Maryland and Delaware - USA	Accuracy rate of 85% for test
Miao (2021)	ANN (MLP) with 1 hidden layer, 10 neurons, ReLU, Adam solver, learning rate 0.01	3386 bridges, Hokkaido - Japan	Accuracy rate of about 65%.
Miao et al. (2021)	RNN (LSTM) with softmax activation, 150 hidden layers	3386 bridges, Hokkaido - Japan	Accuracy rate of 80.79 % for testing
Zhu & Wang (2021)	Combination of RNN (ConvSRUs) and CNN (3 spatio-temporal, 2 fully connected layers)	23104 bridges, Texas - USA	True accuracy above 90%
Althaqafi & Chou (2022)	ANN (MLP) with ReLU, Adam solver, 6 hidden layers, 32-512 neurons	Inspection data, Ohio - USA	Best model with r^2 = 0.88, MAE =0.11; and Accuracy rate of 90 %
Santos et al. (2023)	ANN (MLP) with TanH, 1 hidden layer, 5 neurons	7754 bridges, 17401 data, Brazil	Accuracy rate of 67 % for validation and testing
Jiang et al. (2023)	ANN (ELM) with sigmoid, 1 hidden layer, 20 neurons	539 bridges, China	MAE = 2.412; RMSE=3.003; r^2=0.768
Hu & Liu (2023)	ANN (MPL) with ReLU, 2 hidden layers (5 and 10 neurons)	1000 data, USA	Accuracy of 70 % for best model
Zhang et al. (2024)	RNN (ENN) with Long-Term Predictions (LTP) of 8	5600 data, Texas - USA	Accuracy rate of 93.8%

Sources:(Althaqafi; Chou, 2022; Bu *et al.*, 2012; Choi; Lee; Kong, 2020; Creary; Fang, 2014; Hu; Liu, 2023; Huang, Y. H., 2010; Jiang *et al.*, 2023; Lee *et al.*, 2011; Liu; Zhang, 2020; Miao, 2021; Miao; Yokota; Zhang, 2021; Santamaria; Fernandes; Matos, 2019; Santos *et al.*, 2022; Srikanth; Arockiasamy, 2020; Zhang *et al.*, 2024; Zhu; Wang, 2021)

Table 19 shows the strong predominance of models based on Artificial Neural Networks (ANNs), which represent 62.50% of all the models evaluated. Among them, the MLP stands out, being used in 88.89% of the ANN-based models and in 50% of all the models studied. This evidence confirms the effectiveness of the MLP in capturing the complex interactions between input and output variables, making it a robust and reliable tool for modeling bridge deterioration. The success of the MLP can be attributed to its ability to learn non-linear and complex patterns, which are essential for predictive problems such as structural deterioration behavior.

However, when looking at the evolution of the studies from 2020 onwards, there is an increasing diversification in the choice of neural network types. Of the eleven most recent studies, five use architectures other than ANNs, showing an interest in alternatives that may offer specific advantages in different contexts. This shift suggests that while MLP has proven effective in several applications, the choice of the ideal model is influenced by a few factors, including the nature of the data and the specific goals of the research. Thus, there is no single approach that can be considered "correct," but rather a range of possibilities that researchers can explore to meet the particularities of each situation.

In addition, analysis of the structure of the neural networks reveals significant variability among the models, which is strongly influenced by the databases used. For example, with respect to the activation functions applied to ANNs, there is no dominant function, suggesting that the selection should be guided by the nature of the data and the behavior to be modeled. The same pattern of variability applies to the number of hidden layers and the number of neurons in each layer. This diversity reinforces the need for a customized approach when building neural networks to model bridge deterioration, considering the individuality of the problem and the data, which can directly affect the results obtained.

Although many models show satisfactory results, it is important to recognize a significant limitation: the prediction is limited to a certain range of the overall evaluation. For example, in the studies that used databases from the United States and the rating scale from 1 to 9, most of the models did not predict values below 4. This limitation can be attributed to the fact that bridges often undergo rehabilitation during their service life, resulting in a lack of data related to lower structural conditions. Thus, the database becomes a limiting factor for the models to predict these adverse conditions, highlighting the importance of a comprehensive and representative data set for the effectiveness of the predictions. Therefore, the analysis of bridge deterioration prediction models shows not only the predominance of ANNs, especially MLP, but also the evolution and diversification of the architectures used. It is crucial that researchers adopt a flexible and adaptable approach, considering the specificities of their data and objectives.

4.2.2.2. Analyzing how features affect degradation

In conjunction with the development of predictive models, several studies have highlighted the importance of bridge features in predicting deterioration. There is a growing interest in understanding not only the accuracy of the predictions, but also how the deterioration process evolves and how each parameter influences the results. This approach aims to identify the critical factors that influence the deterioration of structures over time, allowing for more precise and effective interventions.

Looking at Table 20, age is the main variable influencing the deterioration process of bridges. This conclusion is intuitive, since the service life of a bridge has a direct effect on the degradation of the materials used in its construction and on its structural capacity over the years. Several studies, such as those by (Zhang *et al.*, 2024), (Srikanth; Arockiasamy, 2020), and (Yang; Wang; Nassif, 2024), corroborate this observation, highlighting that age exerts a significantly greater influence compared to other variables. This evidence reinforces the importance of considering age as a critical factor in the assessment of bridge structural deterioration.

Table 20 shows each author's top three features, both numerical and categorical, that most influence the deterioration process according to the data set and model analyzed. These characteristics are listed in descending order of importance, providing a clear view of how each factor contributes to the deterioration behavior of bridges. In addition, the table indicates the number of bridges included in the database and the geographic location of these structures, which reinforces the contextual relevance of the results. In this way, it is possible to see how factors such as age, traffic volume, construction materials, and others can vary in importance depending on location and environmental conditions, providing a more comprehensive analysis applicable to different scenarios.

Looking at Table 20, age is the main variable influencing the deterioration process of bridges. This conclusion is intuitive, since the service life of a bridge has a direct effect on the degradation of the materials used in its construction and on its structural capacity over the years. Several studies, such as those by (Zhang *et al.*, 2024), (Srikanth; Arockiasamy, 2020), and (Yang; Wang; Nassif, 2024), corroborate this observation, highlighting that age exerts a significantly greater influence compared to other variables. This evidence reinforces the importance of considering age as a critical factor in the assessment of bridge structural deterioration.

Table 20 – Importance of the features of each model analyzed and its database.

Author	Numerical features	Categorical features	Nº of bridges and location
Creary & Fang (2014)	Age; Width and Nº of spans	Deck treatment; Class of bridge and Typology	Concrete bridges in Connecticut - USA
Santamaria et al. (2019)	Age; ADTT and Length.	Functional classification; Material and Typology	766 concrete decks in Rhode Island - USA
Srikanth & Arockiasamy (2020)	Age; Nº of Spans; and Length	Not analyzed	9398 data, Florida - USA
Miao (2021)	Length; Age (years in service) and ADT	Not analyzed	3386 concrete bridges in Hokkaido - Japan
Zhu & Wang (2021)	Age; Skew; Longitude	Typology; Material and Wearing surface	23104 bridges in Texas - USA
Althaqafi & Chou (2022)	Age; Nº of spans; and Length	Desing load; Typology and Type of support	Bridges in Ohio – USA
Jiang et al. (2023)	Age; Nº of lanes; Width	Typology; Structural configuration; and District	539 Concrete bridges in China
Kong et al. (2023)	Age; Snow influence (Nº snowfall days); and ADT	Wearing surface; Typology; and Deck protection	41660 concrete decks in USA
Yang et al. (2024)	Age; Snow influence (Freeze thaw); and ADTT	Material; Deck protection; and Functional classification	176000 concrete decks in USA
Zhang et al. (2024)	Age; ADTT; and Skew	Material; Deck type; Typology	5600 bridges in Texas - USA

Sources: (Althaqafi; Chou, 2022; Creary; Fang, 2014; Jiang *et al.*, 2023; Kong *et al.*, 2023; Miao, 2021; Santamaria; Fernandes; Matos, 2019; Srikanth; Arockiasamy, 2020; Yang; Wang; Nassif, 2024; Zhang *et al.*, 2024; Zhu; Wang, 2021)

After age, traffic is the second most important characteristic in the deterioration process. In five of the models analyzed, variables such as Average Daily Traffic (ADT) and Average Daily Truck Traffic (ADTT) are identified as essential. This is because an increase in the number of vehicles, especially heavy ones, generates dynamic loads and structural fatigue, accelerating the wear of the bridge. This additional stress is particularly pronounced on bridges located in congested areas, where the frequency and weight of vehicles can further compromise structural integrity. Another notable factor is the length of the bridge, which appears as the third most frequently cited numerical variable and features prominently in three models. Longer bridges face more complex structural challenges because they must span greater distances and have more contact areas. This not only increases the load that the bridge must carry, but also the likelihood of deterioration over time.

Given the fact that age is a predominant and almost universal factor in the deterioration process, it is necessary to look more closely at other aspects that influence deterioration. To this end, age was deliberately excluded from the subsequent analysis to provide a clearer picture of the other variables that contribute to the deterioration process. This procedure allows for a more detailed understanding of the other numerical characteristics without age overshadowing their importance. Table 21, in turn, presents this new perspective, highlighting the main numerical characteristic of each model, in addition to age, and the respective geographical locations of the bridges in the model database.

Table 21 – Number of models with the most important numerical characteristic (except age).

Numerical feature	Number of models	%	Location
ADT and ADTT	2	20%	Rhode Island and Texas
Length	1	10%	Japan
Nº of lanes	1	10%	China
Nº of spans	2	20%	Ohio and Florida
Skew	1	10%	Texas
Snow influence	2	20%	USA
Width	1	10%	Connectcut

Source: Table 20.

Vehicle traffic continues to be a significant factor in bridge deterioration, with two models identifying it as the most important variable. However, when analyzing data from bridges in regions subject to severe climatic conditions, such as snow and freeze-thaw cycles, the influence of snow emerges as a predominant factor. This observation underscores the need to consider the local climate when managing bridges, especially in areas prone to extreme weather events. To guarantee the structural integrity of these infrastructures, it is essential to implement strategies that mitigate the adverse effects of the climate and thus promote the longevity of bridges. In addition to traffic and climatic conditions, other factors such as the number of spans and the length of the bridge play a significant role in the deterioration process. Both elements are related to the size and complexity of the infrastructure and have a direct impact on the strength and durability of bridges. In addition, variables such as width and number of lanes are relevant because the width of the bridge tends to correlate with the volume of traffic: the greater the number of lanes or width, the greater the flow of vehicles, resulting in more pronounced deterioration.

An interesting aspect that stands out in the analysis is the inclination of the bridge (skew), which was mentioned in two studies that focused on bridges in Texas. In the study by Zhu; Wang (2021), skew was identified as the most important numerical factor, while in the work by Zhang et al. (2024), it was ranked as the second most important numerical characteristic, both excluding age. The slope can affect the distribution of loads on the structure, resulting in uneven wear that accelerates deterioration in certain areas of the bridge.

Regarding the categorical characteristics, Table 22 highlights the main categorical characteristic of each model, and the typology of the bridge is the most frequently mentioned categorical characteristic in the models analyzed. This predominance is because different typologies show different behavior with respect to deterioration, influenced by the structural configuration and the materials used. The typology has a direct impact on the resistance of bridges to different types of loads, as well as their susceptibility to environmental factors such as corrosion and fatigue. This relationship highlights the importance of considering typology when modeling deterioration, as different structures require specific maintenance and monitoring approaches.

Table 22 – Analysis of the importance of categorical features.

Feature categorical	Number of models	%
Class of bridge	1	4,17%
Deck protection	2	8,33%
Deck treatment	1	4,17%
Deck type	1	4,17%
Desing load	1	4,17%
District	1	4,17%
Functional classification	2	8,33%
Material	4	16,67%
Structural configuration	1	4,17%
Type of support	1	4,17%
Typology	7	29,17%
Wearning Suface	2	8,33%

Source: Table 20.

Another significant categorical characteristic that emerges from the models is the construction material, which also appears frequently in the analyses. The choice of material directly affects the durability of the bridge and its ability to resist wear over time. In addition, deck protection stands out as a relevant categorical feature, especially in regions subject to severe climatic conditions such as snow and freeze-thaw cycles. Studies such as Kong et al., (2023) and Yang; Wang; Nassif (2024) show that adequate deck protection can extend the useful life of the bridge, minimize adverse environmental impacts, and reduce the need for corrective actions.

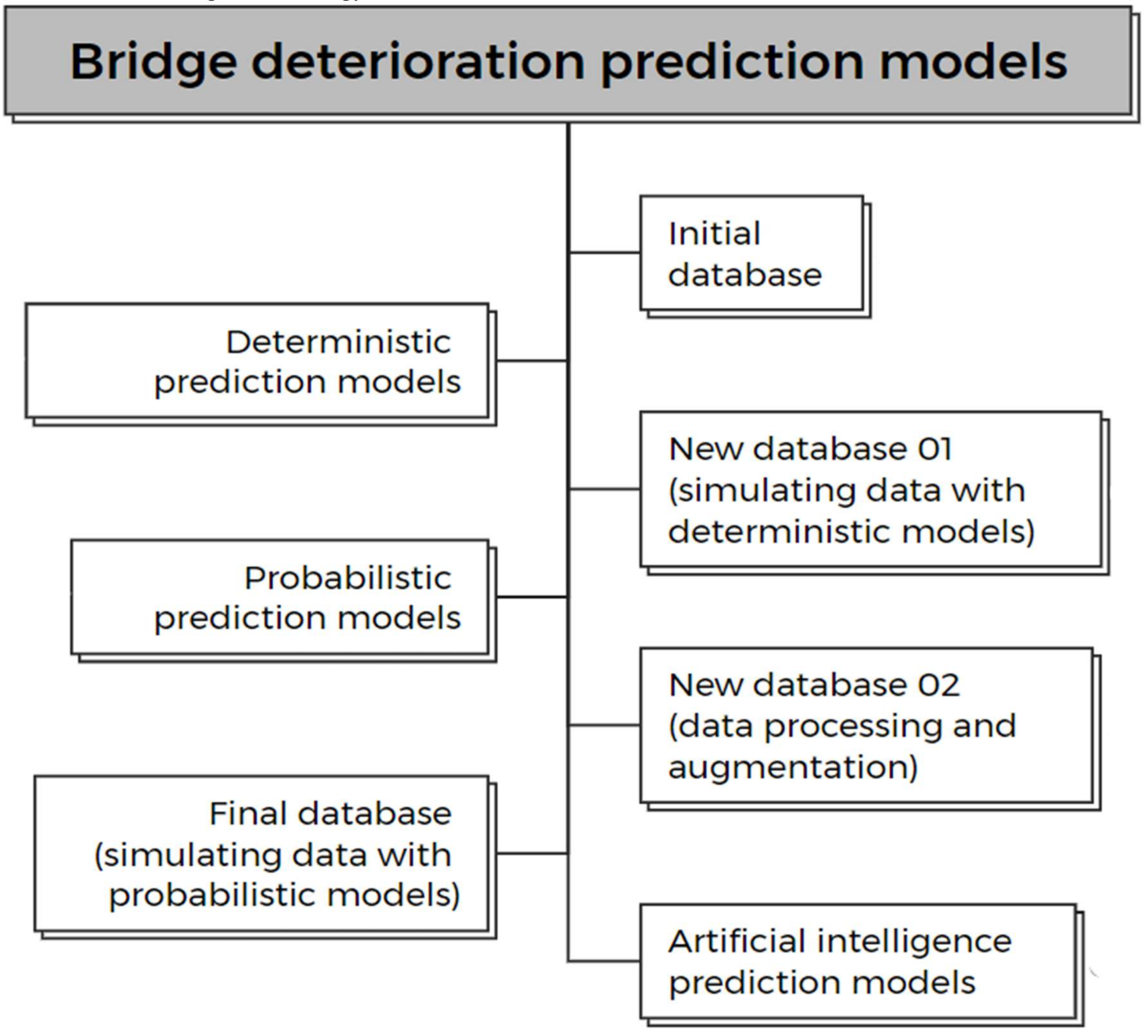
Although other categorical variables appear less frequently, they remain relevant in specific contexts, depending on the geographic location and the type of traffic the bridge supports. This suggests that the analysis of bridge deterioration should be adapted to the conditions of each structure, considering the diversity of factors that may influence its performance.

It is interesting to note that few models have considered the influence of the maritime environment in their investigations, possibly due to a lack of data in specific databases or insufficient information for a comprehensive analysis. However, two studies stand out in the study of this factor: the study by Zhang et al. (2024), which introduced the characteristic " coastline distance " as an important variable among the five main ones influencing deterioration among the 20 analyzed, and the study by Miao (2021), which included the influence of chloride in its analysis, presenting this parameter among the five most relevant characteristics among the twelve analyzed. These studies highlight the need to consider the environment in which bridges are located, especially in coastal regions, for a more complete understanding of the factors that contribute to structural deterioration.

4.3. Method

This study faced significant challenges due to the lack of complete data, as discussed in Section 4.2.1. Neural network modeling requires a significant amount of data to achieve satisfactory performance. To overcome this limitation, a specific methodology was developed to mitigate the lack of information and ensure the validity of the models generated. This methodology was structured in several stages, as shown in Figure 18.

Figure 18 – Structuring methodology.



Source: Author.

All the data collected refers to both the registration information of the bridges and the inspection reports, which include the date of inspection and the assigned condition state. The deterioration process in all the developed models was modeled using a classification approach, i.e., the condition state was used as the output variable. The condition states recorded in the inspection reports follow the methodology established by DNIT, where damages are identified through visual inspection and, subsequently, a condition state is assigned, as detailed in Table 23.

Table 23. Condition States in Brazil.

State	Structural insufficiency	Condition	Bridge Condition Classification
5	There is no damage or structural insufficiency.	Excellent	No problem with the bridge
4	There is some damage, but there are no signs that it is causing structural insufficiency.	Good	Bridge without major problems
3	There is damage leading to some structural failure, but there is no sign of the bridge being compromised.	Regular	Potentially problematic bridge: It is recommended to follow the evolution of the problems through routine inspections.
2	There is damage generating significant structural weakness in the bridge, but there is no risk of structural collapse.	Poor	Problematic bridge: Postponing the recovery of the bridge too long can lead it to a critical state, also implying a serious compromise of the structure's service life.
1	There is damage generating serious structural insufficiency in the bridge, and there is a risk of structural collapse.	Critical	Critical bridge: In some cases, it can configure an emergency, and the bridge recovery can be accompanied by special preventive measures

Source: (DNIT, 2024).

The starting point was the SGO database, which contained information on 6,833 bridges. Of these, 885 bridges were selected based on the availability of three complete inspection cycles, resulting in a total of 2,655 inspection records. This initial filtering followed strict criteria that considered the consistency and relevance of the data to the study. The criteria included excluding bridges with incomplete, inconsistent, or out-of-scope data to ensure that the selected bridges adequately represented actual conditions and behavior over time.

With this selected data, Souza et al. (2023) proceeded to develop deterministic models for predicting bridge deterioration, using third-order polynomial regression. This approach made it possible to capture the relationship between time and the condition of the bridges, resulting in five different models conditioned on the most influential characteristics in the observed deterioration.

The deterministic models performed satisfactorily but had critical limitations. They were highly dependent on bridge construction year, making them too general and therefore less accurate in specific cases, such as rehabilitated bridges. In these situations, the application of the models required an adjustment of the deterioration curve based on the last recorded condition, which compromised the reliability of the results. Given this limitation, it was decided to create a new database combining real data with simulations based on deterministic models to develop probabilistic models using Markov matrices. The existing real data and the data simulated by the deterministic models were used to build a new database (new database 01).

With this new database, it was possible to develop probabilistic models for predicting deterioration. Souza et al. (2024) used Markov matrices for the development, following the same structure as the previously developed deterministic models. Although the probabilistic models had lower coefficient of determination (R^2) values than the deterministic models, they proved to be more effective in practice because they were validated with data from bridges that were not used to build the models.

Before building a new database, testing and model development was done with database 01, but directly applying simulated data from deterministic models to the development of artificial intelligence models presented two major challenges. First, the AI models tended to reflect the results already obtained by the deterministic models without adding any new information. Second, the nature of the simulated data would make it difficult to capture additional characteristics of the bridges that were not considered in the deterministic models.

To overcome these challenges, a new version of the database (new database 02) was created with a different approach, adding data that none of the previous models had seen. First, the existing data was processed to remove outliers and inconsistent records, resulting in 346 bridges and 1,038 inspection records. Next, 301 new bridges were added that were previously excluded because they did not have three complete inspection cycles. These additional bridges contributed 557 new inspection records. A significant challenge identified was the lack of the construction year for 41.70% of the bridges analyzed in the SGO. To fill this gap, the authors of this paper developed an algorithm based on key bridge characteristics (barrier type, width and design load) to estimate the construction year. This algorithm, validated with a coefficient of determination (R^2) of 0.61 and a Mean Absolut Error (MAE) of 4.45 years, considering the transition time of the condition states, the margin of error of five years is considered acceptable, was used to add additional 326 bridges to the database, resulting in a total of 973 bridges and 2,481 inspection records. This new database allowed the AI model to better capture deterioration without significant bias from previous models.

Once the database was completed, the data needed to develop the artificial intelligence models was simulated. Unlike the previous simulation, which considered two-year intervals based solely on the age of the bridge, the new simulation was performed annually based on the probabilistic models developed. The simulation was divided into two stages: (i) simulation of the data from age 0 to the first inspection record, using the deterioration curve associated with condition state (CS) 5; and (ii) simulation of the data after the last inspection record, considering the inspection history of the bridge. This step used the deterioration curve corresponding to the current condition state and the time the bridge has been in that condition.

This process resulted in the simulation of 111 inspection records for each of the 973 bridges, for a total of 108,003 records, of which 105,522 were simulated and 2,481 were real data.

Multilayer Neural Networks (MLPRegressor), implemented using the scikit-learn library in Python, were selected for the artificial intelligence models due to their capacity to capture complex relationships between input and output parameters. Bridge deterioration, an irreversible process over time, was modeled as a regression problem, making the choice of MLPRegressor appropriate.

To optimize the performance of the model, GridSearchCV was used to adjust the hyperparameters, with 5-fold cross-validation and coefficient of determination (R^2) as the main evaluation metric. In addition, the learning curve was analyzed to ensure a balance between model learning and processing time to avoid overfitting. The final hyperparameters selected were: five layers of 50 neurons, logistic activation function, Adam solver, with alpha of 0.01 and constant learning rate.

During training, it was observed that the "age" variable had a dominant influence on deterioration, as expected and highlighted in previous studies (Srikanth; Arockiasamy, 2020; Yang; Wang; Nassif, 2024; Zhang *et al.*, 2024). However, this dominance limited the model's ability to capture the influence of other variables, such as the environment. To address this issue, we split the model into two: one for bridges in non-aggressive environments (classes I and II of NBR 6118 (2023) (ABNT NBR 6118, 2023)) with 99,012 inspection data, and another for bridges in aggressive environments (classes III and IV of NBR 6118 (2023) (ABNT NBR 6118, 2023)) with 8991 inspection data. The performance metrics were evaluated separately for both models, with 15% of the database reserved for the test group.

Two different approaches were proposed for their practical application: (i) the characteristics of the bridge and its age are used to predict the condition, with the AI models generating a specific curve for each bridge; and (ii) generating a deterioration curve for the bridge from age 0 to the minimum condition state. Regarding the second approach, from the last condition state and the corresponding transition year, the model begins to project the future behavior of the bridge, ignoring the previous history of deterioration. Although this methodology is not ideal for application, especially to bridges that have undergone rehabilitation, it is essential to allow the models to be applied to both rehabilitated bridges and those without records of the construction year. Table 24 provides a complete summary of the methodology used. The characteristics of the 973 bridges used to develop the AI deterioration prediction models are shown in Figure 19.

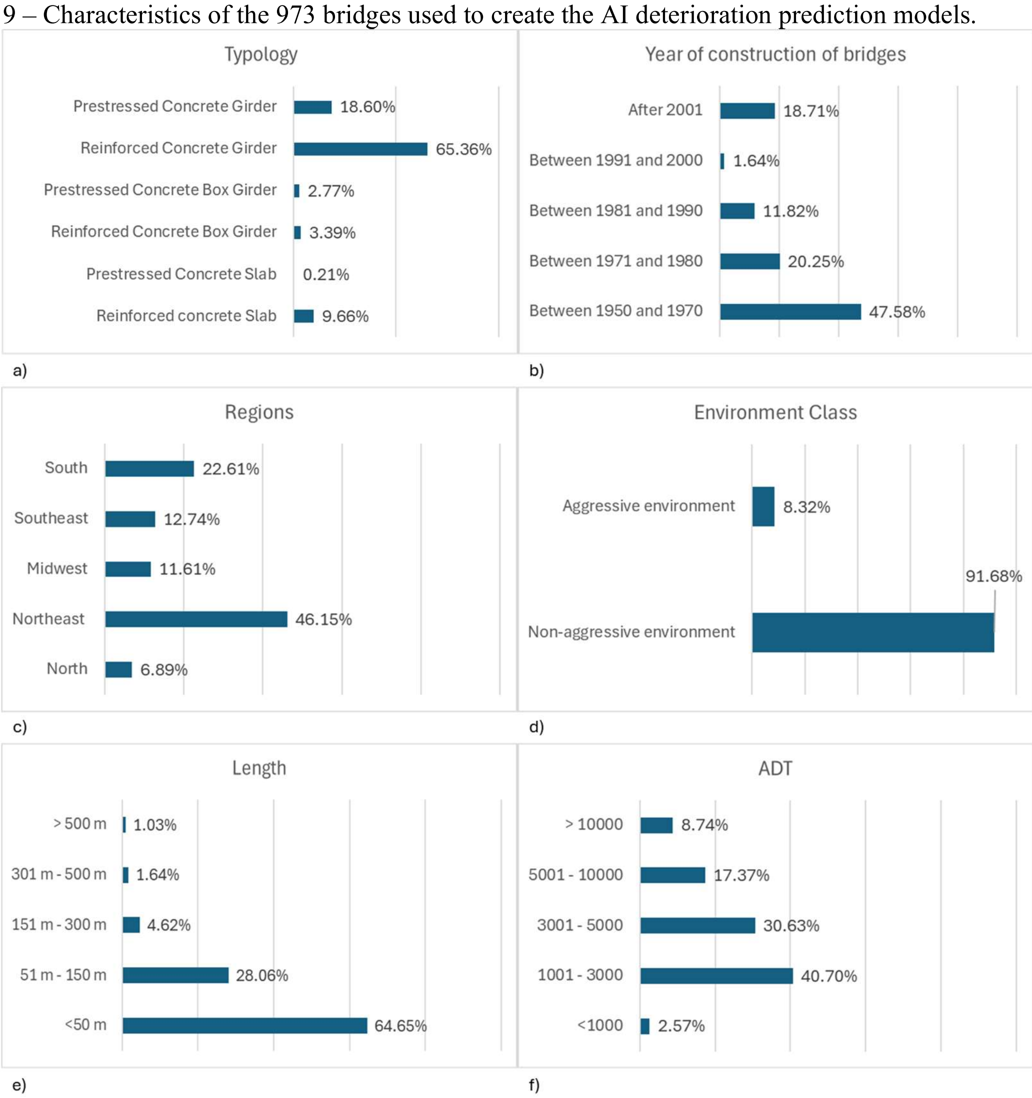
Table 24 – Detailed flowchart of the methodology.

Bridge deterioration prediction models	
Initial database	
Data	6833 bridges in SGO
Data filtering	Reinforced or prestressed concrete bridges Reinforced or prestressed concrete bridges A minimum of three inspection cycles With year-built data
Resulting: 885 bridges and 2655 inspection data	
Deterministic prediction models	
Data	885 bridges and 2,655 inspection data
Method	Third-order polynomial regression
Models	All Bridges Non-aggressive environment (Class I and II of the NBR6118) Aggressive environment (Class III and IV of the NBR6118) Non-aggressive and ADT less than 4,000 Non-aggressive and ADT more than 4,000
New database 01 (simulating data with deterministic models)	
Data	885 bridges and 2,655 inspection data
Data simulation	Data simulation with deterministic models Real and simulated data totaling 42 inspection cycles Simulation of the data based on the year the bridge was built 34,515 simulated inspection data
Resulting: 885 bridges and 37,170 inspection data	
Probabilistic prediction models	
Data	885 bridges and 37,170 inspection data
Method	Discrete-time state-based method Discrete time of 2 years
Models	All Bridges model Non-aggressive environment (Class I and II of the NBR6118) Aggressive environment (Class III and IV of the NBR6118) Non-aggressive and ADT less than 4,000 Non-aggressive and ADT more than 4,000
Validation	274 bridges; 476 inspection data $R^2 = 0.62$, MAE = 0.36, RMSE = 0.65
New database 02 (data processing and augmentation)	
Data selection 01	885 bridges carried over from other models and 2655 inspection data
Data filtering	Removing outliers Removing bridges with inconsistencies
Resulting: 346 bridges and 1,038 inspection data	
Data selection 02	New bridges with less than three inspection cycles
Data criteria	Reinforced or prestressed concrete bridges No improvement in condition state or major interventions With year-built data No selection of outliers
Resulting: 301 new bridges and 557 inspection data	
Data selection 03	New bridges without year of construction
Data criteria	Reinforced or prestressed concrete bridges No improvement in condition state or major interventions
Missing data input	YearBuild algorithm (Algorithm to estimate the year of construction)
Three primary characteristics of the bridge	Design vehicle Type of barrier Total width
Validation	468 bridges $R^2 = 0.61$, MAE = 4.45 and RMSE = 5.37
Resulting: 326 new bridges and 886 inspection data	
Data filtering	Removing outliers Removing bridges with inconsistencies

Resulting: 973 bridges and 2,481 inspection data	
Final database (simulating data with probabilistic models)	
Data	973 bridges 2,481 and inspection data
Data simulation	Data simulation with probabilistic models Real and simulated data totaling 111 inspection cycles per bridge Simulation of data from the bridge's construction year until the first inspection and from the last Condition State transition after the latest inspection. 105,522 simulated inspection data
Resulting: 973 bridges and 108,003 inspection data	
Artificial intelligence prediction models	
Data	973 bridges 108,003 inspection data
Method	Neurais networks
Structure	Five hidden layers of 50 neurons each Activation function: logistic Solver: Adam Alpha: 0.01 Learning rate: Constant
Models	Non-aggressive environment (Class I and II of the NBR6118)
	Aggressive environment (Class III and IV of the NBR6118)
Validation	Cross validation Test metrics

Source: Author.

Figure 19 – Characteristics of the 973 bridges used to create the AI deterioration prediction models.



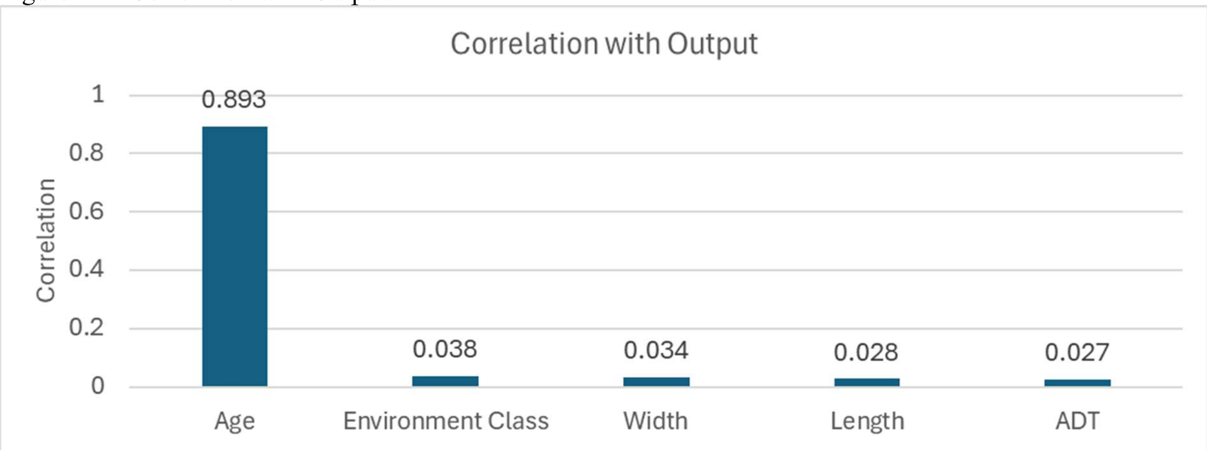
Source: Author.

4.4. Results and discussions

The first step in building the model was to check the correlation between the input parameters and the output variable. Various data was collected for each bridge, but only a few characteristics were considered for the correlations and training. For example, information was collected such as: bridge code, overpass type, typology, state, length, width, year of construction, highway, location on highway, ADT, and environmental aggressiveness class. However, the bridge code, highway, and highway location were discarded because they did not have a direct relationship with deterioration. The year of construction was also discarded because the inspection data was already based on the age of the bridge, which could introduce redundancy into the model. Therefore, the year of construction was only used to calculate the age of the bridge at each inspection. Other data, such as typology, type of crossing, and state, were excluded due to lack of sufficient information for detailed analysis.

The other variables were correlated with the output variable to analyze how each factor influences deterioration. These correlations are shown in Figure 20. As expected, the age of the bridge showed a strong correlation with the output value, confirming that bridges deteriorate over time. The large difference between age and other factors is also explained by the high level of data control in the database creation process. This result reinforces the importance of training two different models to capture the influence of the environmental aggressiveness class, since age tends to overshadow the influence of other parameters.

Figure 20 – Correlation with Output.



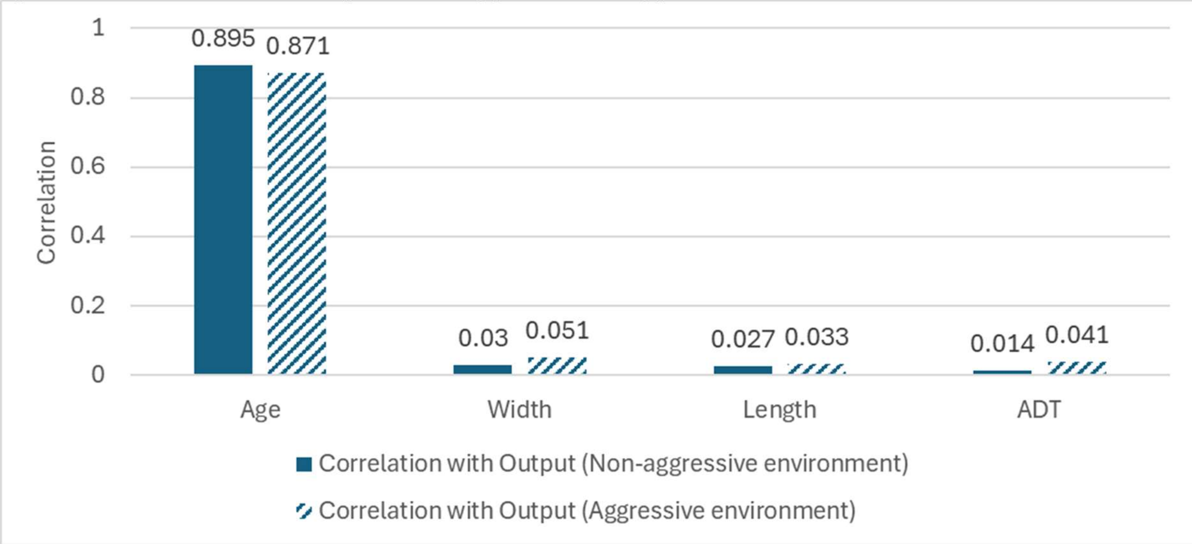
All the results are negative, but for a better presentation, the modulus of the values has been placed.
Source: Author.

When comparing the other parameters without considering age, it was observed that the environment had a greater influence than other factors, consistent with the results of previous models analyzed in Table 20 and in models previously developed by the author Souza et al.

(2024, 2023). All numerical parameters showed a negative influence on deterioration, i.e. as the values increase, the output value decreases, indicating a deterioration of the condition.

To understand how each parameter influences the individual data sets, the data from bridges in a non-aggressive environment and in an aggressive environment were correlated with the output variable, as shown in Figure 21.

Figure 21 – Correlation with Output in non-aggressive and aggressive environment.



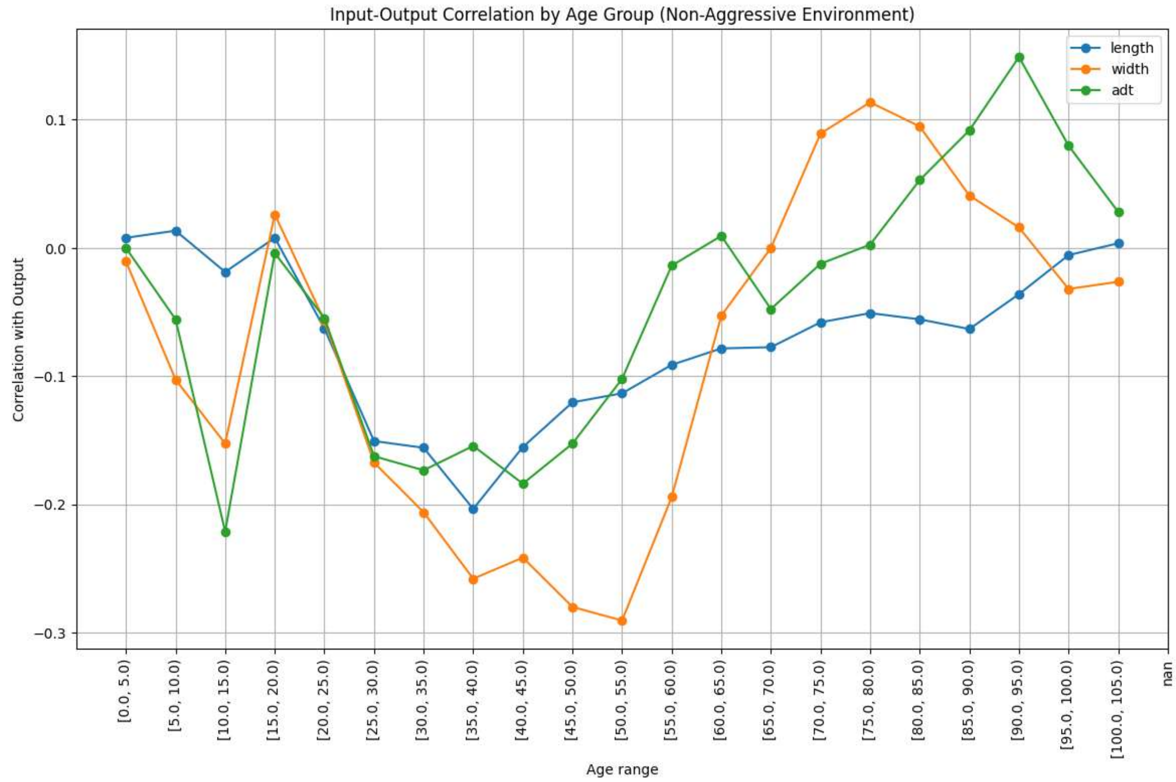
All the results are negative, but for a better presentation, the modulus of the values has been placed.
Source: Author.

It can be observed that all the parameters, except for age, were more pronounced in the aggressive environment. This is because, in these conditions, the synergy between the factors accelerates the deterioration process and increases the influence of the parameters. Age, on the other hand, showed a slightly lower correlation in the aggressive environment compared to the non-aggressive environment, which can be attributed to the increased influence of the other parameters.

In the non-aggressive environment data set, the values were like those of the general data set, which is explained by the fact that 90% of the bridges are in non-aggressive environments, thus reflecting the overall data.

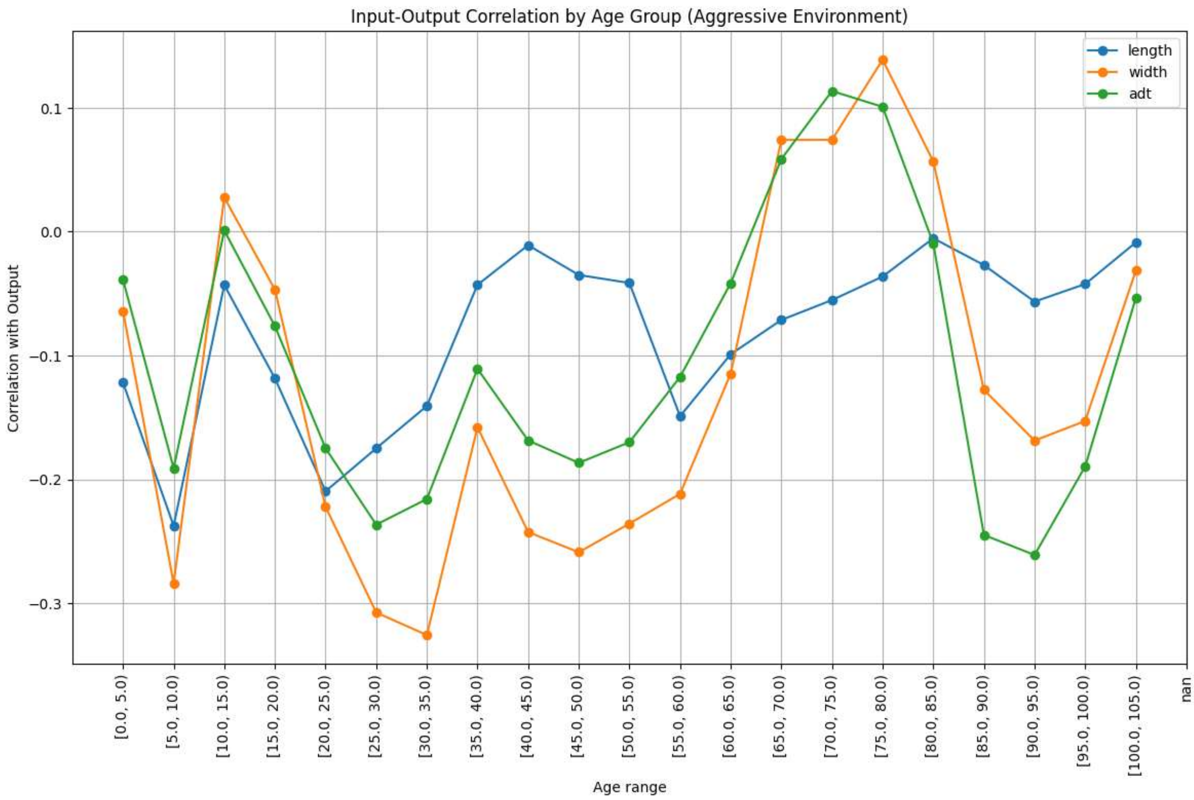
Since age proved to be the most dominant factor in the correlation with the output variable, a more in-depth analysis was performed to understand how the other factors behave over time. This analysis allowed the interactions between the input and output parameters to be examined in more detail, highlighting possible variations and anomalies in the correlations over the life of the bridges. Figure 22 and Figure 23 illustrate these correlations for the two data sets representing the non-aggressive and aggressive environments, respectively.

Figure 22 – Input-Output correlation by age group in non-aggressive environment.



Source: Author.

Figure 23 – Input-Output correlation by age group in aggressive environment.



Source: Author

When analyzing the correlation graphs by age group, a peculiar behavior was observed in the width and ADT parameters, with unexpected oscillations over time and, in certain periods, positive correlations that contradict technical intuition. The influence of ADT on the deterioration of bridges showed a non-linear relationship throughout their useful life. At early ages, there was a negative correlation, indicating that bridges subjected to higher volumes of traffic tend to deteriorate more quickly, due to the cumulative action of cyclical loads and impacts. From the age of 50, however, this correlation softens and even becomes slightly positive, suggesting that these structures, due to their greater economic and social importance, are more frequently subjected to maintenance. On the other hand, bridges with low traffic volumes tend to receive less attention over time, which can result in more critical condition states, even under reduced stresses. From the age of 80, the correlation becomes negatively significant again, reflecting the predominance of the accumulated effects of traffic on deterioration. This pattern is even more evident in aggressive environments, where environmental factors act synergistically with the effects of traffic, accentuating deterioration.

As for width, a similar pattern was identified, since wider bridges generally carry a greater volume of traffic and have greater functional relevance. However, over time, the correlations associated with width showed significant variations between positive and negative values, showing an unstable and inconsistent relationship with the output variable. Although width can, in theory, influence deterioration, the data suggests that this parameter introduces noise into the model and increases the risk of overfitting. In addition, the coexistence of the width and ADT parameters in the model could generate redundancy, given that wider bridges generally serve higher traffic volumes. For these reasons, it was decided to exclude width as an input variable in the modeling process, with the aim of improving the robustness and performance of the predictive models.

Length, on the other hand, showed a more linear behavior with respect to the output variable. The correlations were initially close to zero at the beginning of the life of the bridges but became consistently negative as the deterioration progressed. This relationship is justified because longer bridges have more structural elements and exposed surfaces, making them more susceptible to deterioration. However, when comparing the two sets of data, length has a greater influence on bridges in non-aggressive environments. In aggressive environments, the acceleration of deterioration due to environmental conditions partially overshadows the effect of length, making it a secondary factor compared to the aggressiveness class.

Based on these observations, it was decided to adjust the alpha parameter during model construction by increasing its penalty to more accurately capture the influence of all factors. This adjustment is critical to ensure that the model adequately reflects the complex interactions between the parameters and environmental conditions, and to provide more accurate predictions of bridge deterioration over time.

After analyzing the correlations between the input parameters and the output variable, it was possible to proceed with training and building the bridge deterioration prediction models. As mentioned above, it was decided to create two different models, each trained on a different set of data: one set representing bridges in a non-aggressive environment and the other representing bridges in an aggressive environment.

Two different methods were used to validate the models. The first validation method used was five-fold cross-validation. In this method, the data is divided into five groups (or "folds"). In each iteration, one of these groups is separated as a test set, while the other four are used to train the model. After training, the performance of the model on the test set is evaluated using the coefficient of determination (R^2). This procedure is repeated for each of the five groups, making sure that each part of the data is used for both training and testing, to obtain R^2 values as shown in Table 25.

Table 25 – Cross-validation.

Models	**R^2 in cross validation**				
Non-aggressive model	0.8522	0.8216	0.8222	0.8102	0.8033
Aggressive model	0.7510	0.8052	0.7907	0.6999	0.7279

Source: Author

The performance of the non-aggressive model was better in comparison, but both showed satisfactory results, which is confirmed by the analysis of the other metrics in the following paragraphs.

In the second method, the data was divided into two groups: 85% for training and 15% for testing. This division allows the model to be trained on most of the data, while a smaller portion is reserved for evaluating its performance on data not seen during training. In this way, statistical metrics were obtained from the training and testing groups for the two models, which are detailed in Table 26.

Table 26 – Training and test group metrics.

Models	**Group**	**MSE**	**RMSE**	**MAE**	**Max Error**	**R^2**	**Explained Variance**
Non-aggressive model	Train	0.1818	0.4263	0.3343	3.46	0.8405	0.8412
	Test	0.1838	0.4288	0.3359	3.20	0.8399	0.8407
Aggressive model	Train	0.2242	0.4735	0.3578	2.4190	0.8004	0.8020
	Test	0.2126	0.4611	0.3496	2.3667	0.8121	0.8130

Source: Author

Based on the analysis of the table, the model developed for non-aggressive environments has a superior performance compared to the model developed for aggressive environments, which was already expected since the amount of data used was much larger in the non-aggressive model. This superiority is evidenced by the lower average error values, such as Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE), indicating greater accuracy in the predictions. These lower values suggest that the model is more effective in predicting the condition of bridges in non-aggressive environments. In addition, the higher values of R^2 and explained variance confirm that the model for non-aggressive environments better represents the data by more fully capturing the variability present in the data set.

On the other hand, the model for aggressive environments, despite having greater uncertainty in the overall predictions, is characterized by smaller maximum errors. This means that although the overall accuracy is lower, the aggressive model tends to avoid large discrepancies in predictions. In scenarios where significant errors could result in significant misclassifications, the lower maximum error range of the aggressive model can be seen as an advantage, minimizing the risk of extremely inaccurate predictions that could compromise the assessment of the structural condition of bridges.

It is important to note that the condition state values vary between 1 and 5, which are whole numbers with a unit scale. It is therefore necessary to consider a simple rounding of the predictions to ensure that the results are represented as integers, which can generate new metrics, as detailed in Table 27. This consideration will be incorporated in subsequent analyses to provide a better understanding of the results in relation to practical reality.

Table 27 – Training and test group metrics that account for rounding.

Models	**Group**	**MSE**	**RMSE**	**MAE**	**Max Error**	**R^2**	**Explained Variance**
Non-aggressive model	Train	0.2284	0.4780	0.2171	3	0.7996	0.8015
	Test	0.2284	0.4779	0.2172	3	0.8001	0.8021
Aggressive model	Train	0.2918	0.5414	0.2795	2	0.7394	0.7433
	Test	0.2918	0.5402	0.2807	2	0.7408	0.7447

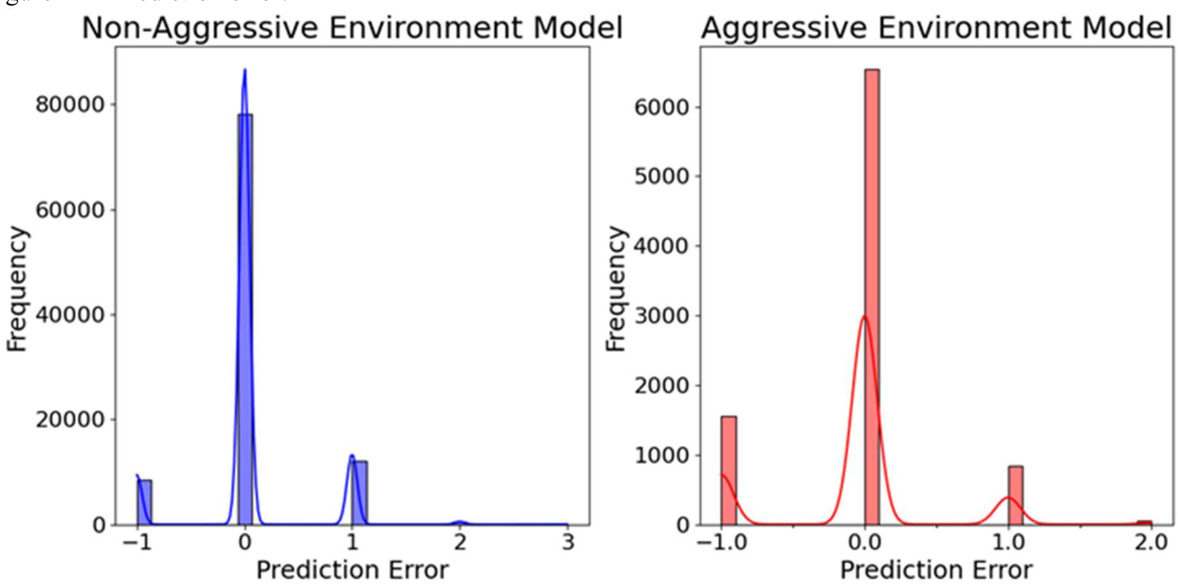
Source: Author

The metrics have slightly deteriorated compared to the metrics previously observed, but overall, the two models individually yielded very positive results. Both models show a high predictive ability, as indicated by the high values of R^2 and variance explained, suggesting that a large part of the variability in the data is well captured by the predictions. In addition, the relatively low MSE, RMSE, and MAE values in both cases indicate that the average errors in the predictions are small, which is particularly satisfactory given that the condition state varies on a scale of 1. Even the model for the aggressive environment, which performed less well than the non-aggressive model, has robust metrics indicating good predictive quality, as it can effectively capture the complexity of the aggressive environment. Therefore, both models are suitable for predicting the condition of bridges, providing a reliable tool for infrastructure management and maintenance.

The use of these two validation methods allowed a robust evaluation of the models, ensuring that they not only fit the training data well, but also can generalize to new data, which is essential for reliable prediction of bridge deterioration in different environments.

Figure 24 analyzes the accuracy of the models and the behavior of the errors in more detail. The errors in the model for non-aggressive environments show a proportional distribution, varying evenly between -1 and 1, with a slight predominance of positive values. Although there are some high maximum errors, they are irrelevant compared to the concentration of errors near 0, 1, and -1. The model for aggressive environments shows a more disproportionate distribution of errors, especially for the negative error of -1. This disproportion indicates that the model for aggressive environments tends to predict worse situations than reality, which may be related to the greater complexity and variability of conditions in more aggressive environments. On the other hand, the model for non-aggressive environments shows a more balanced error, reflecting greater accuracy, as bridges in more predictable environments show more regular deterioration.

Figure 24 – Prediction error.

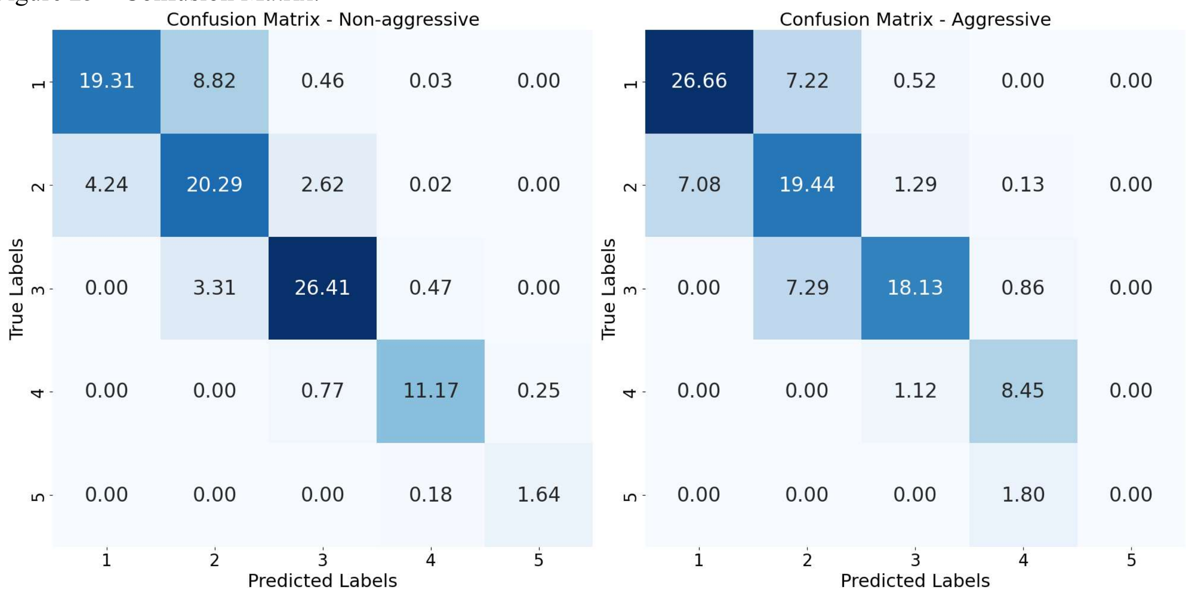


Source: Author

To better capture the behavior of the errors, a confusion matrix was computed, shown in Figure 25 (values as a percentage of the total value of the samples in each model). Both models perform well, with most hits concentrated in CS 3 for the non-aggressive environment and CS 1 for the aggressive environment. However, when analyzing the errors, the model for non-aggressive environments tends to predict conditions better than the real ones, with errors considered positive (in favor of security) amounting to 8.5% of the total sample, and errors considered negative (against security) amounting to 12.67% of the total sample. This aspect is particularly worse when the real data indicates a CS 1. In 8.82% of cases, the model erroneously assigned a CS 2, in 0.46% of the cases it assigned a CS 3, and in 0.03% of the cases it assigned a CS 4, which is of concern because it does not favor structural safety.

On the other hand, the model for aggressive environments showed the opposite effect, with a greater tendency to assign worse condition states than the real ones, with errors considered positive (in favor of safety) amounting to 17.29% of the total sample, and errors considered negative (against safety) amounting to 10.02% of the total sample, especially in CS 3, where only 0.86% of the cases a better condition was predicted, against 7.29% of the cases in which a worse condition was predicted. This behavior can be considered as an advantage since it minimizes the risk of underestimating bridge deterioration, which is crucial in aggressive environments.

Figure 25 – Confusion Matrix.



Source: Author

The tendency of the model to be correct for non-aggressive environments in CS 3 has been discussed in previous studies. Souza et al. (2022) found a faster transition and a longer stay in CS 3, which they attributed to the subjectivity of the evaluation methodology used by DNIT. This methodology allows the inspector greater freedom to define his criteria, making CS 3 a comfortable interval for assessment. In the case of the aggressive environment, most hits are concentrated in CS 1, indicating that bridges in such environments deteriorate faster, resulting in a higher proportion of low values. This reinforces the need for models that accurately capture the accelerated deterioration in these scenarios to ensure a reliable and safe assessment of the structural condition of bridges.

After training the models, the importance of each input feature was evaluated using the permutation importance method, which is particularly suitable for neural network models, as they do not offer direct interpretability of their internal parameters. In this method, the importance of each feature is measured by assessing the increase in prediction error after randomly shuffling the values of that variable while keeping the others unchanged. The greater the increase in error, the higher the influence of that feature on the model's prediction. This analysis allows for the identification of the most relevant variables in the deterioration prediction process. The results of the feature importance analysis are presented in Table 28.

Table 28 – Importance of each model's features.

Models	**Feature**	**Importance**	**Std Dev**
Non-aggressive model	Age	1.666668	0.003527
	Length	0.004118	0.000148
	ADT	0.003163	0.000091
Aggressive model	Age	1.542426	0.024537
	Length	0.005524	0.000427
	ADT	0.002121	0.000254

Source: Author

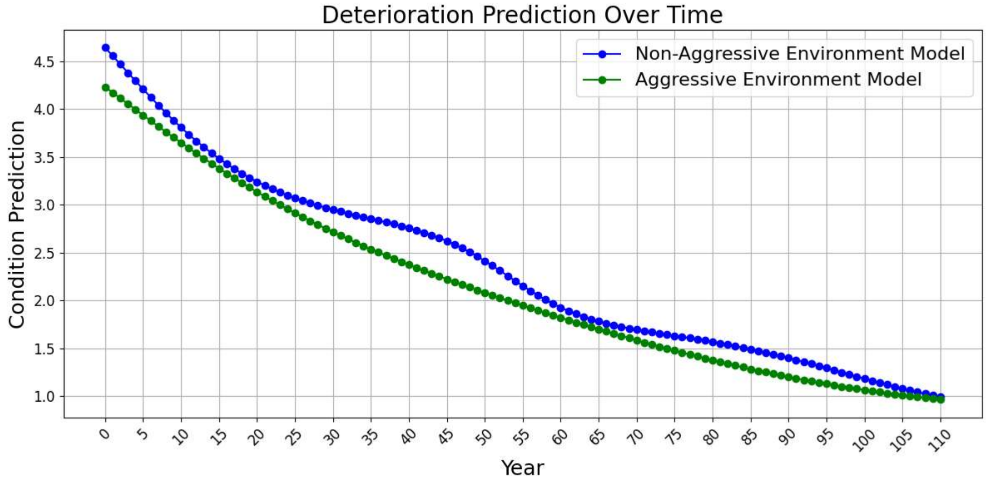
The analysis of the importance of the variables in the prediction models for non-aggressive and aggressive environments highlights the age of the bridge as the main deterioration factor in both scenarios. In the non-aggressive model, age has a high importance value and a very low standard deviation, indicating a consistent and predictive influence in determining the condition state of bridges. This suggests that, in less severe environments, age is a reliable indicator of deterioration.

In contrast, in the aggressive model, age remains the most important variable, but its importance value is slightly lower, and its standard deviation is significantly higher. This increase in variability suggests that, in aggressive environments, the influence of age on predictions is more complex and subject to variable conditions, reflecting the greater difficulty in predicting the behavior of bridges in adverse scenarios.

The variables of length and Average Daily Traffic (ADT) are of less important in both models, with a slight increase in aggressive environments. This indicates that, while age dominates the predictions, factors such as length and traffic may begin to play a secondary role in refining the models.

Finally, a comparative analysis of the deterioration curves generated by the models was carried out to assess how the bridges deteriorate over time in aggressive and non-aggressive environments, as illustrated in Figure 26. The models behaved consistently with expectations, highlighting the significant influence of the aggressive environment on the acceleration of deterioration, a phenomenon widely documented in the literature (Miao, 2021; Roelfstra *et al.*, 2004; Wang *et al.*, 2023; Zhang *et al.*, 2024).

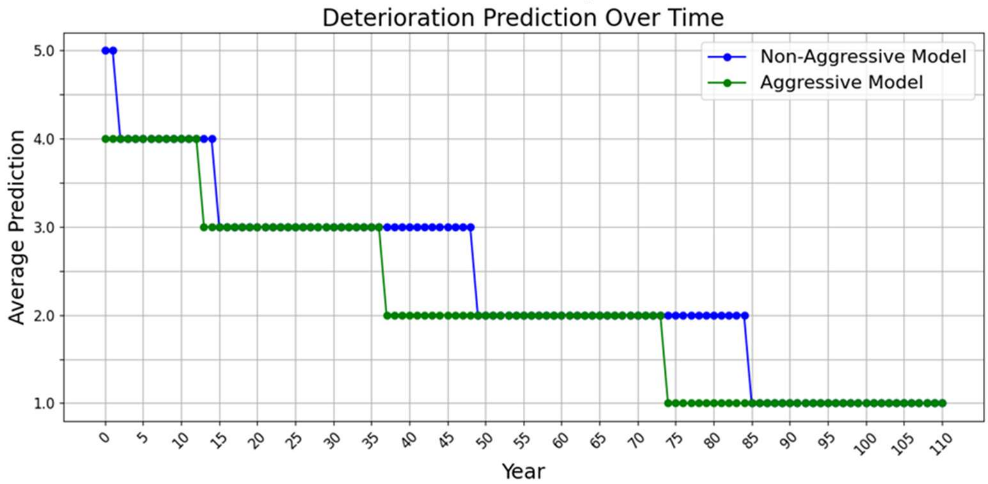
Figure 26 – Deterioration prediction over time (overall curve).



Source: Author

When the predicted values are rounded, this difference becomes even more apparent, as shown in Figure 27 In the aggressive environment model, the bridges reach their minimum condition at about 74 years, while in the non-aggressive environment model, this critical condition is reached about 10 years later, at about 84 years. This discrepancy highlights the accelerated effects of deterioration in aggressive environments, where factors such as the presence of chlorides, high relative humidity, and high rates of reinforcement corrosion play a critical role. Previous studies corroborate these findings and attribute accelerated deterioration in aggressive environments to these adverse environmental factors (Andrade; Possan; Dal Molin DCC, 2019; CEB, 1992; Costa, 1997; fib Bulletin 59, 2011; Mehta, 1991; Miao, 2021; Miranda, 2006; Papadakis, 2013; Souza, 2019; Tang; Nilsson, 1996; Vishwanath; Banerjee, 2023; Zhang *et al.*, 2024).

Figure 27 – Prediction of deterioration over time in discrete CS (general curve).



Source: Author.

Comparing the two graphs in Figure 26 and Figure 27 reveals an important aspect of bridge deterioration: the deterioration process has a continuous behavior, as shown in Figure 26, i.e., the bridge deteriorates continuously over time. However, if discrete states are used, the deterioration ultimately has discrete behavior, as shown in Figure 27, i.e., the bridge moves abruptly from one state to another, which does not capture the nuances of deterioration and is more prone to error.

The entire methodological process, developed in a scenario of scarce data, proved to be satisfactory and extremely useful, evolving from a limited data set to the creation of robust bridge deterioration models using neural networks. Souza et al. (2024) carried out a comparative analysis of the methods for developing deterioration models, considering the qualitative criteria and the steps required to build these models, as shown in Table 29.

Table 29 – Comparison of prediction methods.

Criteria	Deterministic	Probabilistic	Artificial Intelligence
Required Information	Low (4)	High (2)	Very High (1)
Information Processing	Easy (4)	Easy (4)	Hard (2)
Model Development	Easy (4)	Medium (3)	Hard (2)
Model Applicability	Medium (3)	Good (4)	Very Good (5)
Model Reliability	Bad (2)	Medium (3)	Good (4)
Model Updates	Bad (2)	Medium (3)	Very Good (5)

Source: Adapted from Souza et al. (2024).

The author has developed three types of methods, and it is possible to complement the analysis developed previously:

a) Required Information:

The amount of information required for each type of model varied significantly. While deterministic models required a relatively small amount of inspection data (2,655 records), probabilistic models required a larger amount (37,170 records), and AI models required a substantially larger amount of data (108,003 records), the amount used in each model for each method is detailed in Table 30. This escalation reflects the increasing complexity of the models, with AI requiring not only more data, but also more detailed information to accurately capture the nuances of bridge deterioration. This aspect is confirmed in the study by Srikanth; Arockiasamy (2020).

Table 30 – Database for each model.

Method	Number of Data
Deterministic (Souza *et al.*, 2023)	1,308 inspection data for non-aggressive and ADT less four thousand model 1,119 inspection data for non-aggressive and ADT more four thousand model 228 inspection data for the aggressive model
Probabilistic (Souza, C. *et al.*, 2024)	18,312 inspection data for non-aggressive and ADT less four thousand model 15,666 inspection data for non-aggressive and ADT more four thousand model 3,192 inspection data for the aggressive model
Artificial Intelligence	99,012 inspection data for non-aggressive model 8,991 inspection data for the aggressive model

Sources: (Souza, C. *et al.*, 2024; Souza *et al.*, 2023).

The inspection data in the aggressive model using AI was lower than the data of the non-aggressive models using the probabilistic method and obtained better results, which presents a contradiction in the amount of data needed for the models using AI. However, it is worth noting that in the models developed in this article, the data was somewhat controlled, resulting in data without a lot of noise and inconsistencies, so it was only possible to develop satisfactory models using AI without a much larger amount of data. In addition, the non-aggressive model with a larger amount of data proved to be more accurate, indicating that the results are better with a larger amount of data.

Another aspect, such as the amount of data used in the AI method, limited the model's ability to better capture the influence of bridge characteristics on the deterioration process, with the age factor overshadowing the other characteristics, showing that the scarcity of real data influenced this aspect.

b) Information Processing:

Information processing varies according to the complexity of the models. For deterministic and probabilistic models, processing was relatively straightforward, allowing the use of basic statistical methods and Markov matrices, respectively. However, the development of AI models required more sophisticated and complex data analysis, requiring programming in Python, advanced knowledge of data science, and the use of robust hardware to handle the volume and complexity of the information.

An important aspect to note is that the amount of data is inversely proportional to the cost of data processing: the better the data processing, the less data is needed for satisfactory development, but the less data processing, the more information is needed to capture all degradation processes and the influence of parameters on the degradation process. In terms of development, the opposite is true: the better the data processing, the less expensive the model development process.

c) Model Development and Model Applicability:

Model development has become increasingly sophisticated, moving from simple polynomial regressions in deterministic models, to the construction of probabilistic matrices, to the creation of neural networks in AI. This increase in complexity has been accompanied by a significant improvement in the applicability of the models. While deterministic models offered only three generic curves for different environments and ADTs, probabilistic models now allow the application of 15 different curves. On the other hand, AI models can generate a specific curve for each bridge, considering its individual characteristics such as length, ADT, and environmental aggressiveness class, providing much more precise and personalized applicability.

d) Model Reliability and Model Updates:

The reliability of the models also followed this evolution. Deterministic models, with no validation process and highly dependent on the age of the bridge, proved to be less reliable, especially in situations where the bridge had undergone rehabilitation. Probabilistic models showed acceptable validation metrics (R^2=0.62, MAE=0.36, RMSE=0.65), but were outperformed by AI models, which showed superior performance for both non-aggressive (R^2=0.8399, MAE=0.33, RMSE=0.42) and aggressive environments (R^2=0.81, MAE=0.34, RMSE=0.46).

Another study reinforces this point. The comparison carried out by Santamaria et al. (2020) shows performance metrics for AI models with MSE = 0.20, MAE = 0.31 and Accuracy Factor = 1.35. These results were contrasted with the metrics obtained by models based on Markov Processes and Hidden Markov Processes, which showed MSE = 0.33, MAE = 0.53, Accuracy Factor = 2.33 and MSE = 0.33, MAE = 0.42, Accuracy Factor = 1.75, respectively.

In addition, the ability of AI models to automatically update with new data is a significant advantage over deterministic and probabilistic models, which require the creation of new models each time data is updated.

4.5. Conclusions

This study presents a methodology for predicting bridge deterioration that integrates artificial intelligence in scenarios with incomplete data. The results showed that models based on neural networks, particularly MLPRegressor, outperformed conventional forecasting methods, such as deterministic and probabilistic models, in terms of accuracy and applicability. Artificial intelligence proved to be effective in capturing complex relationships between input variables such as age, traffic volume and environmental conditions, providing more robust predictions adapted to the specifics of each bridge.

The methodological evolution during the study, which started with deterministic models based on third-order polynomial functions and moved on to probabilistic models using Markov matrices, culminated in the application of artificial neural networks. This progressive approach has made it possible to overcome the limitation of incomplete data and to create a robust database that combines real inspection data with simulations. The construction and validation of the AI models proved to be extremely efficient in sparse data scenarios, suggesting that this approach can be replicated in other regions with similar problems of lack of complete structural information.

The bibliometric review confirmed the growing importance of AI in predicting bridge deterioration, with a notable increase in publications from 2020 onwards due to technological advances and greater availability of inspection data. MLP networks have emerged as one of the most effective tools in deterioration modelling due to their ability to identify complex patterns between variables. At the same time, the diversity of models used, and the variability of databases emphasises that there is no single solution; instead, the choice of the ideal model must be guided by the particularities of each case and data set.

Analysis of the influence of variables from other studies confirmed that age is the most important factor in bridge deterioration, which was expected, but also indicated that traffic volume (ADT), bridge length and environmental factors have a relevant influence. Categorical characteristics such as the type and material used in the bridges were also found to be important in understanding the deterioration behaviour of the structures. The models developed confirmed the dominance of age and the influence of factors such as ADT, length and environmental conditions.

In the Brazilian context, the scarcity of bridge data posed a significant challenge to the development of predictive models. The decentralization of management and the inconsistency of inspection records, as observed in the data where 41.7% of bridges lacked records of the year of construction, highlight the difficulty of building robust models without a consolidated database. Despite these challenges, the study managed to circumvent the lack of data by creating a database that mixed real and simulated information, allowing the development of accurate and effective models even in data-limited scenarios.

The results show that AI-based models are highly effective in predicting bridge deterioration in both aggressive and non-aggressive environments. The coefficient of determination (R^2) achieved in non-aggressive environments was 0.84 with a mean absolute error (MAE) of 0.33, while in aggressive environments the R^2 was 0.81 and the MAE was 0.34, demonstrating the robustness of the models developed. The deterioration curves showed that bridges in aggressive environments reach critical condition about 10 years earlier than bridges in non-aggressive environments, reinforcing the importance of tuning the models according to the environment.

In conclusion, the use of AI, especially neural networks, has proven to be a viable and highly effective solution for predicting bridge deterioration, even in contexts with limited data, such as Brazil. The models developed can be used to optimize preventive maintenance strategies, allowing infrastructure managers to priorities interventions based on more accurate predictions. With a broader and richer database, these models can achieve even greater accuracy, providing essential support for the long-term management and preservation of bridges. In addition, future studies could explore the inclusion of additional variables and the adaptation of other AI models, such as recurrent neural networks (RNNs), to better capture the temporal evolution of deterioration.

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CHAPTER V

Bridge deterioration index for prioritizing interventions and planning inspections

Abstract

This article proposes a bridge deterioration index to support infrastructure management. It begins with a review of current practices, covering inspection, evaluation, prediction models, safety, and prioritization. Next, it presents the index methodology, tested on 2,135 bridges in Brazil. The results identified thirteen bridges in critical condition requiring immediate intervention. Additionally, the index enables better planning of future inspections and intervals. This approach aims to promote proactive maintenance and enhance infrastructure safety using historical data. However, caution is advised in interpreting the results, especially for extreme cases, recommending further investigations for more informed decision-making.
Keywords: Bridge; Prioritizing; Decision-making; Deterioration; Maintenance; Intervention; Inspection.

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5. BRIDGE DETERIORATION INDEX FOR PRIORITIZING INTERVENTIONS AND PLANNING INSPECTIONS

5.1. Introduction

Effective management of infrastructure is important for economic development and global competitiveness (ASCE, 2013). Ensuring the safety and efficiency of these structures is essential, as they are key to the movement of people and goods. The ongoing aging and deterioration of bridges present challenges that require regular attention and a systematic management approach. In this context, proper resource allocation and data-driven decision-making are key factors.

This article provides a thorough examination of the decision-making process in bridge management, focusing on the development of a deterioration index based on predictive models. Effective bridge management involves evaluating various factors, including the severity of deterioration, rehabilitation costs, and impacts on operation and traffic safety.

The complexity of this decision-making process highlights the need for a detailed literature review to understand current challenges and practices. The first part of this article offers a comprehensive review, establishing a foundation for understanding bridge management and enhancing decision-making in this evolving field. The second part describes the development of the deterioration index and its application to a sample of 2,135 bridges in Brazil. The results demonstrate the index's effectiveness in prioritizing interventions and planning inspection. This index represents a potential tool for improving infrastructure management, optimizing resource allocation, and enhancing the safety and resilience of bridges.

Along with the literature review and its insights, the approach and application study highlight the novelty of this contribution, as it is not present in recent literature. The relevance of this study is underscored by its ability to provide a consistent approach using readily available data, which is valuable in contexts where detailed data is scarce. Other data-driven approaches require more extensive data frameworks, which necessitate changes in inspection methods and data recording. This additional complexity makes such approaches less feasible in the short term, as they demand significant time and financial resources for implementation.

5.2. Contextualization and Literature Review

A bridge management system is built on three fundamental pillars essential for the maintenance and rehabilitation of structures: database, data analysis, and decision-making. The first pillar involves collecting and storing bridge-related data, including cadastral information, inspection history, structural assessment records, and relevant documentation such as rehabilitation projects.

The second pillar focuses on transforming raw data into useful information. Through data analysis, the system identifies trends, patterns, and anomalies, which provides a better understanding of each bridge's condition and helps anticipate potential future issues.

The third pillar translates the insights from data analysis into actionable recommendations. This decision-making support uses the processed data to suggest appropriate solutions for each bridge or group of bridges. Recommendations may include maintenance interventions, emergency repairs, planned rehabilitations, or even the replacement of aging structures. Data-informed decision-making helps allocate resources efficiently, prioritize critical needs, and ensure bridge safety.

The initial step in a management system is data collection, which provides the necessary information for subsequent analysis. Inspection and assessment precede the decision-making process. Visual inspection is commonly recognized as the first stage in evaluating bridges within various Bridge Management Systems (BMS) globally. During this process, each bridge undergoes a visual assessment, and a condition state (CS) is assigned (Quirk *et al.*, 2018). In practice, inspectors estimate the condition state based on engineering experience and rating guidelines that include detailed descriptions of damage and corresponding ratings (AASHTO, 2016; Department of Transport Main Roads, 2016). The condition state serves as an indicator of the structure's performance, represented by a quantitative scale reflecting the observed damage. It is important to note that the definition and scale of condition states may vary among different BMSs worldwide.

While the condition state is a primary indicator of infrastructure status and is widely used, some transportation agencies have developed bridge health indexes to more directly quantify the damage and its relevance to the structure's components. These indices are derived from mapping identified damage, abnormal responses, and deterioration using structural health models, converting this data into discrete values (Wu *et al.*, 2021).

For instance, in the United States, the Florida Department of Transportation employs the Bridge Health Index (BHI) to assess bridge conditions. The BHI is a weighted average of the condition states of bridge components, incorporating factors such as the cost of failures, repair costs, and other weightings defined by the agency. This index summarizes the overall condition of the bridge network, which is crucial for effective planning and monitoring of bridge programs (Inkoom *et al.*, 2017). In Canada, the Bridge Condition Index (BCI) was developed by the

Ministry of Transportation as part of the Ontario Bridge Management System. The *BCI* is a metric that ranges from 0 to 100, where 0 signifies that the bridge is in very poor condition and 100 signifies that the bridge is in excellent condition. In South Korea and China, the health index is integrated with the condition state, resulting in a five-level rating system. These indices, the Damage Index (DI) in South Korea and the Bridge Condition Rating (Dr) in China (Dai *et al.*, 2014; Jeong *et al.*, 2018). Several countries, including the United Kingdom, South Africa, Australia, Austria, Germany, Japan, and Finland, have conducted studies to calculate bridge health indices, as detailed in the FHWA document (2016) (FHWA, 2016). Additionally, Wu et al. (2021) highlight a series of academic studies that have developed indices related to various aspects of bridge assessment, covering indicators of safety, severity, durability, and more.

However, it is important to note that these performance indicators primarily reflect the condition or health of the structure based on identified damage. They do not necessarily represent the actual behavior of the structure and, therefore, do not guarantee complete structural safety. For example, even if the condition states of components are favorable, abrupt failures can still occur (van Noortwijk; Frangopol, 2004). To illustrate this, consider a recent case in Brazil in 2022, where a bridge collapsed on the BR-319 highway, resulting in four fatalities. Surprisingly, the last inspection report rated the bridge at condition state 4 on a 5-level scale, where 5 represented the best condition and 1 the worst (Sassine, 2022).

Jiang et al. (2023) present an approach that divides bridge assessment into two categories: general assessment and adaptability assessment. General assessment involves a comprehensive analysis of the technical state of each component to determine the bridge's condition level. Adaptability assessment, on the other hand, focuses on evaluating the effective load capacity, traffic-carrying capacity, and flood resistance of bridges through structural stress testing and analysis.

Thus, bridge assessments can range from simplified evaluations of the condition state to more complex analyses, including load capacity and risk assessment, among other factors. Consequently, many bridge management systems incorporate not only condition assessments but also comprehensive evaluations involving load capacity and risk, as detailed in the IABMAS report (2014) (Adey; Klatter; Thompson, 2014).

Detailed inspections can provide vital information for conducting load capacity assessments, as demonstrated by various systems that perform this type of analysis. These assessments estimate the likelihood of a load exceeding the bridge's design capacity. The load includes the permanent weight of the bridge components, and the live loads generated by traffic and environmental factors such as wind and temperature. Different causes and components can lead to various failure modes, including force, moment, and bending (Liu; Fan, 2020).

Load assessments can be applied in both normal and extreme situations. The former involves evaluating the structure's fatigue due to repetitive loads, while the latter addresses extreme load scenarios such as earthquakes (Guo; Trejo; Yim, 2015), hurricanes (Mondoro; Frangopol; Soliman, 2017) and exceptionally heavy vehicles (Li *et al.*, 2017). These assessments adhere to the same requirements as conventional structural projects. However, due to uncertainties stemming from the lack of detailed design information, they account for a greater reduction in resistance properties and an increase in applied loads (Luechinger *et al.*, 2015).

In a bridge management system, risk assessment plays a crucial role by analyzing the probability of undesirable incidents occurring on bridges, thus supporting decision-making. Generally, risk can be approached in two ways: event-based simulation and random field analysis. In the first approach, risks (whether deterministic or stochastic) are hypothetically applied to a network of bridges. This simulation-based technique has been widely used to assess various types of risks, such as earthquakes, floods, and overweight trucks (Yang; Frangopol, 2020). The second approach uses random field theory to approximate the spatial correlation of bridge failure (Bocchini; Frangopol, 2011; Zhang; Wang, 2016). Although random field models were initially developed for certain disasters (e.g., earthquakes), they are also considered applicable to deteriorating bridge networks under normal traffic conditions (Setunge *et al.*, 2016; Yang; Frangopol, 2018).

The probability of failure is typically assessed using structural health models informed by the afore mentioned data and specific distributions (Kala, 2019). Some studies also train machine learning models with similar input data to detect the severity and progression of deterioration (Hoang; Liao; Tran, 2018). Additionally, the probability of failure can be directly assessed using distributions that describe the decay of components (van Noortwijk; Frangopol, 2004).

In BMS data analysis, deterioration models are widely used to support decision-making. An IABMAS report covering 25 BMS found that approximately 80% of these systems incorporate deterioration prediction models (Adey; Klatter; Thompson, 2014). Another study reinforces this trend, indicating that 67% of the analyzed BMS include such models (Souza, C. A. F. *et al.*, 2024). These findings highlight the importance of deterioration forecasting in bridge management. Deterioration models can be categorized into three main types: physical, deterministic, and probabilistic (Souza, C. A. F. *et al.*, 2024). This classification provides a comprehensive approach to understanding and predicting structural degradation through different methodologies.

In addition to these models, others have been developed and validated but have not yet been implemented in BMS (Santamaria; Fernandes; Matos, 2019). These include reliability-based models, Artificial Intelligence (AI) models, Bayesian networks, and Petri net models. It is important to recognize the significant advancements in AI across various fields today, suggesting that this technology holds great potential for future implementation in bridge management systems (Althaqafi; Chou, 2022; Souza *et al.*, 2025b). Many of these models are discussed in more detail in two studies by Souza et al. (Souza, C. *et al.*, 2024; Souza *et al.*, 2025b), which compares various examples of physical, deterministic, probabilistic, and AI models.

In Souza, C. et al. (2024), five bridge deterioration models were developed using Markov matrices. These models were built based on real and simulated data from deterministic deterioration prediction models. The resulting probabilistic models, which incorporate Markov matrices, cover the following categories: a model applicable to all bridges, specific models for non-aggressive and aggressive environments, and models for Average Daily Traffic (ADT) below and above 4,000. These models play a central role in this article, contributing to the development of the indices discussed in Item 5.3.

Different types of data analysis and evaluation provide essential insights into the decision-making process, addressing aspects such as cost models, environmental conditions, ADT, and economic and social considerations. This data can serve as the foundation for developing new information processing strategies, such as prioritization and vulnerability indexes, or can be directly incorporated into decision-making support, leading to concrete actions related to infrastructure maintenance, rehabilitation, or repair.

Bridge maintenance, rehabilitation or repair activities generally fall into two main categories, as discussed by (Li *et al.*, 2018). The first is time-based maintenance, which focuses on preserving the structure to extend its service life. The second is condition-based maintenance, which aims to strengthen the structure and improve its structural performance. However, deciding when and on which bridges to apply these measures is a complex task. The parameters mentioned above rarely provide sufficient information to guide the decisions that managers must make over time in managing bridges. Generally, it is necessary to consider the combination or inclusion of additional factors.

There are two possible approaches to address this complexity. One is a manual approach, where the manager must weigh the parameters and evaluate the available options. The other involves the creation of methodologies for prioritizing structures, conducting multi-criteria analyses, and employing other supplementary techniques. Additionally, it is important to recognize that knowledge and information related to the bridge maintenance process are often fragmented across different teams. Individuals with diverse skills and professional backgrounds perform various functions, and engineers may focus exclusively on their own results, often working in isolation. This can lead to a lack of effective sharing of information and knowledge between departments. Without effective computer-assisted tools, mastering the comprehensive knowledge of multiple domains becomes challenging for any single individual or team. As a result, decision-makers may rely on subjective experience to address critical issues, which does not always lead to well-rounded or complete solutions (Jiang *et al.*, 2023).

The criteria weighted in a decision support methodology vary according to the management system, reflecting the main concerns for a specific set of bridges. However, when conducting an analysis based on multiple criteria, it is essential to consistently consider the parameters related to the level of performance, as defined in the evaluation type.

Describing the relationship between factor variations and decision-making objectives with mathematical and mechanical precision is challenging. However, a data processing approaches can help reduce subjectivity and automate the manager's role to a greater extent. This approach is prioritization indices, which are like health indices but consider a broader range of parameters beyond just condition and damage assessment.

Prioritization indices (PI) offer a needs-based approach to bridge maintenance, allowing for short-term maintenance decisions (Echaveguren *et al.*, 2014). Prioritization is defined as the process of ranking maintenance options based on predefined qualification criteria to select those that meet the predetermined requirements (Echaveguren; Dechent, 2019). (Kurt, 1988) defines them as a combination of weighted qualitative criteria.

Most indices, including both health and prioritization indices, share a common structure that relies on weighted averages and coefficient-based approaches. These methods are used to calculate the condition of individual elements as well as the overall condition of bridges. In the United States, State Departments of Transportation use a prioritization index calculated through a computer program to assign ratings for prioritizing interventions in transportation infrastructures. This system is known as the "Bridge Sufficiency Rating" (SR), derived from the database generated by inspections. The SR is determined by combining four factors, resulting in a numerical value that reflects a bridge's ability to remain in service (FHWA, 2012). The FHWA uses the *SR* to allocate the budget to the repair/rehabilitation and replacement of bridges. When the *SR* is less than 50, the bridge is eligible for replacement. When the *SR* is between 50 and 80, the bridge is eligible for rehabilitation (FHWA, 2012).

Various authors have developed priority indices that consider a wide range of aspects related to the management and maintenance of bridges. Table 31, shows a summary of these studies, highlighting the main factors that were considered.

Table 31 – Summary table of prioritization indices.

Authors	Priority index	Factors considered
(Ryall, 2001)	Maintenance priority number (MPN)	Bridge condition factor, bridge location factor, bridge route factor
(Rashid; Herabat, 2008)	Total prioritization utility for bridges (Ubtotal)	Value of service, value of condition, value of safety, value of cost, value of socioeconomic, and value of fuel consumption.
Valenzuela et al. (2010)	Integrated bridge index (IBI)	Level of damage to the structure, hydraulic vulnerability, level of damage modeled for each structure, and importance of the bridge in the road network
(Rashidi; Gibson; Ho, 2014)	Priority Index (PI)	Structural efficiency, functional efficiency, and client impact factor.
(Yoon; Hastak, 2017)	Total prioritization scale (TPS)	Performance, economic, and criticality.
(Echaveguren; Dechent, 2019)	Index Priority (IP)	Bridge conditions, strategic importance, and vulnerability

Sources: (Echaveguren; Dechent, 2019; Rashid; Herabat, 2008; Rashidi; Gibson; Ho, 2014; Ryall, 2001; Valenzuela; de Solminihac; Echaveguren, 2010; Yoon; Hastak, 2017).

Based on the discussion, it is evident that data collection and processing are crucial in supporting decision-making and enhancing bridge management efficiency. In Brazil, the *Departamento Nacional de Infraestrutura de Transporte* (DNIT) utilizes the *Sistema de Gerenciamento de Obras de Arte Especiais* (SGO), which plays a key role in identifying and prioritizing bridge interventions. The SGO method relies primarily on two parameters: the bridge's performance and average daily traffic volumes (DNIT, 2023). However, these parameters and the manual decision-making process alone are often insufficient for effective management. Additional factors and the development of indices that reduce managerial subjectivity are essential, especially given the constraints of limited resources. For instance, data from the *Confederação Nacional do Transporte* (CNT, 2021) reveal a significant reduction in federal investments for highways in Brazil, which decreased from BRL 31.44 billion in 2012 to BRL 5.8 billion in 2021, marking an 81.6% decline. This reduction directly affects the resources available for bridge maintenance and rehabilitation.

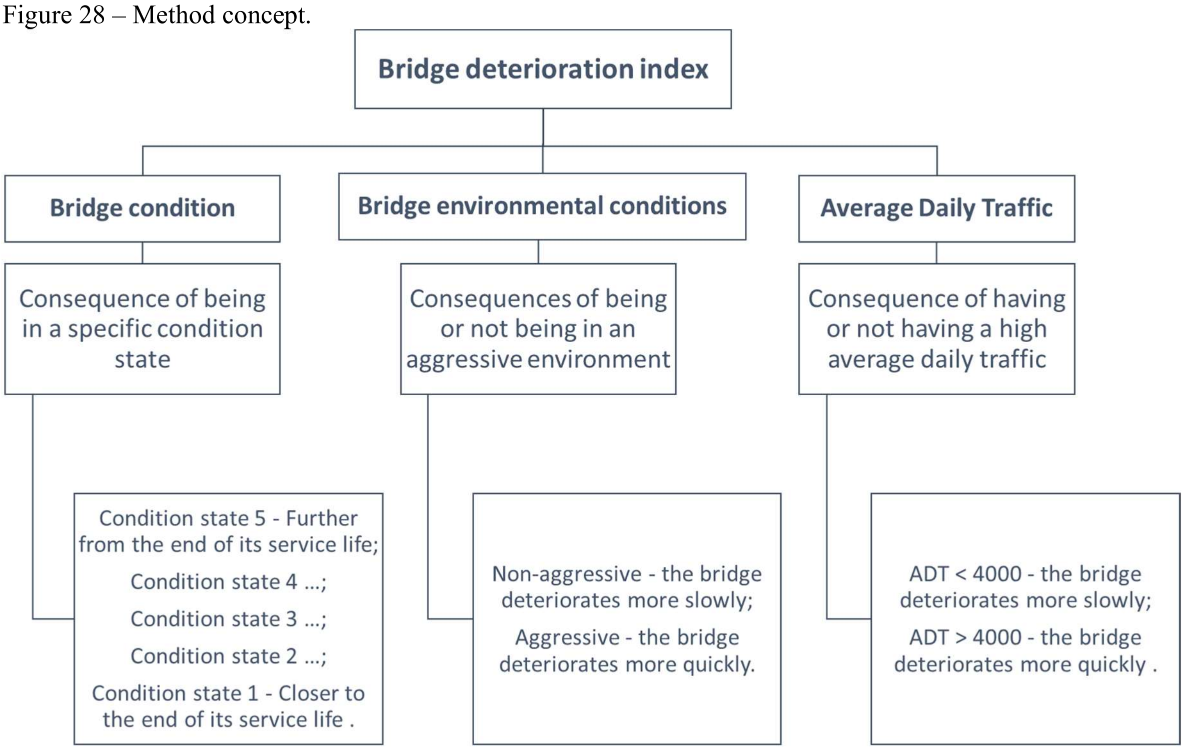
To address these challenges and contribute to global bridge management practices, this article proposes a bridge deterioration index based on predictive models. This index considers factors such as infrastructure condition, environmental context, and traffic volume. The primary goal of the proposed methodology is to prioritize interventions and planning bridge inspection effectively, focusing on those most in need of attention.

5.3. Methodologies

5.3.1. Method

In this study, the deterioration index is defined in a similar way to the concept of risk and is determined by the combination of probability and consequence. However, unlike traditional approaches, this article focuses on the assessment after an event has occurred, i.e., considering that the probability of the event is 1 because it has already occurred. In this context, the event refers to the condition of the bridge, including its current state, environmental characteristics, and traffic conditions. Thus, the deterioration index is calculated by multiplying the consequences associated with these factors, as shown in Figure 28. The details of the calculation of this index are presented in Section 5.3.2.

Figure 28 – Method concept.



Source: Author.

The condition state of a bridge is a key factor in the proposed methodology as it directly reflects its level of deterioration and its position in the life cycle. When a bridge reaches a critical condition, such as a CS 1 classification, it means that it is nearing the end of its useful life, indicating an advanced stage of deterioration and, therefore, a high priority. On the other hand, a bridge classified as Condition 5 has a high level of preservation, indicating that it has a long useful life remaining and therefore a lower priority. In addition, the impact of environmental conditions and traffic volume is assessed based on their respective rates of deterioration. Factors such as exposure to aggressive agents and traffic intensity directly influence the rate of structural deterioration. Therefore, the methodology considers whether deterioration will occur at an accelerated or slower rate compared to different operational scenarios.

The approach adopted is based on probabilistic deterioration prediction models that use Markov matrices to describe the transitions between different states over time. To ensure the applicability of the calculated coefficients and indices, a reference service life was established. Assuming ideal maintenance and operating conditions, the models indicate that a bridge would reach the minimum acceptable state of repair (CS 1, or less than 1.5 due to rounding) after 94 years, in the model with a non-aggressive environment and an ADT of less than four thousand. Based on this value, a total service life of 100 years was defined for the purpose of developing the indices, allowing for adjustments if necessary. However, this limit will not be less than the useful life observed in the forecasting models.

The developed methodology is applied in two main ways: (I) prioritization of inspections on a set of bridges and (II) individual scheduling of inspections over time.

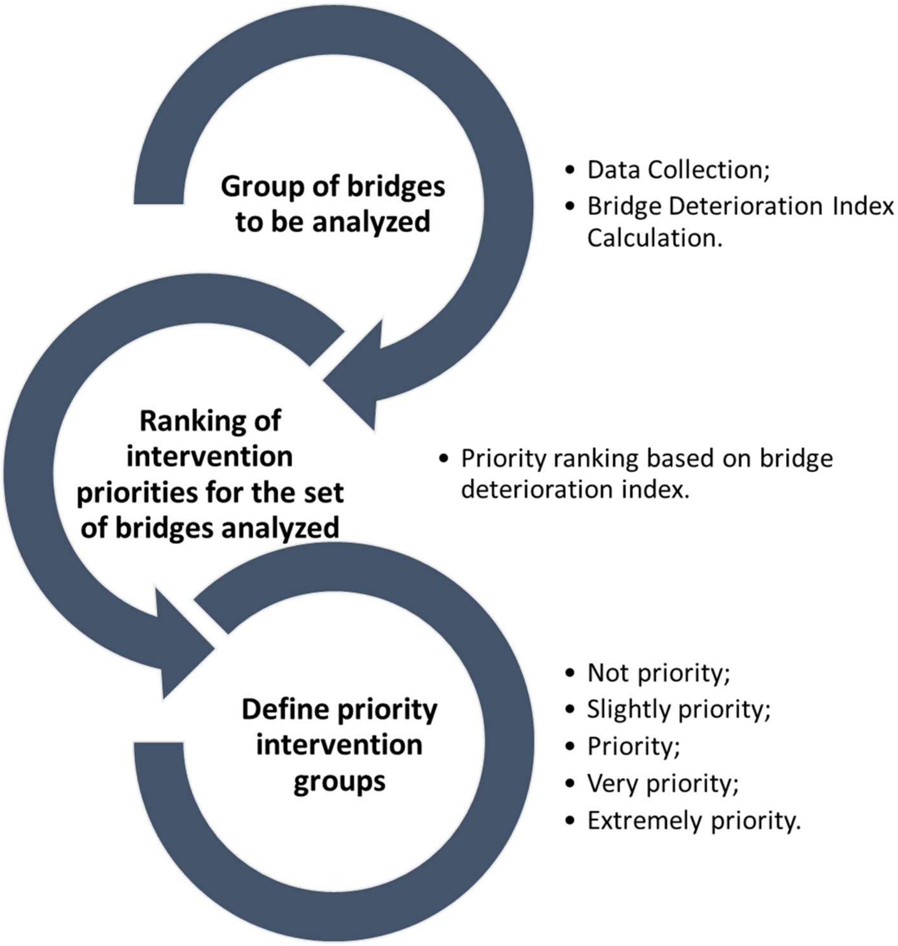
I. Prioritization of interventions on a group of bridges

The first application of the methodology consists in calculating the deterioration index for each bridge within a group of infrastructures, which makes it possible to classify and rank the structures that require priority intervention. This ranking can be done for the present, helping to define short-term actions, or projected to a future date, allowing strategic maintenance planning. For this future planning, predictive models of the evolution of the condition of the bridges are used, ensuring a proactive approach.

Figure 29 illustrates the application of this stage of the methodology. The priority classifications based on the calculation of the Bridge Deterioration Index are detailed in Section 5.3.3.

The priority classification based on the deterioration index was validated by analyzing a set of 2,135 bridges covering all five Brazilian regions. These bridges are distributed in three environmental aggressiveness classes, as defined by ABNT NBR 6118 (2023), and belong to two Average Daily Traffic (ADT) groups. The structures analyzed were built between 1930 and 2019, represent eight different structural types, and vary in length from 2.5 to 2,830 meters. Details of the data used are described in Table 32.

Figure 29 – Prioritization of interventions on a group of bridges.



Source: Author.

Table 32 – Characterization of the bridges where the index is applied.

Criteria	Data	Quantity	Percentage
Brazilian region	North	48	2.19%
	Northeast	1,187	54.27%
	Midwest	291	13.30%
	Southwest	356	16.27%
	South	312	14.26%
Environmental aggressiveness class (NBR 6118)	Environmental aggressiveness class I	1,697	77.59%
	Environmental aggressiveness class II	352	16.09%
	Environmental aggressiveness class III	145	6.63%
ADT	Less than four thousand	1,265	57.84%
	Larger than four thousand	922	42.16%
Year of bridge construction	Before 1983 (over 40 years)	811	37.08%
	Between 1983 and 2003 (20 to 40 years)	111	5.07%
	After 2003 (Under 20 years)	154	7.04%
	No information	1,118	51.11%
Type of structure (structural typology)	Reinforced concrete lower arch bridge	8	0.37%
	Prestressed concrete lower arch bridge	1	0.05%
	Reinforced concrete slab bridge	442	20.70%
	Prestressed concrete slab bridge	3	0.14%
	Reinforced concrete beam bridge	1,256	57.83%
	Prestressed concrete beam bridge	270	12.65%
	Reinforced concrete box beam bridge	109	5.11%
	Prestressed concrete box beam bridge	53	2.48%

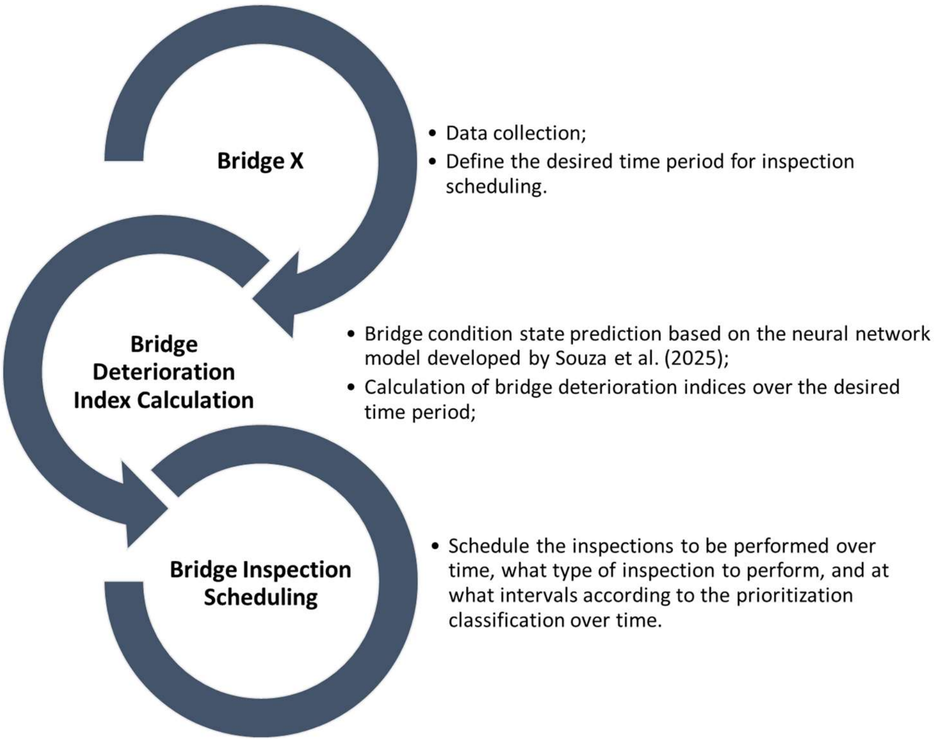
Source: Author.

II. Planning individual inspections over time

The second application of the methodology involves predicting the evolution of the state of condition of a single bridge over time, enabling efficient planning of future inspections. The condition states are calculated using predictive models based on neural networks developed by Souza et al. (2025b). These models, which follow on from previous work using probabilistic methods, showed superior performance in the validation processes.

With the condition states estimated over time, it is possible to calculate the evolution of the bridge's deterioration index and, based on this, define the ideal times to carry out inspections. Figure 30 shows the application of this part of the methodology.

Figure 30 – Planning individual inspections over time.



Source: Author.

The types of inspections used in the planning were developed by (Souza *et al.*, 2025c), who, based on a comprehensive review of existing methodologies, adapted an approach to the Brazilian reality. This approach includes six types of inspection, organized into three levels of depth, as well as an emergency inspection. However, for the purposes of periodic planning, only three types of inspection were considered: Regular inspection and detailed inspection, carried out periodically for continuous monitoring; Structural inspection, applied in critical cases that require an in-depth assessment. More details on the criteria for applying these inspections are presented in Section 5.3.4.

To validate this second application of the methodology, inspection planning was carried out for five bridges for 16 years, i.e. from 2024 to 2040, one representing each priority level defined in the first stage of the methodology. The five bridges selected are shown in Table 33.

Table 33 – Methodology validation bridges selected.

Bridge code	Typology	Length/Width (m)	ADT	Environmental aggressiveness class
060030	Reinforced concrete beam bridge	37.6/ 10.05	3265	III
060046	Reinforced concrete beam bridge	8.6/ 7.9	5281	III
060328	Reinforced concrete beam bridge	32/ 10	2172	I
060090	Reinforced concrete beam bridge	15.4/ 10.1	7091	I
060041	Reinforced concrete slab bridge	8.6/ 10.2	3168	III

Source: Author.

5.3.2. Bridge deterioration index (B_{DI})

The bridge deterioration index was developed using probabilistic models to predict deterioration over time, with a focus on a specific service life. Three indices were created to assess key parameters related to deterioration. The Condition Deterioration Index (C_{DI}) quantitatively assesses a bridge's condition over time. It uses probabilistic degradation prediction models and considers a reference service life, measured in years. The Environmental Deterioration Index (E_{DI}) measures the impact of environmental conditions on a bridge's deterioration. This index relies on probabilistic models that account for different levels of environmental aggressiveness and their effects on the structure. The Traffic Deterioration Index (T_{DI}) evaluates how vehicle traffic affects a bridge's deterioration. It uses probabilistic models to analyze varying levels of ADT and their contributions to structural degradation. The bridge's deterioration index is calculated by multiplying these three indices, using the Equation 1, where B_{DI} is the Bridge Deterioration Index; C_{DI} is the Condition Deterioration Index; E_{DI} is the Environmental Deterioration Index ($0 \leq E_{DI} \leq 1$); and T_{DI} is the Traffic Deterioration Index ($0 \leq T_{DI} \leq 1$).

$B_{DI} = C_{DI} * E_{DI} * T_{DI}$ (1)

5.3.2.1. Condition Deterioration Index (C_{DI})

This index is calculated using the bridge's current condition, deterioration curves, and the established reference service life. It measures, in percentage, the remaining service life after the bridge reaches the minimum state of repair specified in the model, known as the coefficient of degradation (C_{degr}). The main goal of the coefficient of degradation is to determine how much additional time the bridge needs to achieve the reference service life after reaching this minimum state of preservation. This approach allows for a comparative analysis of different condition states, creating indices that facilitate effective comparisons across various condition states and models.

The C_{DI} calculation process starts with the bridge's useful life, set at 100 years. Deterioration curves from the prediction models are examined for each time point. The year when each curve reaches the minimum condition state 1 is identified, as shown in Table 34. This is done by rounding, applied when the model's condition state is less than 1.5.

Table 34 – The year that each curve reaches the minimum condition state for the all bridges model.

Initial condition state	**Year of minimum condition state**
5	92
4	90
3	52
2	10
1	0

Source: Author.

The difference between the service life and the year obtained in Table 34, reveals how many years are still needed for the bridge to reach its service life after reaching this minimum level. To incorporate these differences and calculate a meaningful index, C_{degr} is used, calculated according to Equation 2, where S_{life} is the service life adopted; $S_{life} > 94$ years, the maximum service life observed by the models; and $Year_{(CS)min}$ is the year of the minimum condition state of the model curve. Considering the service life adopted of 100 years, C_{degr} is calculated for all the condition curves based on all bridges model, as presented in Table 35.

$$C_{degr(CS)} = \frac{(S_{life} - Year_{(CS)min})}{S_{life}} \quad (2)$$

Table 35 – Coefficient of degradation for a service life of 100 years.

Condition State	**Coefficient of degradation**
5	0.08
4	0.10
3	0.48
2	0.90
1	1.00

Source: Author.

It's important to consider that the condition state of a specific bridge might be closer to or further from the transition between condition states. Therefore, C_{degr} alone is insufficient to calculate the C_{DI}. To address this, an adjustment coefficient was incorporated into the C_{DI} calculation to better represent the bridge's state. This adjustment, denoted as C_{adj}, is based on the time of deterioration index analysis and the last year of transition or rehabilitation, using the lowest value in Equation 3.

The final C_{DI} is calculated by adding C_{degr} to C_{adj}, as shown in Equation 4. This combined value represents the bridge's vulnerability based on its condition state. In the equations, S_{life} refers to the adopted service life, and $\Delta T_{p\ max}$ is the time interval between the year of B_{DI} analysis and the last year of transition or rehabilitation, with the lowest value considered. For condition states 5, 4, 3, and 2, $C_{VI} < C_{degr(CS-1)}$.

$C_{adj\,(CS)} = \frac{\Delta T_{p\,max}}{S_{life}}$ (3)

$C_{DI} = C_{degr(CS)} + C_{adj\,(CS)}$ (4)

5.3.2.2. Environmental Deterioration Index (E_{DI})

The environmental deterioration index aims to quantify and compare how different environments affect bridge deterioration, highlighting the deterioration of bridges in more aggressive environments. To calculate the E_{DI}, the C_{degr} values for all curves in the models were determined using Equation 2.

Two environmental aggressiveness models were used: one for classes I and II (non-aggressive environments) and another for class III (aggressive environments) (ABNT NBR 6118, 2023). The year when each curve in these models reaches the minimum condition state 1 is recorded, as shown in Table 36. With this data and the adopted service life of 100 years, the C_{degr} values presented in Table 37 are obtained.

Table 36 – The year that each curve reaches the minimum condition state for the non-aggressive environment model and the aggressive environment model.

Initial condition state	**Year of minimum condition state**	
	Non-aggressive environment model	**Aggressive environment model**
5	92	80
4	90	78
3	52	52
2	10	6
1	0	0

Source: Author.

Table 37 – Coefficient of degradation for a service life of 100 years for the non-aggressive environment model and the aggressive environment model.

Initial condition state	**Coefficient of degradation**	
	Non-aggressive environment model	**Aggressive environment model**
5	0.08	0.20
4	0.10	0.22
3	0.48	0.48
2	0.90	0.94
1	1.00	1.00

Source: Author.

After obtaining the C_{degr} for both models, the percentage deterioration of each environmental aggressiveness class is determined relative to the model with the greatest deterioration. This is done by summing the C_{degr} values for the reference model and dividing by the highest sum obtained among all the models analyzed, as described in Equation 5. Essentially, this index reflects the impact of environmental conditions on bridge deterioration. For the two environmental aggressiveness classes considered in the deterioration prediction models, the E_{VI} values are calculated using Equations 6 and 7.

$$E_{DI} = \frac{\sum C_{degr\ (CS)}}{\sum_{max} C_{degr(Cs)}} \ (5)$$

$$E_{DI\ non-aggressiv} = \frac{\sum C_{degr(CS)} Non-aggressive}{\sum_{max} C_{degr(CS)}} = \frac{2.56}{2.84} = 0.90 \ (6)$$

$$E_{DI\ aggressive} = \frac{\sum C_{degr(CS)} aggressive}{\sum_{max} C_{degr(CS)}} = \frac{2.84}{2.84} = 1.00 \ (7)$$

The result of calculating the Environmental Deterioration Index (E_{DI}) provides a quantitative assessment of how varying levels of environmental aggressiveness impact bridge deterioration over time. This index is essential for understanding how factors such as humidity, atmospheric pollutants, and other environmental elements influence the rate of degradation. It helps determine the required maintenance and conservation measures needed to address the effects of these environmental factors on the bridge.

5.3.2.3. Traffic Deterioration Index (TDI)

The Traffic Deterioration Index aims to quantitatively assess how ADT influences bridge deterioration. Similar to the E_{DI}, the C_{degr} values are calculated for the curves of the two ADT models using Equation 2. These models consider two ADT groups: one for ADT under 4,000 and another for ADT over 4,000. The index calculates the percentage deterioration for each ADT group by summing the C_{degr} values of the model and comparing it to the highest sum obtained among all models.

The goal is to evaluate how traffic intensity affects bridge deterioration. The year when each curve in each model reaches the minimum condition state 1 is recorded, as shown in Table 38. Using this data and the adopted service life of 100 years, the C_{degr} values in Table 39 are obtained.

Table 38 – The year that each curve reaches the minimum condition state for the ADT < 4,000 model and ADT > 4,000 model.

Initial condition state	**Year of minimum condition state**	
	ADT < 4000 model	**ADT > 4000 model**
5	94	90
4	92	86
3	48	54
2	8	8
1	0	0

Source: Author.

Table 39 – Coefficient of degradation for a service life of 100 years for ADT < 4,000 model and ADT > 4,000 model.

Condition state initial	**Coefficient of degradation**	
	ADT < 4000 model	**ADT > 4000 model**
5	0.06	0.10
4	0.08	0.14
3	0.52	0.46
2	0.92	0.92
1	1.00	1.00

Source: Author.

After obtaining the C_{degr} values for both ADT models, the percentage deterioration for each ADT group is determined relative to the model with the greatest deterioration. This is achieved by summing the C_{degr} values for the reference model and dividing by the highest sum obtained among all the models, as described in Equation 8. This index reflects how traffic conditions influence bridge deterioration. For the two ADT groups considered in the deterioration prediction models, the $\mathrm{T_{VD}}$ values are calculating using Equations 9 and 10.

$$\mathrm{T_{DI}} = \frac{\sum \mathrm{C_{degr\,(CS)}}}{\sum_{\max} \mathrm{C_{degr(Cs)}}} \quad (8)$$

$$T_{DI\ ADT\ less\ four\ thousand} = \frac{\sum C_{degr(CS)} ADT\ less\ four\ thousand}{\sum_{max} C_{degr(CS)}} = \frac{2.58}{2.62} = 0.98 \quad (9)$$

$$T_{DI\ ADT\ larger\ four\ thousand} = \frac{\sum C_{degr(CS)} ADT\ larger\ four\ thousand}{\sum_{max} C_{degr(CS)}} = \frac{2.62}{2.62} = 1.00 \quad (10)$$

The Vehicle Traffic Deterioration Index (T_{DI}) offers a quantitative assessment of how vehicle traffic intensity affects bridge deterioration over time. This index is important for evaluating how factors such as repeated loads, vibrations, and traffic-induced stress affect the durability and condition of the bridge structure.

5.3.3. Prioritization classification

According to the DNIT standard guidelines (Table 40), condition state 5 is assigned only to structures without defects. Thus, even under adverse environmental and traffic conditions, these bridges are not considered priority. Similarly, bridges rated as condition 4, despite showing some deterioration, do not face structural failure and do not require corrective measures.

However, a bridge in the process of transitioning to condition 3 and facing unfavorable conditions may show some degree of priority. In this case, it would be classified as "slightly priority" because, although the bridge displays damage that leads to structural issues, there is no significant impairment yet. Monitoring of this damage is advised to assess the need for potential rehabilitation.

Table 40 – Condition States in Brazil.

State	Structural insufficiency	Condition	Bridge Condition Classification
5	There is no damage or structural insufficiency.	Excellent	No problem with the bridge
4	There is some damage, but there are no signs that it is causing structural insufficiency.	Good	Bridge without major problems
3	There is damage leading to some structural failure, but there is no sign of the bridge being compromised.	Regular	Potentially problematic bridge: It is recommended to follow the evolution of the problems through routine inspections.
2	There is damage generating significant structural weakness in the bridge, but there is no risk of structural collapse.	Poor	Problematic bridge: Postponing the recovery of the bridge too long can lead it to a critical state, also implying a serious compromise of the structure's service life.
1	There is damage generating serious structural insufficiency in the bridge, and there is a risk of structural collapse.	Critical	Critical bridge: In some cases, it can configure an emergency, and the bridge recovery can be accompanied by special preventive measures

Source: (DNIT, 2024a).

As mentioned earlier, in condition state 3, damage leads to structural insufficiency, but there is no severe structural impairment. This state suggests an apparently satisfactory condition where recovery may be deferred, hence it is classified as "slightly priority." However, like condition 4, condition 3 may be close to transitioning to condition 2. Adverse environmental and traffic conditions can heighten priority, potentially leading to a "priority" classification.

In condition 2, the bridge is already rated as "priority" and requires intervention soon. The structure's stability can be considered precarious, and the situation can worsen if the bridge faces aggressive environmental conditions and high ADT. If the bridge is near condition 1, its vulnerability is intensified, resulting in a "very priority" classification.

Condition 1 represents the most critical situation, which can indicate severe structural insufficiency or even imminent risk of collapse. Immediate intervention is advised, and such bridges are classified as "very priority". Special attention is needed for bridges in condition 1 that have been in this state for an extended period or are exposed to high environmental aggressiveness (classes III and IV of NBR 6118) and high ADT. Deterioration prediction models show more pronounced degradation under these conditions. The potential loss of service life due to collapse also contributes to a classification of "extremely priority".

Based on the reasoning outlined, the vulnerability classification is structured into five levels: "not priority," which includes bridges in conditions 5 and 4; "Slightly priority", which includes bridges in conditions 4 and 3; "priority", which includes bridges in conditions 3 and 2; "very priority", which includes bridges in conditions 2 and 1; and "extremely priority", which applies to bridges in condition 1 under specific situations. After establishing the classification procedure, the service life needs to be defined to calculate the maximum and minimum values of the Bridge Deterioration Index B_{DI} for each condition state. With a service life of 100 years, the maximum and minimum B_{DI} values for each condition state are detailed in Table 41.

Table 41 – Maximum and minimum BDI values that each condition state can have.

Condition State	B_{DI} maximum	B_{DI} minimum
5	0.0999	0.0705
4	0.4799	0.0882
3	0.8999	0.4233
2	0.9999	0.7938
1	∞	0.8820

Source: Author.

Continuing with the previously established classification and considering the maximum values of the Bridge Deterioration Index in each condition state, as described in Table 41, the maximum values of B_{DI} for each category were determined, in line with the condition states, as evidenced in Table 42. Consequently, the values of the Bridge Deterioration Index in each category, for an adopted useful life of 100 years, will be consistent with Table 43.

Table 42 – Maximum BDI values that each priority rating can have.

Priority	Condition State	Maximum B_{DI}
Not priority	5 and 4	0.4233
Slightly priority	4 and 3	0.7938
Priority	3 and 2	0.8820
Very priority	2 and 1	1
Extremely priority	1	∞

Source: Author.

Table 43 – Priority Rating.

Priority	B_{DI}
Not priority	$B_{DI} < 0.42$
Slightly priority	$0.42 \leq B_{DI} < 0.79$
Priority	$0.79 \leq B_{DI} < 0.88$
Very priority	$0.88 \leq B_{DI} < 1$
Extremely priority	$1 \leq B_{DI}$

Source: Author.

5.3.4. Inspection planning based on priority classification

As previously mentioned, the planning of inspections was developed based on the methodology proposed by Souza et al. (2025c), considering three of the six types of inspection suggested.

Regular inspection aims to periodically monitor the condition of the bridge by means of visual damage assessments, which are recorded in a database. This process enables early identification of faults and guides preventive actions to avoid more serious deterioration. This type of inspection is carried out every two years, ensuring continuous monitoring of the infrastructure (Souza *et al.*, 2025c).

The detailed inspection, on the other hand, takes place every six years and follows the same procedures as the regular inspection, but with a more in-depth level of analysis. In addition to the visual assessment, non-destructive tests and computer models are used to examine the internal and structural condition of the bridge. The data collected allows for a more accurate diagnosis and provides detailed recommendations for corrective interventions, when necessary (Souza *et al.*, 2025c).

Structural inspection, on the other hand, is carried out on demand and includes all the aspects of a detailed inspection, but with an even more comprehensive approach. At this stage, destructive tests can be applied, as well as an analysis of the structure's probability of failure. This type of inspection is essential for supporting intervention projects, providing cost estimates and guiding decisions on repairs or structural reinforcements (Souza *et al.*, 2025c).

The inspection schedule defined in the methodology follows the same interval for bridges classified as “Not a priority”, “Slight priority” and “Priority”, as defined in the methodology by Souza et al. (2025c). However, for structures classified as “Very priority”, the interval between inspections is halved, ensuring more frequent monitoring. In these cases, the regular inspection is carried out annually, while the detailed inspection takes place every three years.

When the bridge is classified as “Extremely Priority”, indicating a critical state and an urgent need for intervention, the deadlines are reduced even further. The detailed inspection is now carried out every two years, ensuring a more rigorous assessment. In addition, the structural inspection, which was previously carried out only on demand, becomes mandatory if no intervention is carried out within a three-year period, ensuring close monitoring of the infrastructure.

It should be noted that in the event of two inspections in the same year, the more detailed inspection will take precedence. The inspection intervals for each type of bridge, according to their priority, are detailed in Table 44.

Table 44 – Inspection interval based on priority rating.

Priority	Regular Inspection	Detailed Inspection	Structural Inspection
Not priority	Each two Years	Each six years	As needed
Slightly priority	Each two Years	Each six years	As needed
Priority	Each two Years	Each six years	As needed
Very priority	Every Year	Each three years	As needed
Extremely priority	Every Year	Each two years	Each tree years

Source: Author.

5.4. Application of bridge deterioration index and discussions

5.4.1. Priority ranking

The method was applied to 2,135 bridges across Brazil, encompassing various condition states, environmental classifications, and average daily traffic levels. These bridges were selected based on data from three complete inspection cycles. The results show that 40.94% (874) of the bridges were classified as having no priority. Approximately 41.64% (889) were deemed to have slight priority. A total of 11.90% (254) were classified as priority, 4.96% (106) as very priority, and 0.59% (12) as extremely priority. Table 45 presents the number of bridges in each vulnerability range. Table 46 provides information on the distribution of bridges in each vulnerability category, based on their condition.

Table 45 – Number of bridges in each vulnerability range.

Priority	**Number of bridges**	**%**
Not priority	874	40.94%
Slightly priority	889	41.64%
Priority	236	11.05%
Very priority	123	5.79%
Extremely priority	13	0.61%

Source: Author.

Table 46 – Number of bridges in each vulnerability range by condition state.

Priority	**Number of bridges by condition state**				
	5	**4**	**3**	**2**	**1**
Not priority	3	871	0	0	0
Slightly priority	0	0	889	0	0
Priority	0	0	0	236	0
Very priority	0	0	0	62	61
Extremely priority	0	0	0	1	12

Source: Author.

The thirteen bridges classified as extremely priority are in the minimum condition state, situated in aggressive environments, and have high ADT. Additionally, nine of these thirteen bridges have B_{DI} values greater than one, indicating they have been in the most critical condition for at least two inspection cycles, which is concerning. For the proposed method, immediate intervention is recommended for bridges in this priority classification. However, the authors emphasize that these results are based on the available data and the proposed method, and a more detailed evaluation is necessary for a precise diagnosis and more informed decision-making.

Following the assessment, 123 bridges were classified as very priority, and intervention is advisable for them. Among these, 61 bridges are already in the minimum condition state, while 62 are in condition 2 but face unfavorable scenarios, requiring special attention. Details are provided in Table 46.

Bridges classified as priority need short-term intervention, though this can be deferred based on other priorities. Bridges classified as slightly priority require attention, but interventions can be postponed since the condition can indicate some damage with structural insufficiency but does not compromise safety. Bridges classified as non-priority show no significant damage or structural failure and only need routine maintenance.

Another important consideration is that interventions are typically carried out in lots due to the high costs associated with construction sites, materials, equipment, and other resources. Addressing each bridge individually would be significantly more expensive. Therefore, interventions are grouped into sets of bridges, often selected based on geographical criteria. The proposed classification system is useful for organizing these lots by prioritizing bridges with the greatest priority and simplifying the selection process.

For instance, among the thirteen bridges classified as extremely high priority, four are located in the same Brazilian state. These could form the core of an intervention lot, with additional bridges selected based on priority and proximity. In the same state, another fifteen bridges are classified as very high priority. Thus, a hypothetical intervention lot could include nineteen bridges, maximizing efficiency by focusing on a single region.

Similarly, another state with three extremely high-priority bridges also has twenty-nine classified as very high priority. This could justify an intervention lot of thirty-two bridges, ensuring that resources are allocated efficiently while addressing the most urgent needs within the same state.

When analyzing the indices individually, the Condition Deterioration Index is notable for its detailed assessment of various conditions, assigning appropriate weight to the most critical situations. The Environmental Deterioration Index considers the environment in which the infrastructure is situated, acknowledging that structures in more aggressive environments typically deteriorate more quickly. This phenomenon is supported by numerous studies (Andrade; Possan; Dal Molin DCC, 2019; CEB, 1992; Costa, 1997; fib Bulletin 59, 2011; Miao, 2021; Miranda, 2006; Papadakis, 2013; Silvestro; Andrade; Dal Molin, 2019; Souza, 2019; Souza *et al.*, 2023; Vieira *et al.*, 2018; Vishwanath; Banerjee, 2023; Wang *et al.*, 2023; Zambon *et al.*, 2019).

Finally, the Traffic Deterioration Index addresses two main aspects. First, it evaluates the impact of Average Daily Traffic (ADT) on bridge deterioration, as supported by several studies (Miao, 2021; Santos *et al.*, 2022; Souza, C. *et al.*, 2024; Souza *et al.*, 2023). Second, it indirectly considers socio-economic factors, given that the collapse of a bridge with high traffic can lead to significant loss of life, financial losses, and social disruption. A notable example is the I-35W Bridge collapse in June 2007 in Minnesota, USA, which resulted in 13 deaths (Witcher, 2007). The state experienced substantial economic losses totaling around $60 million over 2007 and 2008, with compensation costs reaching $38 million. The cost of building a new bridge was estimated between $300 and $350 million (Branco, 2013; Subramanian, 2008). Additionally, the Minnesota Department of Transportation reported that passengers seeking alternative routes incurred a daily cost of approximately $400,000 (Subramanian, 2008).

In Brazil, DNIT manages federal bridges with manual assessments of condition state and ADT, which can be subjective. A bridge deterioration index could offer a more objective prioritization method, reducing subjectivity and enhancing clarity. However, the index does not address costs, social, economic, and political impacts, or sustainability, indicating areas for further development. Additionally, classifying bridges by their priority, especially those in critical condition, implies significant responsibility, and more informed decision-making requires a deeper investigation.

Future developments will focus on enhancing the current index by integrating economic, social, political, and sustainable factors. Incorporating artificial intelligence into the analysis of these factors could significantly advance decision support and management, improving both effectiveness and scope.

5.4.2. Bridge Inspection Scheduling

As shown in Figure 30, the planning of a bridge inspection follows a structured sequence of steps. The first step is to collect data and define the time horizon to be analyzed, which in this case was set to 16 years as described in Section 3.1. The information on the selected bridges was initially presented in Table 33 and supplemented in Table 47 to provide a detailed basis for the analysis.

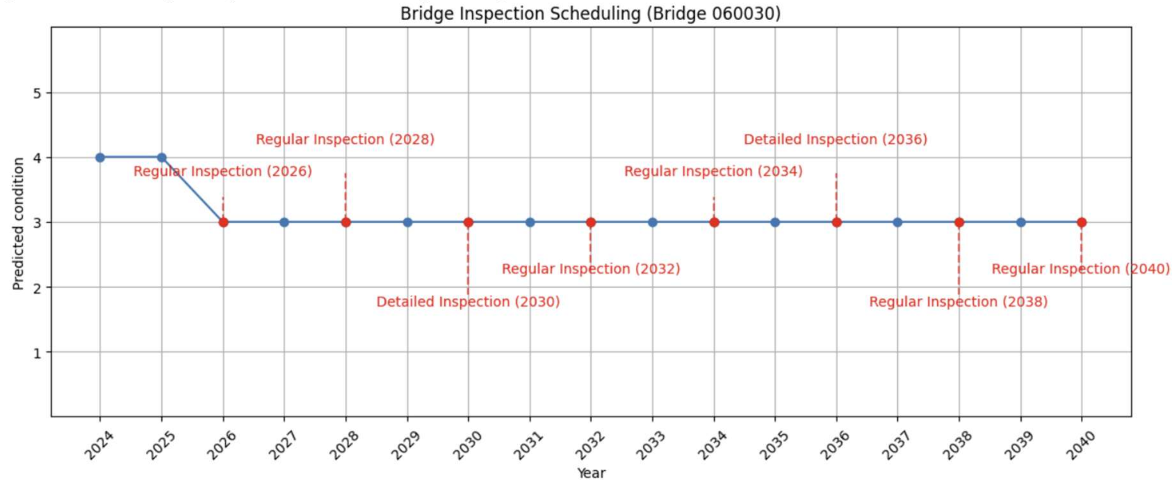
Table 47 – Bridge data for inspection planning.

Bridge Code	**1º Inspection (Year/ CS)**	**2º Inspection (Year/ CS)**	**Last Inspection (Year/ CS)**	**B_{DI} in 2024**	**Priority**
060030	2013/ 4	2018/ 4	2020/ 4	0.2058	Not priority
060046	2013/ 3	2018/ 3	2020/ 3	0.5900	Slightly priority
060328	2015/ 2	2018/ 2	2020/ 2	0.8731	Priority
060090	2015/ 2	2018/ 1	2020/ 1	0.9450	Very priority
060041	2014/ 2	2018/ 1	2020/ 1	1.0290	Extremely priority

The second planning step consists of predicting the condition of the bridge over the defined period and calculating the deterioration index. The deterioration was estimated using the neural network models developed by Souza et al. (2025), while the deterioration index was calculated using the equations presented in section 3.2. This process makes it possible to classify the priority of the bridge from year to year, allowing a dynamic monitoring of the bridge. With the priority classification established, it becomes possible to determine which inspections should be carried out over time and at what intervals, ensuring efficient planning and targeting the specific needs of each structure.

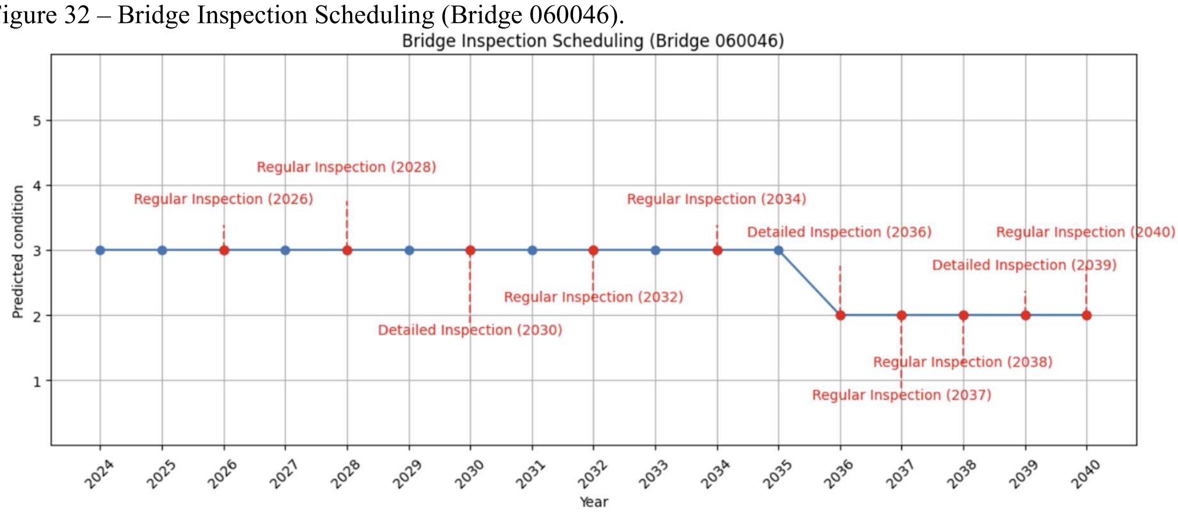
By applying this methodology to the selected bridges, the results shown in Figure 31, Figure 32, Figure 33, Figure 34 and Figure 35 were obtained, which illustrate the evolution of the condition and the distribution of the inspections over the period analyzed.

Figure 31 – Bridge Inspection Scheduling (Bridge 060030).



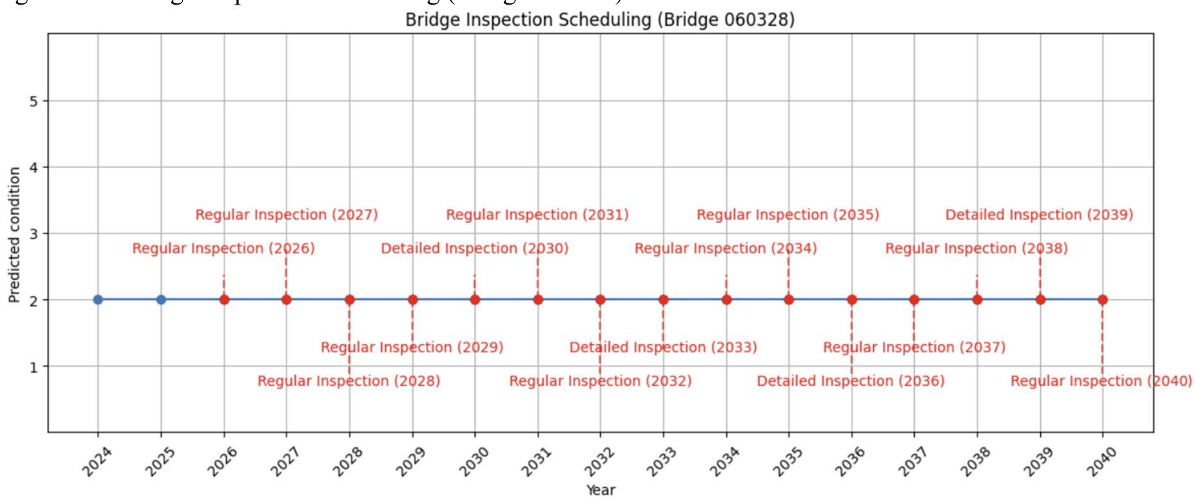
Source: Author.

Figure 32 – Bridge Inspection Scheduling (Bridge 060046).



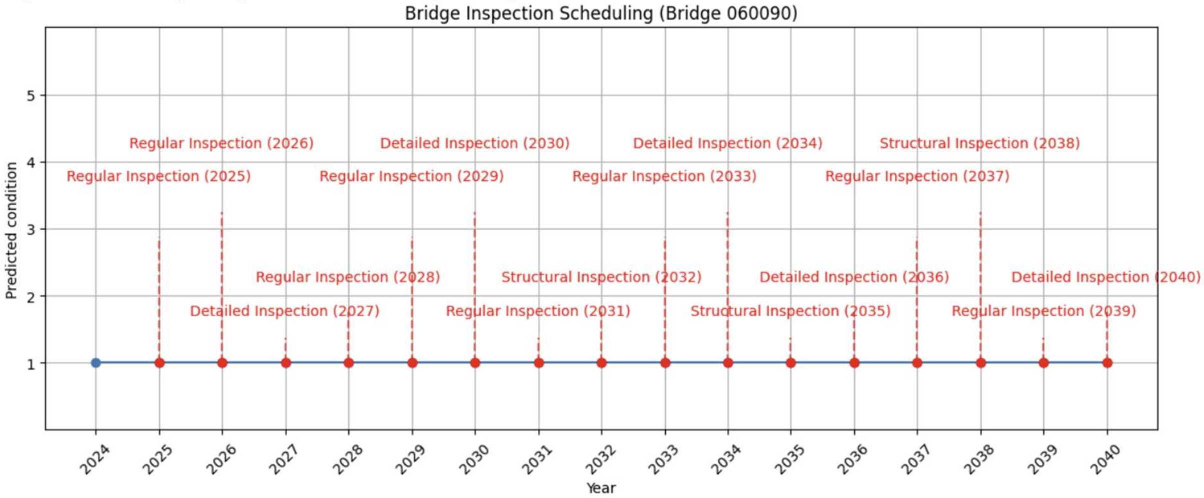
Source: Author.

Figure 33 – Bridge Inspection Scheduling (Bridge 060328).



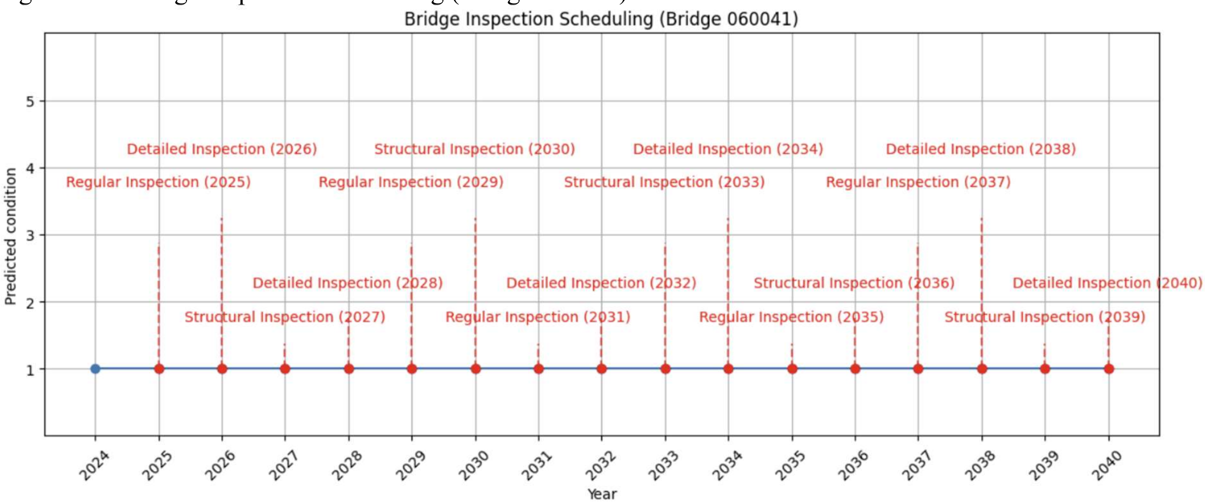
Source: Author.

Figure 34 – Bridge Inspection Scheduling (Bridge 060090).



Source: Author.

Figure 35 – Bridge Inspection Scheduling (Bridge 060041).



Source: Author.

On the first bridge (Figure 31), classified as "Not priority" in 2024, there was a transition in the condition state between 2025 and 2026, from level 4 to 3. However, the inspection intervals remain unchanged until the bridge reaches the "Very priority" classification, which does not occur in this case, thus maintaining Regular Inspections every 2 years and Detailed Inspections every 6 years until the end of planning.

On the second bridge (Figure 32), classified as "Slight Priority" in 2024, there was a single transition in condition between 2035 and 2036, from level 3 to 2. Before this change, the bridge had already been reclassified as "Priority", but as soon as it reached state 2, it became "Very Priority" due to the high ADT (5281) and the aggressive environment (environment aggressiveness class III). From 2036 onwards, it will require Regular Inspections every year and Detailed Inspections every 3 years.

On the third bridge (Figure 33), classified as "Priority" in 2024, there was no change in condition. However, as the bridge already had a high BDI (0.8731) and had been in state 2 since

2015, the adjustment coefficient increased over the years, raising its priority to “Very Priority” in 2025. This classification is maintained until 2039, with Regular Inspections annually and Detailed Inspections every 3 years. The transition to “Extremely high priority” only occurred in 2039, after 24 years in the same state of condition, due to the low ADT (2172) and environment aggressiveness class I. As planning ends in 2040, no further changes are planned.
On the fourth bridge (Figure 34), classified as “Very Priority” in 2024, the condition state was already at the minimum level, requiring Regular Inspections every year and Detailed Inspections every 3 years. Despite the high VMD (7091), the bridge was not classified as “Extremely Priority” due to the less aggressive environment (environment aggressiveness class I) and a relatively low adjustment coefficient (0.06). However, after 10 years in state 1, the bridge reaches the “Extremely Priority” classification in 2032, requiring triennial Structural Inspections, as well as Detailed Biennial and Regular Annual Inspections until the end of planning.
Finally, on the fifth bridge (Figure 35), classified as “Extremely Priority”, the inspection intervals were already at the minimum required. The first Structural Inspection takes place in 2027 and is repeated every 3 years, while Detailed and Regular Inspections are carried out every 2 years and annually respectively.
Although planning has been carried out until 2040, bridges classified as “Very high priority” and “Extremely priority” require interventions in the short term. If such interventions are carried out, the condition may improve, changing the priority classification and, consequently, the planning of inspections.

5.5. Conclusions

The literature review conducted in the initial section of this paper presented a simplified view of the decision-making process in bridge management, encompassing bridge assessment, data processing, and the application of prioritization and vulnerability indices. The primary aim was to consolidate and validate the study's importance, providing a comprehensive review that contributes academically.
The bridge deterioration index demonstrated its effectiveness in both development and practical application. During its development, the index quantified various condition states comparatively, considering environmental and traffic conditions, which offered insights into a bridge's susceptibility to deterioration. This index was grounded in deterioration prediction models and the classification system established by DNIT.

In its application, the index produced promising results. In the first phase, it facilitated the prioritization of bridges requiring urgent intervention, optimized the formation of intervention lots, reduced subjectivity in managerial decisions, and enhanced the reliability of intervention planning, ultimately benefiting bridge users. In the second phase, it enabled inspection planning based on prioritization classification, defining variable intervals according to the index. This approach improved decision-making accuracy and contributed to greater infrastructure safety.

The authors, however, emphasize the preventive nature of the approach and that the results obtained are based on the available data and the proposed method. The results of the application study must be evaluated with caution and responsibility, and a more detailed evaluation of the bridges classified in the highest levels of vulnerability is necessary for a precise diagnosis and more informed decision-making.

This research underscores the significance of the study within the Brazilian context and emphasizes the ongoing need for improvements in bridge management. It highlights both the challenges encountered and the opportunities for future advancements in decision support for bridge infrastructure.

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CHAPTER VI

Final considerations

Abstract

This chapter presents the main conclusions of the research, highlighting the contributions of the thesis to bridge management. It also proposes directions for future work, including improvements to the prediction models, application in different contexts, updating of the deterioration index, and development of decision support algorithms to optimize the management of road infrastructure.

6. FINAL CONSIDERATIONS

6.1. General Conclusions

The studies developed in this thesis resulted in significant contributions to the efficient management of bridges with methodologies that integrate inspection, deterioration prediction and prioritization of interventions, proposing solutions that are applicable to the Brazilian context and in line with international best practices. However, the research also faced challenges, mainly related to the scarcity of data, which required strategies to mitigate these limitations and allow a satisfactory development of the investigation. The main limitation faced throughout the study was the lack of complete and standardized historical data on Brazilian bridges. The lack of detailed information hindered the development of the models and required the development of alternative approaches to reduce this gap. The generation of synthetic data, the use of statistical techniques to infer information, and the integration of deterministic and probabilistic models were essential strategies to make the research feasible. However, these solutions still depend on improving the collection and storage of bridge condition data. In addition, the strong interconnection between the different studies of the thesis stands out, with each stage contributing directly to the progress of the others.

Initially, the analysis of bridge inspection methodologies revealed that the systems adopted worldwide vary between centralized and decentralized approaches, as well as types and levels of inspection, depending on the size of the road network, specific needs and the level of research development in each country. In Brazil, the need for a more structured and standardized approach to bridge inspection was identified, leading to the proposal of a new methodology with different levels of inspection adapted to national conditions.

Probabilistic deterioration modeling, based on Markov matrices, made it possible to predict the evolution of the condition of bridges over time. The results showed that these models are useful tools for estimating infrastructure degradation and helping to define maintenance strategies. However, the accuracy of the predictions can be affected by the quality and availability of the data, highlighting the need for continuous improvement of the information bases used in bridge management.

The application of artificial intelligence to predict bridge deterioration showed more accurate results than probabilistic methods. Artificial neural networks were able to more accurately estimate the evolution of bridge conditions, even in limited data scenarios. The integration of real and simulated data proved to be an effective solution to compensate for gaps in historical information, reinforcing the potential of artificial intelligence as a complementary tool in infrastructure management.

Finally, the development of a bridge deterioration index made it possible to establish objective criteria for prioritizing interventions and planning inspections. This index proved to be efficient in classifying structures according to the urgency of maintenance, enabling better allocation of resources and increasing the efficiency of the management process. Its dynamic application over time allows decisions to be made based on the evolution of deterioration, making planning more strategic and proactive.

The results of this thesis reinforce the importance of integrating inspection, deterioration prediction and intervention prioritization in bridge management. The combination of different methodologies allows for a more efficient and data-based approach, which is essential for ensuring the safety and durability of road structures.

6.2. Proposals for future works

Given the complexity and importance of the topic covered in this thesis, several avenues for future research can be explored to continuously improve the developed methodologies and tools. Some of the most important directions are highlighted below:

- Predictive models for bridges that have undergone interventions using artificial intelligence (AI): Develop predictive models that consider the effects of structural repairs and rehabilitations to more accurately predict the behavior of post-intervention bridges. Incorporating these factors can improve the accuracy of models and provide more reliable support for infrastructure management.
- Apply the methodology of the thesis in different international scenarios: Adapting and testing the models and indices developed in this research in other countries, considering their structural, climatic, regulatory and operational specificities. This approach would make it possible to assess the universality of the proposed methodologies and to identify the adjustments needed for their global applicability.
- Improvement of the Deterioration Index based on an expanded database and AI models: Updating and expanding the database used to construct the deterioration index to include a greater amount of historical and regional information. In addition, traditional probabilistic models will be replaced by AI-based techniques to provide more accurate and reliable predictions of the evolution of the structural condition of bridges.

- Incorporate new parameters into the Index of Deterioration: Expanding the Deterioration Index to include not only technical and structural factors, but also social, economic, and political variables. Incorporating these aspects can help prioritize interventions in a more comprehensive way and in line with society's needs, ensuring more equitable and strategic infrastructure management.
- Use the deterioration index to plan interventions: Integrate the deterioration index into the definition of maintenance and intervention strategies, using the priority ranking as the basis for efficient planning of preventive and corrective actions. This approach can optimize available resources and reduce costs associated with accelerated deterioration of structures.
- Develop an AI-based decision support algorithm: Create an intelligent system that integrates the deterioration forecast, deterioration index, and priority classification to automatically recommend which bridges should be prioritized for intervention. This algorithm could not only indicate which structures require immediate attention, but also suggest the most appropriate type of action (preventive maintenance, correction or replacement) and estimate the ideal timing for its execution within a set of managed bridges.

The implementation of these research directions can significantly contribute to the modernization of bridge management, increase the accuracy of deterioration prediction, improve decision making, and optimize the use of resources in road infrastructure maintenance.

APPENDIX

Appendix A. Book chapter at the "*Bridge Safety, Maintenance, Management, Lifecycle, Resilience and Sustainability*", ISBN 978-1-032-35623-5 and DOI: 10.1201/9781003322641-64.

Bridge Safety, Maintenance, Management, Life-Cycle, Resilience and Sustainability – Casas, Frangopol & Turmo (eds)

Comparative study of bridge structural condition assessment methodologies

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ABSTRACT: Bridges, viaducts, and footbridges are essential elements in the country's transport network. Their proper functioning is critical for economic and social development; therefore, defining the performance of an existing bridge through an adequate assessment of its condition in an effective bridge management system is mandatory. In Brazil, the National Department of Transport Infrastructure – DNIT, classifies the bridges' conditions on a scale of 1 to 5. However, the perception of other methodologies and their critical analyses are valuable routes for proposing improvements and updating Brazil's current method. This article compares the current assessment method with two other methodologies in a set of bridges. They are the one adopted by the American Association of State Highway and Transportation Officials (AASHTO), and the GDE (degree of deterioration, from the acronym in Portuguese) method developed at the *Universidade de Brasília* (UnB). Three bridges in Brazil, were selected for inspection, evaluation and modelling.

1 INTRODUCTION

Cases of early deterioration are frequent and notorious in important structures of a country's road transport infrastructure, such as bridges, tunnels, viaducts and footbridges. In Brazil, such structures are known as Special Artworks (*Obras de Arte Especiais* - OAEs) and have great importance since a large part of the transport of goods and people goes by road. According to SENAT (2019), the road modal is the one that has the greatest participation in the Brazilian transport matrix, concentrating approximately 61% of the movement of goods and 95% of the passengers.

Brazil has continental dimensions and had 1,720,700 km of highways in 2019, with 213,453 km of paved highways and 1,349,938 km of unpaved roads (SENAT, 2019). The high number of roads led to the need for a high number of OAEs, and the Management Report indicates the existence of 8,037 OAEs in Brazil, 90% of which are bridges and viaducts, totaling 7,190 (DNIT (2017)). The same Management Report shows that 97.52% of the OAEs were built in reinforced and prestressed concrete.

For an adequate performance of such infrastructure, investments in maintenance, strengthening, and rehabilitation are necessary throughout the lifetime. In this sense, implementing OAE management systems are mandatory to optimize administrative decisions to manage these structures.

One of the main features of a Bridge Management System is its ability to assess the bridge's current level of performance, taking this as one of the main aspects in decision-making and planning. Re-evaluating and updating the conservation state analysis methods adopted by DNIT is a constant task, aiming to implement the advances provided by new studies, technologies and methodologies by defining new parameters, comparing results and evaluating the advantages and disadvantages.

The main objective of this investigation is to contribute to improvements in the DNIT management system by comparing the current assessment method with two others developed in Brazil and abroad, evaluating the main features of each one and providing comments and discussions aiming to point out opportunities for improvement.

2 ASSESSMENT OF THE STRUCTURAL CONDITION STATUS OF A BRIDGE

Assessments and inspections proved to be extremely important for the maintenance and durability of a bridge, with inspection practices being cited in several manuals and standards and various assessment methodologies implemented according to their level of detail and classifications obtained following the inspections.

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Due to its importance for durability and maintenance, several agencies are concerned with the definition of inspection practices and their periodicity to obtain better results regarding management and lifespan. In Brazil, two standards regulate and recommend the type and frequency of inspections: NBR 9452 (ABNT (2019)) and DNIT (DNIT, (2004b)).

From the records made in inspections, the evaluation of the reinforced concrete structure can be carried out element by element or globally.

According to Almeida (2013), the management systems can be differentiated at their level of assessment into three categories, defined according to the main type of performance indicator adopted, involving increasing levels of detail, respectively: Condition Status (CS), Structural Safety Index (SSI) and Risk Level (RL).

The Condition State is evaluated through visual observations, photographic records, and non-destructive tests in its main (routine) inspections. This performance indicator is structured on a simple quantitative scale related to the identified damages, making it an expeditious methodology and easy to implement (Almeida, 2013).

Several countries use the Condition State approach in their standards and manuals for the initial assessment of the state of repair of a bridge, each with its rating scale. In Brazil, DNIT assesses the conservation status of a bridge through a classification of technical grades varying from 1 (the worst) to 5 (the best) (Table 1).

Table 1. Technical grades according to DNIT (2004b).

Technical grade (TG)	Element damage/ Structural failure	Stability condition	Bridge condition classification
5	No damage or structural failure.	Very good	No problems noted
4	There is some damage, but no signs of structural failure.	Good	Some minor problems
3	There are damages causing some structural deficiency, but no signs of structural failure.	Fair	Potentially problematic structure It is recommended to monitor the evolution of the damages through routine inspections, to detect, in a timely manner, any worsening of the structural health.
2	Thare are damages causing significant structural deficiency, but no apparent imminent risk of colapse.	Poor	Problematic structure Delaying the structure's intervention can lead it to a critical state, also implying a serious impact in the structure's lifespan.
1	There are damages causing serious structural deficiency; the element is in a critical state, with imminent risk of collapse.	Critical	Critical structure In some cases, it can be an emergency situation, and the recovery of the structure may be accompanied by special preventive measures, such as: load restriction, total or partial interdiction to traffic, temporary shoring, instrumentation with continuous monitoring of displacements and deformations.

Also in Brazil, a methodology was developed by Fonseca (2007) called GDE/UnB (an acronym for "Degree of Deterioration" from the Portuguese, developed by the University of Brasília) for the evaluation of building structures, which was later adapted for application in bridges by Verly (2015).

This methodology consists of calculating a degree of deterioration, using weighting factors to classify the damage, structural relevance and its intensity, in order to classify both the element and the structure in levels of deterioration as indicated in Table 2.

From the damage, the methodology reaches a Degree of deterioration of the element through the following formulation:

$$Gde = D_{\max}\left(1 + \frac{\left(\sum_{i=1}^{n} Di\right) - D_{max}}{\sum_{i=1}^{n} Di}\right) \quad (1)$$

Where the degree of deterioration D is calculated by:

$$D = 0,8\ xFi\ xFp\ if\ Fi \leq 2;$$

$$D = (12.Fi - 28)FpifFi > 2; \tag{2}$$

n: is the number of damages in the element; *Fi* is the damage intensity factor; *Fp* is the damage weighting factor; *Fi* and *Fp* are defined according to the element in which the damage is found and its intensity, pointed out in Verly (2015).

Fonseca (2007) calculates the degree of deterioration from the degree of deterioration of the element by the following formulation:

$$\frac{Gd = \left(\sum_{i=1}^{k} Gdf,\ i\ x\ Fr, i\right)}{\sum_{i=1}^{k} Fr, i,} \tag{3}$$

where *Fr* is the structural relevance factor, defined according to the structural relevance of the element in the bridge as a whole, as pointed out in Verly (2015).

The degree of deterioration of the Gdf element family is calculated by:

$$Gdf = Gde_{max}\sqrt{1 + \frac{\left(\sum_{i=1}^{m} Gde'i\right) - Gde_{max}}{\sum_{i=1}^{m} Gde'i}}, \tag{4}$$

where m is the number of elements; Gde_{max} is the major deterioration degree of the element.

Verly (2015) suggested adapting the formulation to calculate the degree of deterioration of the structure by the following formulation:

$$Gdmod = \frac{Kmax}{7,07}\sqrt{1 + \frac{\left(\sum_{i=1}^{k} Ki\right) - Kmax}{\sum_{i=1}^{k} Ki}} \tag{5}$$

Where *K* is the product of the degree of deterioration of the family of elements by the structural relevance factor of the element, and *kmax* is its highest value.

The FHWA (2012) describes the alphanumeric codes that inspectors should use to classify the State of Condition on a scale from 0 to 9 of the items defined in the Coding Guide. These items are subdivided into three: Item 58 (Deck), Item 59 (Superstructure) and Item 60 (Substructure), as indicated in Table 3.

Table 2. Deterioration levels and actions to be taken according to the GDE method (Verly (2015)).

Deterioration level	G_{de}	Actions to be taken
Low	0 – 15	Acceptable state. Preventive maintenance.
Moderate	15 – 50	Define deadline/ nature for a new inspection. Plan long-term intervention (maximum two years).
High	50 – 80	Define deadline/ nature for detailed specialized inspection. Plan medium-term intervention (maximum 18 months).
Serious	1. – 100	Define deadline/ nature for detailed specialized inspection. Plan short-term intervention (maximum one year).
Critical	> 100	Special emergency inspection. Plan immediate intervention.

According to Table 3, the National Bridge Inventory (NBI) classifies the bridge in Rating Scales based on the classification shown in Table 4. The NBI uses this classification to measure the percentage of bridges in good or poor condition.

Although the FHWA Coding Guide is mandatory to classify the bridge by the condition status of the three items described before, for asset management purposes, it does not provide sufficient information about the cause of deterioration to predict future conditions or select appropriate maintenance actions (Boettger, 2018).

Bearing this challenge in mind, a complimentary assessment system at the element level was elaborated and implemented.

This element-level assessment was developed by the American Association of State Highway and Transportation Officials in its Bridge Element Inspection Guide Manual (AASHTO (2016)). This manual defines for each element, description, a set of four standard condition states (1-Good, 2-Fair, 3-Poor and 4-Severe) and feasibility actions (AASTHO, 2016, Boettger, 2018).

Taking the methodology developed by AASHTO, the New York State Department of Transport used the Bridge Inspection Manual (NYSDOT (2017)), with condition status classification parameters on a scale from 1 to 4 at the element level, as adopted in the

Table 3. State of Condition scale according to FHWA (2012).

Condition State	General description of the condition
9	Excellent: a new bridge.
8	Very good condition: no problems detected.
7	Good condition: some minor problems.
6	Satisfactory condition: structural elements show some minor deterioration.
5	Sufficient Condition: Primary structural elements sound but may have minor section loss, deterioration, spalling or scour.
4	Insufficient condition: advanced section loss, deterioration, palling and scour.
3	Serious condition: loss of section, deterioration, spalling or scour with severe damage to primary structural elements.
2	Critical condition: advanced deterioration of primary structural elements. Cracks in steel or shear cracks in concrete may be present, or scour may have removed structural support. If not monitored, it may be necessary to close the bridge until rehabilitation is carried out.
1	Imminent failure: major deterioration or loss of section present in critical structural components or obvious vertical or horizontal movement affecting structural stability. The bridge is closed to traffic, but corrective actions may put back in light service.
0	Out of service, no possibility of rehabilitation.
N	Not applicable.

Table 4. Bridge condition classification according to rating scales.

Condition	Grade
Good	9, 8 and 7
Fair	6 and 5
Poor	4, 3, 2 and 1

Inspection Guide Manual (AASHTO (2016)), shown in Table 5.

Table 5. Condition Status (NYSDOT (2017) aput AASHTO (2016)).

Condition Status	Condition Type
CS-1	Good
CS-2	Fair
CS-3	Poor
CS-4	Severe

3 METHOD

Two methods were defined to be compared with the one currently used by DNIT, which are GDE/UnB and AASTHO.

Bridges with different structural conditions and geographic feasibility were selected; they are the bridges with DNIT codes 140132, 140134 and 140136 located in the Rio Grande do Norte State, between kilometers 127 and 171 of the highway BR-405

Visual inspections, photographic and quantitative surveys of the three bridges were carried out following the inspection manuals indicated for each method. Subsequently, they were then modeled using the computer program Sketchup and evaluated according to the methods selected to compare results and point out improvement opportunities for the current assessment method used in Brazil.

4 RESULTS AND DISCUSSION

4.1 *Inspection and evaluation*

4.1.1 *Bridge code 140132*

Figure 1 shows the 22 meters long and 8 meters wide reinforced concrete “Km 127 bridge”. According to the DNIT bridge management system, in the inspection carried out on July 2020, the bridge was in a good state of conservation, receiving a technical grade 4.

4.1.1.1 Inspection

In the inspection carried out on 05/29/2021, no structural damage was found in the slab, beams and transverse beams, only damp spots and biological degradation.

Also, there was no structural damage to the wall pillar or the abutments (Figure 2a). All the elements showed dump spots, and in abutment 2, a slight disaggregation of the material was observed (Figure 2b).

Figure 1. Km 127 bridge: (a) view of the pavement; (b) lateral view; (c) Sketchup 3D model.

On the asphalt pavement, cracks caused by the deficiency in the expansion joints were noted; on the New Jersey barrier, damp spots were observed; finally, the approach slab was the element with the most relevant damage, showing disaggregation and exposed rebars.

Figure 2. Bridge 140132: (a) abutment 2; (b) dump spots and biological degradation.

4.1.1.2 Evaluation

Table 6 lists the structural condition states of bridge 140132 according to the three methods. Figures 3, 4 and 5 show the results in the 3D model using color scales.

Table 6. Results for bridge 140132.

Element	NT	Gde	CS
Reinforced concrete slab 01	4	8	1
Reinforced concrete slab 02		8	
Reinforced concrete beam 01	4	8	1
Reinforced concrete beam 02		4.8	
Reinforced concrete beam 03		4.8	
Reinforced concrete beam 04		8	
Reinforced concrete transverses 01	4	4.8	1
Reinforced concrete transverses 02		4.8	
Reinforced concrete transverses 03		4.8	
Reinforced concrete transverses 04		4.8	
Reinforced concrete transverses 05		4.8	
Reinforced concrete transverses 06		4.8	
Wall pillar in reinforced concrete	4	4.8	1
Abutment in stone wall 01	4	4.8	1
Abutment in stone wall 02		28	
Asphalt pavement	4	8	1
New Jersey barrier 01	4	4.8	2
New Jersey barrier 02		4.8	
Approach slab 01	3	40	2
Approach slab 02		40	
Expansion joint 01	3	40	2
Expansion joint 02		40	
Expansion joint 03		40	
Bridge Technical Note (DNIT)	4		
Bridge damage degree (Verly)	24.71		
Bridge damage degree (Fonseca)	18.82		

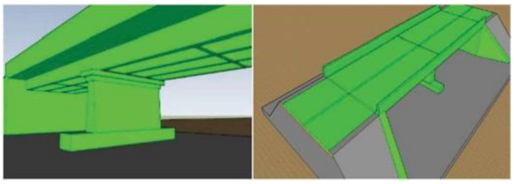

Figure 3. Bridge 140132 by DNIT method.
Green: GT 4; yellow: TG 3; orange: TG 2; red: TG 1

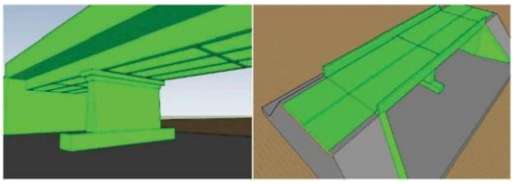

Figure 4. Bridge 140132 by AASHTO method.
Green: CS-1; yellow: CS-2; orange: CS-3; red: CS-4

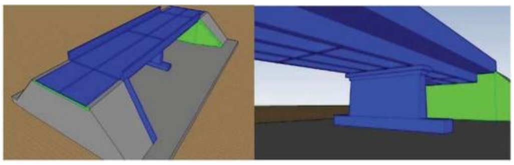

Figure 5. Bridge 140132 by GDE method.
Blue: Gde<15; green: 15<Gde<50; yellow: 50<Gde<80; orange:80<Gde<100; red:Gde>100.

4.1.2 *Bridge code 140134*

Figure 6 shows the "Cabelo bridge" in reinforced concrete, 32,7 meters long and 8 meters wide. According to the DNIT bridge management system, in the inspection carried out on July 2020, the bridge was in a fair state of conservation, receiving a technical grade 3.

4.1.2.1 Inspection

In the inspection on 05/29/2021, the beams and transverse beams showed similar pathological manifestations, such as biological degradation, dump spots, cracks, concrete reinforcement corrosion, and leaching. The slabs showed corrosion in an advanced state with broken steel rebars and concrete spalling (Figure 7a).

No major damage was observed in pillars and abutments, with only a few dump spots (Figure 7b).

In the asphalt pavement, cracks caused by the deficiency in the expansion joints and holes were noticed. In the New Jersey barrier, damp spots, cracking and exposed reinforcement were observed; Finally, no damage was observed in the access landfills.

Figure 6. "Cabelo" bridge: (a) view of the pavement; (b) lateral view; (c) Sketchup 3D model.

Figure 7. Bridge 140134: (a) spalling and corrosion of rebars; (b) dump spots and biological degradation.

4.1.2.2 Evaluation

Table 7 lists the structural condition states of bridge 140134 according to the three methods. Figures 8, 9 and 10 show the results in the 3D model using color scales.

Table 7. Results for bridge 140134.

Element	NT	Gde	CS
Reinforced concrete slab 01	2	130.17	4
Reinforced concrete slab 02		64.35	
Reinforced concrete slab 03		64.35	
Reinforced concrete beam 01	3	63.60	3
Reinforced concrete beam 02		39.62	
Reinforced concrete beam 03		52.97	
Reinforced concrete beam 04		59.59	
Reinforced concrete transverses 01	3	7.2	2
Reinforced concrete transverses 02		56.74	
Reinforced concrete transverses 03		56.74	
Reinforced concrete transverses 04		56.74	
Reinforced concrete transverses 05		32.34	
Reinforced concrete transverses 06		56.74	
Reinforced concrete transverses 07		56.74	

(Continued)

Table 7. (Cont.)

Element	NT	Gde	CS
Reinforced concrete transverses 08		32.34	
Reinforced concrete transverses 09		7.2	
Wall pillar in reinforced concrete 01	4	4.8	1
Wall pillar in reinforced concrete 02		4.8	
Abutment in stone wall 01	4	4.8	1
Abutment in stone wall 02		4.8	
Asphalt pavement	3	60	2
New Jersey barrier 01	3	4.8	3
New Jersey barrier 02		47.15	
Access landfill 01	4	0	1
Access landfill 02		0	
Expansion joint 01	3	40	3
Expansion joint 02		100	
Expansion joint 03		40	
Bridge Technical Note (DNIT)	2		
Bridge damage degree (Verly)	140.78		
Bridge damage degree (Fonseca)	81.08		

Figure 8. Bridge 140134 by DNIT method.
Green: GT 4; yellow: TG 3; orange: TG 2; red: TG 1

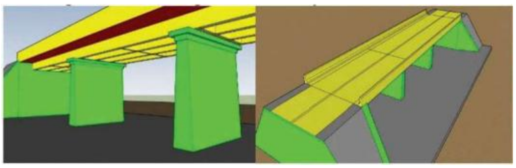

Figure 9. Bridge 140134 by AASHTO method.
Green: CS-1; yellow: CS-2; orange: CS-3; red: CS-4

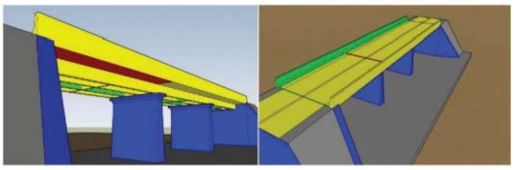

Figure 10. Bridge 140134 by GDE method.
Blue: Gde<15; green: 15<Gd<50; yellow: 50<Gde<80; orange:80<Gde<100; red:Gde>100.

4.1.3 *Bridge code 140136*

Figure 11 shows the "Catolezinho bridge" in reinforced concrete, 9,9 meters long and 10,8 meters wide. According to the DNIT bridge management system, in the inspection carried out on July 2020, the bridge was in a poor state of conservation, receiving a technical grade 2.

4.1.3.1 Inspection

In the inspection carried out on 05/29/2021 in the reinforced concrete slabs, damages were observed, but none indicated structural risk. The main damages were: leaching, concrete infiltration, superficial cracks, uncoated reinforcement, disaggregated concrete, concrete spalling and exposed and corroded reinforcement.

In the pillar wall, non-structural damage was observed, such as erosion of the pillar base, damp patches, leaching and carbonation, and a loss of pillar section causing structural damage.

Figure 11. "Catolezinho" bridge: (a) view of the pavement; (b) lateral view; (c) Sketchup 3D model.

In addition to the damage observed in the pillar wall, significant structural damage was also observed in the abutments of the reinforced concrete walls, such as excessive deformation (Figure 12b), deep cracks with openings greater than 0.03 mm, and a large diagonal slit in the abutment 01, cutting the entire element (Figure 12a).

The asphalt pavement had cracks caused by the deficiency in the expansion joints; the New Jersey barrier showed damp spots, concrete spalling and cracks; finally, no damage to the access landfill was observed.

Figure 12. Bridge 140136: (a) a large diagonal slit of abutment 01; (b) excessive deformation and deep cracks.

4.1.3.2 Evaluation

Table 8 lists the structural condition states of bridge 140136 according to the three methods. Figures 13, 14 and 15 show the results in the 3D model using color scales.

Table 8. Results for bridge 140136.

Element	NT	Gde	CS
Reinforced concrete slab 01	3	34.15	3
Reinforced concrete slab 02		60.39	
Wall pillar in reinforced concrete 01	2	61.81	3
Abutment (wall pillar) in reinforced concrete 01	1	160.31	4
Abutment (wall pillar) in reinforced concrete 02		171.59	
Asphalt pavement	4	8	1
New Jersey barrier 01	4	28	2
New Jersey barrier 02		36.17	
Access landfill 01	4	0	1
Access landfill 02		0	
Expansion joint 01	3	40	2
Expansion joint 02		40	
Bridge Technical Note (DNIT)	1		
Bridge damage degree (Verly)	133		
Bridge damage degree (Fonseca)	104.88		

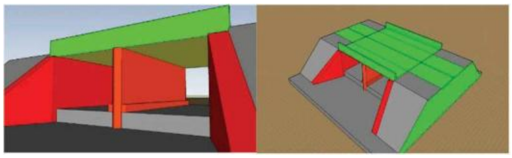

Figure 13. Bridge 140136 by DNIT method.
Green: GT 4; yellow: TG 3; orange: TG 2; red: TG 1

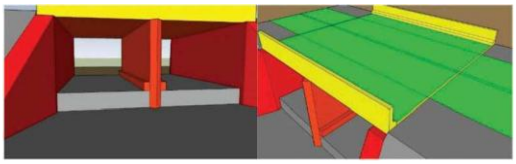

Figure 14. Bridge 140136 by AASHTO method.
Green: CS-1; yellow: CS-2; orange: CS-3; red: CS-4

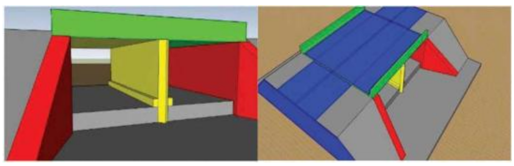

Figure 15. Bridge 140136 by GDE method.
Blue: 15<Gde; green: 15<Gde<50; yellow: 50<Gde<80; orange:80<Gde<100; red:Gde>100.

4.2 *Comparisons between methodologies*

The structural condition states of the bridges were compared using the DNIT and GDE methodologies, both in the Fonseca and Verly formulations. In contrast, the AASHTO methodology addressed in this article evaluates only element-by-element and not the bridge as a whole.

Figure 16 shows the difference in results for the Fonseca and Verly formulations. The highest damage weight is in the family of elements with the highest structural relevance factor by the first method. In contrast, by the second, the weight is the highest product between the relevance factor and the degree of deterioration of the element family (*Kmax*).

Regarding the comparison of the two formulations with the DNIT technical note, the assessments agree for Bridges 140134 and 140132, since in the first case, the damages presented a critical situation and, in the second, the bridge shows minor damage, being in good condition.

The evaluation through Verly's formulation for the Bridge 140134 differs from the others since the weight of the highest product between the relevance factor and the degree of deterioration is considered for the family, as well as the weight of damage caused by corrosion of the steel rebars in slabs becomes similar to damage caused by the same pathology in elements with a higher relevance factor, such as columns and beams (although broken rebars into slabs do not have the same structural importance as broken rebars into a beam, for example). This same fact led to a higher DGE for bridge 140134 than for bridge 140136.

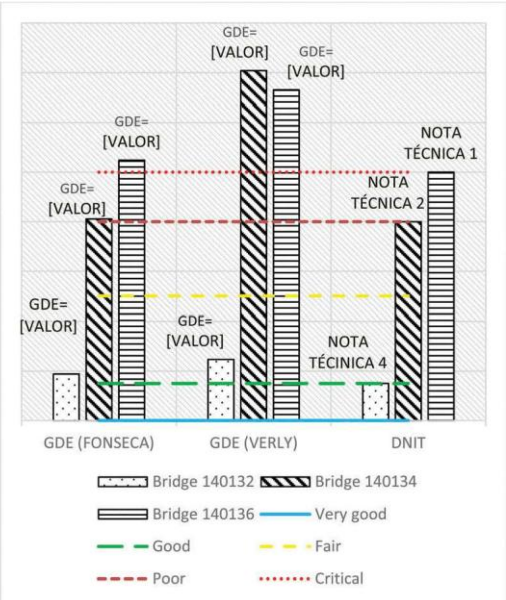

Figure 16. Comparison of the assessment of the structural condition of bridges.

The element-by-element evaluations are shown in Figures 17 (slabs) and 18 (beams). There is a considerable discrepancy only in the classification of Slab 1 of bridge 140134, which was the only one to present broken steel rebars.

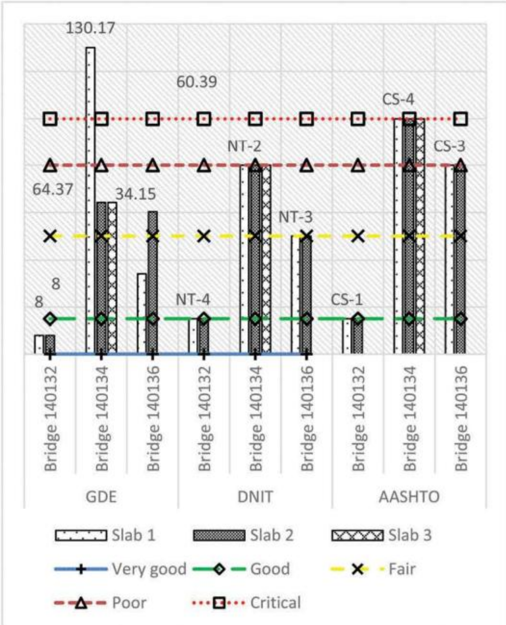

Figure 17. Comparison of structural condition assessments at element level (Slab).

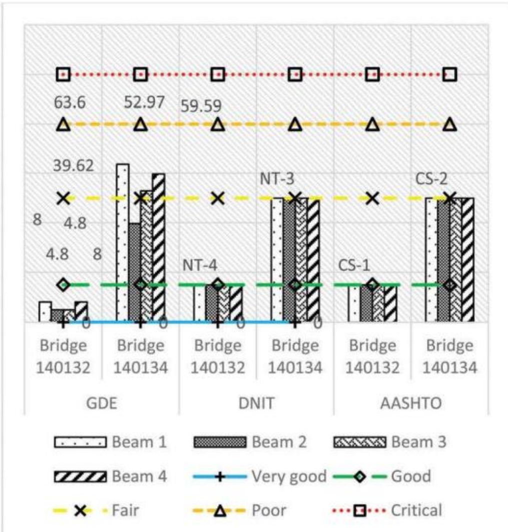

Figure 18. Comparison of structural condition assessments at element level (Beams).

Figure 18 shows the importance of the element-level assessment. In this regard, the GDE methodology classifies the four beams independently, indicating in a specific way which beam has the greatest damage and the best way to intervene.

In the case of very specific damage, such an assessment at this level prevents an exaggerated classification of the bridge's structural condition, as well as the structural relevance factors adopted by the GDE. The methodology currently adopted by the DNIT, on the contrary, classifies the bridge only by the worst grade of the structural element.

Comparing the DNIT methodology with the AASHTO methodology, we noticed similarities regarding the classification of the condition status, with the main difference not being directly related to the classification but in how the damage assessment is carried out. While in the DNIT methodology, the classification is at the inspector's sole discretion, AASTHO links the damage classification to specific criteria in the manual.

4.3 *Improvement opportunities for DNIT methodologies in Brazil*

The element-by-element classification approach, numbering and evaluating separately, as proposed in the GDE method, proves to be quite effective in perceiving damage at a more detailed level, aiding in future interventions and decision support.

The modeling used in this study with color classification is a relevant visual tool in damage perception, in line with future BIM approaches, which supports high levels of detail at the element level in models, and even future modeling of the damage itself

Another point to be considered is the reduction in inspection subjectivity, as observed in the AASHTO methodology, which more objectively points out the classification of each damage in the definitions and the state of condition in its manuals.

AASHTO introduces element-level assessment into the NBI, making information processing more effective. Differently, the DNIT feeds the management system only with the condition state of the OAE as a whole. The conscious input of data at the element level must be taken into account, supported by computational tools. It can represent a more effective and economical management.

5 CONCLUSION

This article aimed to compare the methods of evaluating the structural condition state in a set of bridges to analyze, compare and improve the current DNIT methodology.

From the data obtained, it was possible to note and point out which improvements could be made, thus contributing to the methodology currently adopted in Brazil.

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Appendix B. Conference paper at the "*Congresso Brasileiro de Pontes e Estruturas 2023 (CBPE)*", ISBN 978-65-00-66224-5.

Modelos determinísticos de previsão de degradação de pontes por regressão polinomial de 3ª ordem.

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Resumo

Um aspecto fundamental para que uma ponte tenha um bom desempenho durante seu período de vida útil, assegurando um determinado nível de segurança e funcionalidade, é a forma como são implementadas as intervenções. A gestão de pontes tem como um dos principais objetivos a otimização dessas intervenções, para que sejam planejadas e executadas de forma a garantir o melhor nível de desempenho com um menor risco associado a esse tipo de estrutura, ajudando a fundamentar as decisões de investimentos. A possibilidade de previsão da deterioração de uma ponte ao longo do tempo apresenta-se como um grande balizador no âmbito da gestão de pontes, importando ter o conhecimento da evolução do desempenho das pontes no determinado período, podendo assim planejar de melhor forma as intervenções. Nos modelos de previsão da degradação determinísticos é estimado que a estrutura deteriore ao longo do tempo de acordo com uma determinada função. A partir de um banco de dados extenso é possível desenvolver modelos determinísticos com funções resultantes que consideram que a estrutura comece com um valor de 100% e decresça até 0% no final da sua vida útil. O atual trabalho desenvolveu modelos determinísticos de previsão de degradação de pontes por regressão polinomial de 3ºordem a partir de dados de 885 pontes no Brasil, considerando o histórico de cada ponte individualmente para projeção do comportamento do conjunto. Cinco modelos foram obtidos: um para globalidade das 885 pontes, dois modelos divididos de acordo com a classe de agressividade ambiental, e por fim dois com base no VMD (Volume Médio Diário de veículos) de cada ponte. A partir dos resultados, observou-se grande influência tanto da agressividade ambiental quanto do VMD na deterioração do conjunto de pontes analisados, sendo mais acentuada em pontes com classe de agressividade III e VMD acima de 4 mil.

Palavras-chave

Ponte; Previsão de degradação; Estruturas; Gestão de pontes; Modelo determinístico.

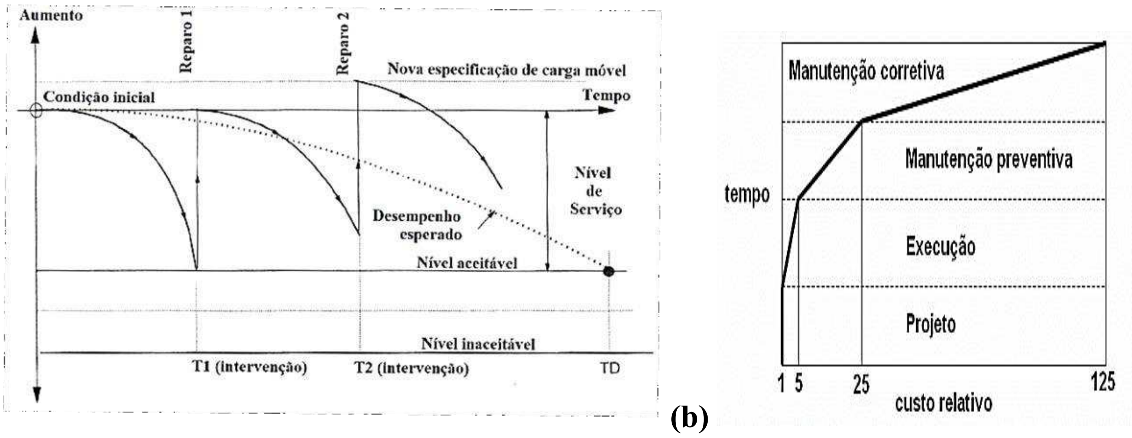
Introdução

Atualmente existe um crescimento do interesse de investigação na área de gestão de estruturas importantes da infraestrutura de um país, tais como pontes, pontilhões e viadutos que servem de conexão e suporte para rodovias, ferrovias, hidrovias, dutos de transporte de fluidos e estruturas para passagem de pedestre, sendo estas conhecidas como passarelas. No Brasil denominamos essas infraestruturas como Obras de Arte Especiais (OAEs) (DNIT, 2004a, 2004b).

A previsão de degradação de OAEs é um dos alvos deste crescente interesse, devido ao alto nível de responsabilidade adjunto a essas infraestruturas, das grandes degradações das mesmas e outros impactos socioeconômicos associados à integração em redes rodoviárias.

Para que essas infraestruturas tenham um desempenho adequado, é necessário um investimento ao longo de toda vida útil em manutenções, reforços, reabilitações, entre outros. Além disso, segundo a Lei de Sitter (1984), quanto mais tempo demorar para iniciar ações de manutenção e reabilitação de uma estrutura mais trabalhosa e dispendiosa ficará a intervenção, seguindo uma progressão geométrica de razão cinco, relacionadas com as etapas de projeto, execução, manutenção preventiva e manutenção corretiva.

Na Figura 1 (a), demonstra-se uma curva genérica de uma OAE quando submetida ou não à reabilitações e reparos durante determinado período, ampliando sua vida útil. Já na Figura 1 (b), exemplifica-se a lei de Sitter.



(a) (b)

Figura 1- (a) Comportamento de uma OAE submetida a intervenções ao longo do tempo (OLIVEIRA, 2019); (b) Evolução dos custos pela etapa de intervenção (HELENE, 1997).

No cenário brasileiro é preciso levar em consideração a conjuntura atual do país, que possui um parque de obras de arte cada vez mais envelhecido, sendo a maioria das OAEs construídas durante a década de 1970 (OLIVEIRA, 2019).

Outro ponto é que, ao longo do tempo as solicitações das OAEs vão aumentando, seja pelo incremento do volume de tráfego ou por acréscimos de cargas. Dados da CNT (2021) mostram o aumento da frota total de veículos de 64.817.974 em 2010 para 107.948.371 em 2020, gerando um crescimento de 66,5% de veículos na malha rodoviária do Brasil. Além do acréscimo de carga pelo aumento da quantidade de veículos, para as pontes projetadas de 1960 a 1985 eram consideradas carga moveis para veículos de 36 tf, que representava os veículos da época. Já de 1985 até os dias atuais, são consideradas cargas móveis de 45 tf (DNIT, 2004a, 2004b).

Adicionando a estes fatores, uma manutenção de conservação muitas vezes ausente ou ineficiente, e alterações relativas à exposição ambiental, essas infraestruturas padecem de uma aceleração da degradação.

Ademais, os recursos financeiros destinados a manutenção sofreram significativa redução nos últimos anos. A CNT (2021) aponta uma queda de 31,44 bilhões de reais em 2012 para 5,8 bilhões de reais em 2021, uma redução de 81,55 % do investimento público federal autorizado em rodovias no Brasil.

Dada a limitação de recursos, parque de obras de arte envelhecido e o aumento das solicitações nas estruturas, surge a necessidade de priorização das intervenções a serem realizadas. A metodologia utilizada pelo Sistema de Gerenciamento de Obras de Arte Especiais (SGO) do DNIT (DNIT, 2023a), baseia sua tomada de decisão em dois grandes parâmetros: nível de desempenho da ponte e volumes médios diários. Apesar de se mostrar um sistema de gestão eficiente, muitas vezes esses dois parâmetros não são suficientes e outros fatores de decisão, como a previsão de degradação, devem ser levados em consideração para uma gestão que leve a resultados ótimos.

Desta forma, a implementação de um modelo de previsão de degradação em um sistema de gestão de obras de arte se mostra fundamental para otimizar as decisões das administrações que gerem o investimento nessas estruturas. O presente trabalho se propõe ao desenvolvimento de modelos de previsão de degradação, utilizando dados de OAEs brasileiras, que permitam avaliar a situação futura da estrutura, visando, no futuro, otimizar o processo de decisão e o gerenciamento das intervenções as serem realizada no período de vida útil das OAEs.

Previsão de degradação

No cenário da Gestão de Obras de Artes Especiais, a previsão de degradação demonstra grande importância, dado que os principais sistemas de gestão utilizados no mundo contemplam de alguma forma, modelos de degradação em seu conjunto, como por exemplos alguns sistemas utilizados em diversos países, demonstrado na Tabela 1.

Tabela 1- Sistema de Gestão de Obras de Arte Especial com previsão de degradação.

Designação	OBMS	FBMS	GBMS	APTBMS	RPIBMS	BatMan	KUBA	Pontis
País	Canada	Finlândia	Alemanha	Itália	Japão	Suécia	Suécia	EUA

A geração de modelos de previsão de degradação de uma OAE permite a antecipação de necessidades futuras, e um planejamento mais otimizados das intervenções e dos recursos alocados em um horizonte de médio ou longo prazo. Os modelos de previsão de degradação podem ser de natureza empírica ou mecanicista e divididos, principalmente, entre modelos determinísticos, probabilísticos e de inteligência artificial (SETUNGE; HASAN, 2011).

Conforme Almeida (2013), a partir de um conjunto significativo de registros históricos do Estado de Condição de diversas OAEs, podem se desenvolver métodos de previsão da degradação baseados em técnicas de inteligência artificial, como por exemplo as redes neurais[1]. Estes modelos procuram encontrar a relação entre o Estado de Condição e as variáveis externas e internas à ponte, conseguindo prever sua degradação. Entretanto necessita de grandes conjuntos de dados, nem sempre sendo possível o desenvolvimento. O mesmo ocorre com os modelos probabilísticos, a grande diferença que estes dados podem ser simulados de outros modelos de deterioração ou a partir de modelos teóricos associados aos mecanismos de deterioração, que considera que a deterioração ao longo do tempo é desconhecida, mas há uma probabilidade de a deterioração vir a se processar de acordo com uma determinada lei (ALMEIDA, 2013; OLIVEIRA, 2019).

Por fim, baseados em uma fórmula matemática ou estatística, os modelos determinísticos relacionam o histórico dos estados de condição com o período de vida útil das OAEs, podendo também ser relacionados com outros fatores que influenciam na degradação. Os principais métodos desenvolvidos para criação destes modelos são os ajustes das curvas de extrapolação, regressões e método linear (GARCÍA-SÁNCHEZ, 2016; MADANAT; WAN IBRAHIM, 1995; MORCOUS; HATAMI, 2011; MOSCOSO, 2017).

Os modelos determinísticos mais desenvolvido atualmente são as regressões, que consistem em regressões lineares ou não-lineares, no qual procuram uma relação empírica entre uma ou mais variáveis, sendo uma variável dependente da outra, e as demais independentes, caso existam.

Segundo Ruckstuhl (2010), a regressão de modo geral estuda a relação entre uma variável de interesse Y_i e uma ou mais variáveis explanatórias ou preditoras $X^{(j)}$, dada pela seguinte forma:

$$Y_i = f(x_i^{(1)}, x_i^{(2)}, \dots, x_i^{m}; \theta_1, \theta_2, \dots, \theta_p) + \varepsilon_i \qquad i = 1 \dots\dots, n \tag{1}$$

onde,

f: uma função que depende das variáveis explicativas e parâmetros, que querem se resumir com vetores $x_i = [x_i^{(1)}, x_i^{(2)}, \dots, x_i^{(m)}]^T$ e $\theta = [\theta_1, \theta_2, \dots, \theta_p]^T$; ε_i: erros aleatórios que descrevem os desvios não estruturados da função f, a distribuição norma é assumida para a distribuição desse erro aleatório, mostrada na equação **(2)**, onde N e a distribuição e σ^2 é a variância do sistema, então,

$$\varepsilon_i \sim N\langle\langle 0|\sigma^2\rangle \tag{2}$$

A regressão mais simples é a regressão polinomial linear que contempla apenas uma variável independente e uma variável dependente que muda a uma taxa constante à medida que o valor da variável independente muda, podendo ser regressão polinomial de 1ª ordem (3) ou de 2ª, 3ª, ..., nª (4).

$$\varepsilon(Y_i) = \beta_0 + \beta_1 . x_i \tag{3}$$

[1] (Almeida, 2013) cita, de forma simplificada, que nas redes neurais são determinadas as melhores leis que, a partir de uma parte dos dados, melhor conseguem prever a outra parte, relativamente a diversas divisões e subdivisões da amostra.

$$\varepsilon(Y_i) = \beta_0 + \beta_1 . x_i + \beta_2 . x_i^2 \ldots + \beta_n . x_i^n \quad \textbf{(4)}$$

Onde,

n : ordem da regressão; β_0 é a interseção, o valor de $\varepsilon(Y_i)$ quando $x = 0$, e $(\beta_1, \beta_2, \ldots, \beta_n)$ a inclinação da linha (regressão polinomial de 1ªordem) ou curva (regressão polinomial de 2ª ordem em diante), a taxa de mudança em $\varepsilon(Y_i)$ por unidade de variação em x.

Segundo Ruckstuhl, (2010), na regressão não linear, são consideradas as funções f que não podem ser escritas como lineares nos parâmetros.

Metodologia

A partir das 6833 OAEs presentes no Sistema de Gerenciamento de Obras de Arte Especiais (SGO) do DNIT (DNIT, 2023a), foram adotandos os seguintes critérios de filtragem: OAEs em concreto armado ou protendido, com ano de construção em seu cadastro, sem melhorias de nota técnicas e sem grandes reabilitações, e pelo menos 3 ciclos de inspeção completos, para o desenvolvimento de melhores modelos. Foram obtidos dados de 885 pontes, englobando as 5 regiões brasileiras (Tabela 2), 3 Classes de Agressividade Ambiental[2] (Tabela 3) e subdivididos em 2 grupos de Volume Médio Diário de veículos[3] (VMD)(Tabela 4), contemplando 2655 inspeções, com nota técnicas atribuídas de acordo com a Norma do DNIT (2004b) com escala de 5 de estados de condição, sendo 5 a melhor nota e 1 a pior. Esses dados são insuficientes para a geração de modelos de previsão de degradação probabilísticos ou por inteligência artificial, optando-se, então, pelo desenvolvimento de modelos determinísticos.

Tabela 2 – Distribuição geográfica das OAEs selecionadas por região.

Região	Norte	Nordeste	Centro-Oeste	Sudeste	Sul
Quantidade de OAEs	35	276	131	124	319
Porcentagem %	3,95%	31,2 %	14,8 %	14,01%	36,04 %

Tabela 3 - Classe de agressividade ambiental das OAEs selecionadas.

Classe de agressividade ambiental	I	II	III
Quantidade de OAEs	651	158	76
Porcentagem %	73,56%	17,85%	8,59%

Tabela 4 - VMD das OAEs selecionadas.

VMD (Volume médio diário de Veículos)	VMD menor que 4 mil	VMD maior que 4 mil
Quantidade de OAEs	452	433
Porcentagem %	51,07 %	48,9 %

Os critérios de filtragem foram definidos de acordo com o tipo de material empregado nas infraestruturas estudadas, qualidade dos dados e necessidade do modelo determinístico, dado que a estrutura parte de um estado de condição perfeito, ou seja, nota técnica 5 e decresce de acordo com a idade da OAE até a pior nota técnica, no caso 1.

Os modelos foram desenvolvidos utilizando o software OriginPro (ORIGINLAB CORPORATION, 2023), por meio de regressão polinomial de 3ª ordem não-linear para o modelo das OAEs com classe de agressividade III[4] ((5)), e regressão polinomial de 3ª ordem linear para as demais ((6)). Esses modelos foram adotados por representarem melhor os dados de inspeção das OAEs, com gráficos obedecendo as seguintes funções:

$$y = A + Bx + Cx^2 + Dx^3 \quad \textbf{(5)}$$

$$y = B0 + B1x + B2x^2 + B3x^3 \quad \textbf{(6)}$$

[2] As classes de agressividade ambiental foram atribuídas pelo autor seguindo as recomendações da NBR 6118 (2014).
[3] O VMD foi retirado do programa VGeo do DNIT (https://servicos.dnit.gov.br/vgeo/) para todas OAEs (DNIT, 2023b).
[4] Os modelos determinísticos de previsão de degradação por regressão polinomial de 3ª ordem linear para OAEs com classe de agressividade III apontavam melhorias no estado de condição da OAEs em determinado ponto do gráfico. Como no modelo não são consideradas tais melhorias, recorreu-se à regressão não-linear para o desenvolvimento.

Dos diversos fatores considerados, verificou-se uma grande influência da Classe de Agressividade Ambiental III, e influência significativa do VMD nas curvas de deterioração com relação ao modelo desenvolvido para todas 885 OAEs. Os demais fatores não demonstraram ter importância para os modelos analisados (Tabela 5).

Tabela 5 – Influência dos fatores na curva de degradação.

Fator	Influência
Classe de Agressividade Ambiental I	Sem influência
Classe de Agressividade Ambiental II	Sem influência
Classe de Agressividade Ambiental III	Muito influente
VMD (Volume Médio Diário de Veículos)	Influente
Regiões Brasileiras	Sem influência
Aspectos especiais[a]	Sem influência

[a] Aspectos especiais considerados de acordo com o a Norma e Manual de Inspeção de Pontes do DNIT (DNIT, 2004a, 2004b)

Sendo assim, foram desenvolvidos 5 modelos determinísticos de previsão de degradação de Obras de Artes Especiais por regressão polinomial de 3ª Ordem:

- Um modelo para globalidade das 885 OAEs (denominado 885 OAEs);
- Um modelo para Classe de Agressividade Ambiental I e II (denominado Classe I/II);
- Um modelo para Classe de Agressividade Ambiental III (denominado Classe III)[5];
- Um modelo para Classe de Agressividade Ambiental I e II e VMD menor que 4 mil (denominado VMD < 4 mil);
- Um modelo para Classe de Agressividade Ambiental I e II e VMD maior que 4 mil (denominado VMD > 4 mil);

Resultados e discussões

Após inserção dos 2655 dados de inspeção das 885 OAEs no software OriginPro, foram desenvolvidos modelos seguindo as equações (5) e (6), com coeficientes de acordo com a Tabela 6.

O valor de interceptação no eixo y foi fixado em 5, uma vez que no modelo determinístico é considerado que a OAE parta do estado de condição perfeito, ou seja, nota técnica 5 quando x=0. Os demais coeficientes descrevem a inclinação da curva do modelo. Quanto maior o módulo desses coeficientes, maior a inclinação da curva e consequentemente mais rápido a OAE se deteriora.

Tabela 6 – Coeficientes de cada modelo desenvolvido.

Modelos	A ou B0	B ou B1	C ou B2	D ou B3
885 OAEs	5	-0,1294	0,0032	$-2{,}8371E^{-5}$
Classe I/II	5	-0,1186	0,0028	$-2{,}4328E^{-5}$
Classe III	5	-0,1500	0,0038	$-3{,}4309E^{-5}$
VMD < 4 mil	5	-0,0944	0,0018	$-1{,}5508E^{-5}$
VMD > 4 mil	5	-0,1360	0,0034	$-3{,}0142E^{-5}$

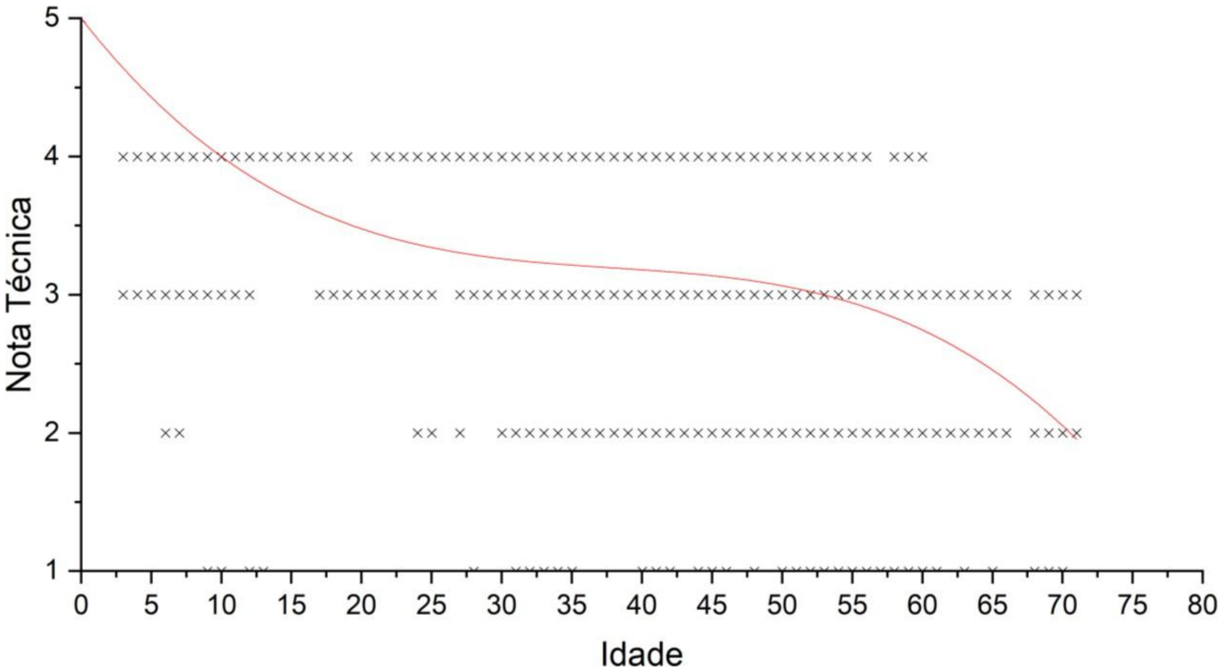
Foram analisadas algumas métricas estatísticas de avaliação dos modelos, que demonstraram a qualidade dos modelos e representatividades dos dados analisados, como mostrado na Tabela 7. Os coeficientes de determinação ao quadrado (r^2) próximos de 1 demonstram quão representativo são os modelos diante dos dados. O Erro médio quadrado inferior a 1 representa um erro baixo do modelo, dado que a nota técnica transita de 1 em 1 em sua escala de avaliação, então, por exemplo, uma nota técnica gerada pelo modelo de 2,75 seria plausível atribuir tanto a nota 2 como a nota 3, sendo o erro de 0,75 para nota 2 ou 0,25 para nota 3. Neste caso, um desvio inferior 1 não afeta a nota técnica.

[5] Como a influência da classe de agressividade ambiental III se sobressaia diante à influência do VMD, optou-se por não levar em consideração o VMD na obtenção do modelo da Classe III.

Tabela 7 - Métricas estatísticas de avaliação.

Dado estatístico	885 OAEs	Classe I/II	Classe III	VMD <4 mil	VMD >4 mil
Coeficiente de determinação (r^2)	0,9735	0,9542	0,9990	0,9746	0,9749
Erro médio quadrado (MSE)	0,6104	0,6908	0,6854	0,5946	0,5977

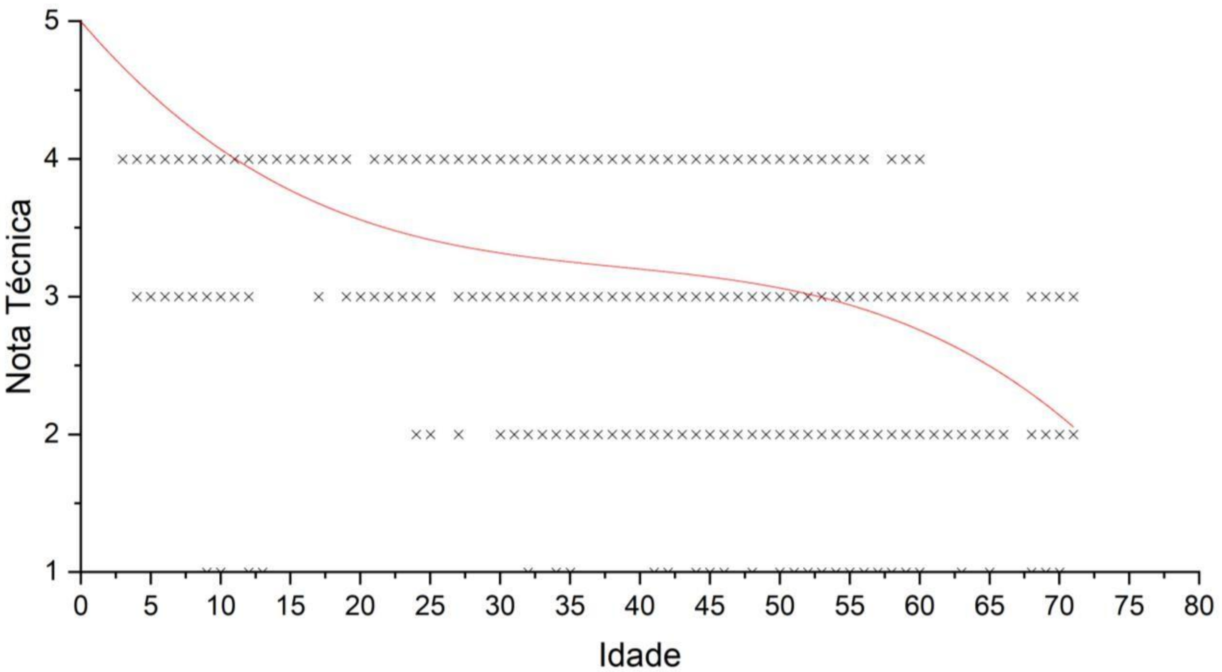
Para o modelo 885 OAEs foram utilizadas a globalidade das inspeções (2655), resultando na curva de deterioração da Figura 2.



x: Notas técnicas das inspeções no decorrer da idade das OAEs; ——: Curva de deterioração.

Figura 2– Modelo de previsão de degradação 885 OAEs.

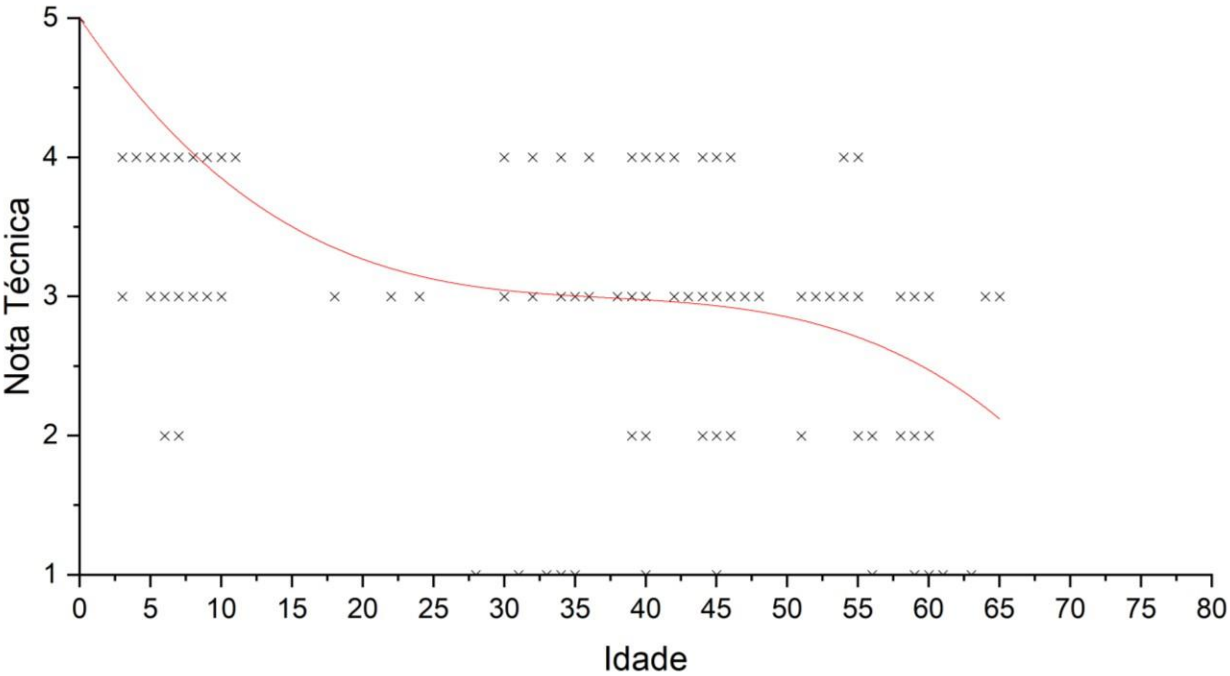
Para o modelo Classe I/II foram utilizados dados de 809 OAEs contemplando 2427 inspeções, resultando na curva de deterioração da Figura 3.



x: Notas técnicas das inspeções no decorrer da idade das OAEs; ——: Curva de deterioração.

Figura 3– Modelo de previsão de degradação Classe I/II.

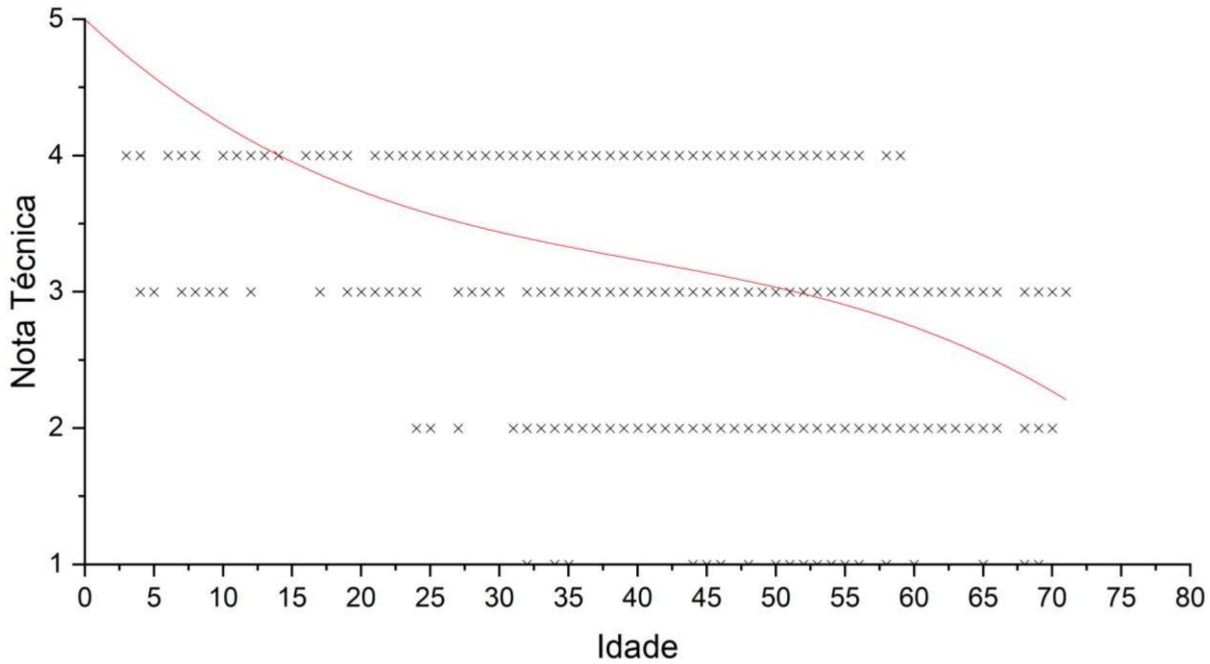
Para o modelo Classe III foram utilizados dados de 76 OAEs contemplando 228 inspeções, resultando na curva de deterioração da Figura 4.



x: Notas técnicas das inspeções no decorrer da idade das OAEs; ——: Curva de deterioração.

Figura 4– Modelo de previsão de degradação Classe III.

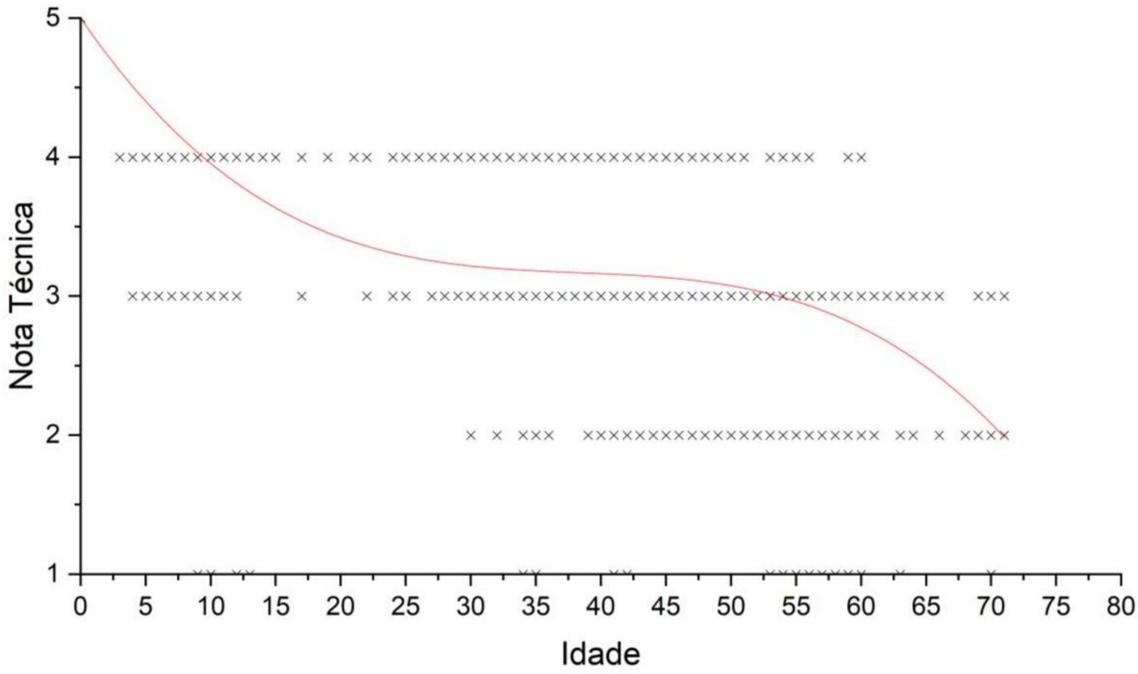
Para o modelo VMD < 4 mil foram utilizados dados de 436 OAEs contemplando 1308 inspeções, resultando na curva de deterioração da Figura 5.



x: Notas técnicas das inspeções no decorrer da idade das OAEs; ——: Curva de deterioração.

Figura 5 – Modelo de previsão de degradação VMD < 4 mil.

Para o modelo VMD > 4 mil foram utilizados dados de 373 OAEs contemplando 2427 inspeções, resultando na curva de deterioração Figura 6.



x: Notas técnicas das inspeções no decorrer da idade das OAEs; ——: Curva de deterioração.

Figura 6 – Modelo de previsão de degradação VMD > 4 mil.

Fundamentado nos gráficos, se justifica a grande influência da Classe de agressividade ambiental III na degradação de uma OAE, evidenciado nos gráficos pela a maior inclinação da curva no modelo Classe III (Figura 4) em comparação ao demais. Essa deterioração mais rápida devido aos maiores módulos dos coeficientes (B, C e D) (Tabela 6), é resultante de um ambiente mais agressivo, geralmente associado ao ambiente marítimo. Vários autores atrelam essa deterioração acelerada a grande influência dos cloretos, umidade e taxas elevadas de corrosão da armadura (CEB, 1992; COSTA, 1997; MEHTA, 1991; MIRANDA, 2006; SOUZA, 2019).

Não foi notada diferenciação entre as Classes de agressividade I e II, uma vez que a Classe I da NBR 6118 não engloba bem essas obras de infraestrutura, tendo a norma um enfoque maior em edificações convencionais. Por mais que uma OAE esteja presente em um ambiente Classe II, como por exemplo o ambiente urbano com altas concentrações de CO_2, o fato das OAEs, de modo geral, estarem em ambientes com umidades relativas elevadas e possuírem zonas microclimáticas (microambientes), mesmo em ambientes rurais, os principais processos de deterioração são acentuados, fazendo assim com que as duas classes tenham comportamento parecido (CEB, 1992; MIRANDA, 2006; SOUZA, 2019).

Referente ao VMD, o modelo com OAEs com VMD maior que 4 mil (Figura 6) apresentou uma deterioração mais elevada em comparação ao modelo com menores VMDs (Figura 5) para OAEs com Classe de agressividade ambiental I e II. Os principais motivos são as cargas atribuídas e frequência: quanto maior a quantidade de veículos maior a carga transferida e, quanto maior a frequência maiores vibrações e fadiga na estrutura, ocasionando uma deterioração mais acentuada.

O mesmo efeito do VMD na estrutura não foi observado para OAEs com Classe de agressividade ambiental III, por razão da influência dos processos de deterioração em ambientes agressivos apresentarem uma elevada velocidade de degradação, ofuscando o efeito do VMD.

A Tabela 8 simplifica alguns dados dos modelos, elucidando, de forma contundente, o comparativo entre os modelos e a relação com seus devidos parâmetros. Nota-se o modelo Classe III decaindo a nota técnica de forma mais acentuada, chegando a nota mínima em 75 anos, já o modelo VMD < 4 mil, apresenta um decaimento mais gradual, sendo o modelo com menor velocidade de degradação, chegando a nota mínima com 86 anos.

Tabela 8 - Nota técnica dos modelos no decorrer dos anos.

Idade	885 OAEs	Classe I/II	Classe III	VMD < 4 mil	VMD > 4 mil
0 anos	5	5	5	5	5
5 anos	4,43	4,47	4,34	4,57	4,40
10 anos	4,00	4,07	3,85	4,22	3,95
20 anos	3,47	3,55	3,26	3,73	3,42
30 anos	3,23	3,31	3,04	3,43	3,21
40 anos	3,18	3,19	2,98	3,23	3,16
50 anos	3,06	3,06	2,86	3,03	3,07
60 anos	2,74	2,75	2,48	2,74	2,77
70 anos	2,05	2,13	1,64	2,26	2,08
75 anos	1,51	1,66	1[a]	1,93	1,53
79 anos	1[a]	1,19	-	1,61	1[a]
81 anos	-	1[a]	-	1,42	-
86 anos	-	-	-	1[a]	-

[a] Ano da menor nota técnica a ser atribuída no modelo de acordo com Manual de inspeção de Pontes (DNIT, 2004a).

Outro ponto importante a se analisar é que, com exceção do modelo VMD < 4 mil, existe uma tendência de transição mais rápida para nota técnica 3 e uma tendência de permanência nesse estado de condição por mais tempo, o principal motivo disto é a subjetividade da metodologia de avaliação adotada pelo DNIT, que dá ao inspetor maior liberdade para definir seus critérios, fazendo com que uma nota técnica 3 seja um estado de condição amplo e confortável de avaliar.

Segundo Fonseca et. al (2010), quando o ser humano está diante de um processo de tomada de decisão, utiliza-se de esquemas mentais inconscientes e semiconscientes, ou seja, no processo decisório, fatores com viés cognitivo, como aspectos pessoais e de personalidade, refletem na decisão estratégica do indivíduo. O mesmo autor cita também que a cognição quando não pautada na racionalidade, obstaculiza a reflexão estratégica, trazendo alguns aspectos da abordagem cognitiva no processo decisório. Desta forma quão mais subjetivo foi a metodologia de avaliação, mais fatores de viés cognitivos podem estar presentes na decisão da nota técnica do inspetor.

Um estudo comparativo de metodologias de avaliação do estado de condição desenvolvido por Souza et al. (2022), demonstra essa subjetividade presente na avaliação adotada pelo DNIT, assim como aponta melhorias para otimização do processo de avaliação. As principais melhorias apontadas foram a avaliação da estrutura elemento a elemento, ao contrário da metodologia do DNIT que avalia um conjunto de elementos, e a definição de forma mais objetiva da classificação dos danos e estado de condição em seu manual de inspeção.

No caso do modelo VMD < 4 mil, como a deterioração ocorre de forma mais lenta, as OAEs levam um tempo maior para transitar entre os estados de condição, se comportando de forma uniforme e gradativa.

Conclusões

Com uma ampla quantidade de dados das OAEs, se desenvolveu de forma satisfatória os 5 modelos determinísticos de previsão de degradação considerando diversos aspectos da infraestrutura, apresentando boa representatividade diante das métricas estatísticas, e gerando resultados condizentes com a realidade e com os aspectos discutidos.

Os modelos evidenciaram a grande influência da Classe de agressividade ambiental III na deterioração, e a similaridade das demais classes (I e II) devido as diversas zonas microclimáticas e elevada umidade relativa. Verificou-se a influência do VMD nas curvas de deterioração em estruturas das Classes I e II, sendo mais acentuadas para VMD maiores de 4 mil, entretanto não foi possível verificar a mesma influência diante da Classe de agressividade ambiental III por causa das grandes velocidades de degradação que ofuscam tal efeito. Os modelos ainda evidenciaram uma tendência de transição e permanência na Nota Técnica 3, conexo com a metodologia e a subjetividade da avaliação do estado de condição utilizada pelo DNIT.

Por fim, a previsão de degradação de Obras de Arte Especiais é de extrema importância para o gerenciamento de OAEs, e os modelos propostos se demonstraram uma realidade viável dentro do cenário brasileiro, abrindo espaços para novos estudos e implementações em sistemas de gestão existentes e a serem desenvolvidos no Brasil.

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Appendix C. Conference paper at the *"XX International Conference on Building Pathology and Constructions Repair (CINPAR 2024)"*, ISBN 2175-5159 and DOI: http://doi.org/10.46848/2175515911.

XX International Conference on Building Pathology and Constructions Repair
29th to 31st May 2024 - Fortaleza, Brazil

Recurrence of damage to reinforced concrete bridges after repair: case study

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Abstract:

This study investigates damage recurrence in reinforced concrete bridges after repair interventions. A case study of two bridges in northeastern Brazil was used to examine the persistence of structural damage. It was found that problems related to water infiltration and drainage deficiencies were the primary causes of reinforcement corrosion and structural deterioration. The results highlight the need for a comprehensive bridge management approach not limited to repairing visible damage but also addressing the underlying causes of structural problems. Flaws in the widening design and the lack of efficient drainage facilities emerged as critical issues contributing to the recurrence of damage. It was concluded that a proactive and holistic approach for the management of reinforced concrete bridges is essential to ensure bridges' safety and durability over time. This study highlights the importance of comprehensive preventive and corrective measures that address the visible symptoms and the root causes of structural problems. By addressing the root causes of damage, the longevity and sustainable performance of reinforced concrete bridges can be ensured.

Keywords: Bridges; Repairs; Damage; Inspection; Pathology.

1. Introduction

Bridge infrastructure plays a crucial role in the connectivity and mobility of modern societies. In the Brazilian context, reinforced concrete bridges represent a significant portion of the road network, accounting for 97.52% of the bridges managed by the *Departamento Nacional de Infraestrutura e Transporte – DNIT* ((DNIT, 2017) apud (Medeiros et al., 2020)). To ensure the proper performance of these structures throughout their useful life, continuous investment in maintenance, strengthening, rehabilitation, and other interventions is essential.

In Europe, although bridges account for only 2% of the length of the road network, the costs associated with these structures represent 20% to 30% of the total (Woodward, 2001). This trend can be seen in Portugal, where in 2006 the maintenance of bridges consumed 75 million euros, representing 30% of the total budget allocated to the road network (Poças, 2009). In 2012, *Estradas de Portugal* allocated 30% of its investments to the repair and rehabilitation of bridges(Horta & Lopes, 2012). In Brazil, the average annual federal public investment in the road network over the last 16 years (2006-2021) was 15.5 billion BRL (CNT (2021)). If the Brazilian reality were to follow the same ratio of 30% of investments to bridges, it is estimated that the average annual expenditure would be 4.65 billion BRL.

Therefore, maintaining the integrity and safety of these structures over time, with efficient optimization of financial resources, is extremely important and requires a systematic understanding of the challenges associated with their management. The recurrence of damage after repair is a waste of financial resources and a social inconvenience. In this context, this paper presents a literature review on bridge inspection, assessment, and intervention, which serves as the basis for the case study. The analysis focuses on the recurrence of damage in reinforced concrete bridges after repair interventions and identifies the causes. It emphasizes the importance of a holistic approach to bridge management in identifying the original causes of damage and the proper corrections, using comprehensive solutions that transcend the repair of visible damage. The research shows that the lack of efficient drainage and water infiltration problems are the main causes of damage recurrence of the analyzed reinforced concrete bridges. Ultimately, this paper highlights the need to intrinsically link repair measures to solving the real cause of the damages.

2. Literature review

In bridge management, it is crucial to understand all aspects, from inspection and assessment to infrastructure intervention. In this article, some aspects deserve special attention in the literature review, including bridge inspection, bridge evaluation, bridge deterioration, and bridge intervention. These points will be covered in more detail in the subsequent sections.

2.1 Bridge Inspection

Due to their importance for the durability and maintenance of bridges, various agencies are concerned with defining inspection practices and their periodicity to obtain better management results and extend the useful life of structures.

The International Prestressing Federation established an inspection procedure for reinforced and prestressed concrete structures in 1988. This procedure defines time intervals based on the structure class, environmental condition, and loading (Fonseca, 2007). The collapse of the Silver Bridge in the United States in 1967 killed 46 people and prompted the United States Department of Transportation and the American Transportation Association (AASHTO) to create and publish American standards for bridge inspection in 1971, in addition to establishing a national database (Mark Hurt; Steven Schrock, 2016). The AASHTO Inspection Manual has eight levels of bridge inspection, as detailed in Table 1.

Table 1 – Inspection levels prescribed by the AASHTO (AASHTO, 2016)

Inspections	Description
Initial	First inspection of a bridge when it becomes a part of the bridge inventory. Used to determine baseline structural conditions.
Routine	Regularly scheduled inspection consisting of observations and/or measurements needed to determine the physical and functional condition of the bridge (every two years).
Damage	Unscheduled inspection to assess structural damage resulting from environmental factors or human actions (as needed).
In-depth	A close-up inspection that investigates deficiencies not detected during Routine Inspections (as needed).
Special	An inspection scheduled at the discretion of the bridge's owner is used to monitor a particular known defect or suspected deficiency (as needed).
Underwater	Inspection of the underwater portion of a bridge substructure and the surrounding channel (every five years).
Hands-on	Inspection within arm's length of the component. Inspection uses visual techniques that may be supplemented by non-destructive tests (as needed).
Fracture – Critical Member	A hands-on inspection of a fracture-critical member or components that may include visual and other non-destructive evaluation (every two years).

Based on these initiatives, various countries and bridge management systems have developed inspection methodologies with different numbers of inspection levels, ranging between one and eight levels, as in the case of the United States. Table 2 shows a compilation of bridge management systems and the respective number of inspection levels.

Table 2 – BMS inspection levels

Country/ BMS	Levels	Reference
Australia/ NSW	4	(Melhem et al., 2018; Traffic Authority of NSW, 2007)
Brazil/ (SGO)	5	(DNIT, 2004a; Souza et al., 2022)
Canada/ (OBMS)	1	(Ministry of Transportation Ontario, 2008)
China/ (CBMS)	3	(Dai et al., 2014; Ministry of Transport of the people's Republic of China, 2011)
France/ LAGORA	3	(Saback et al., 2021; Sédra, 2010)
Germany/ (GBMS)	3	(Adey et al., 2014; Saback et al., 2021)
India/ (UBMS)	3	(Joshi, 2022; Maharajpur, 1997)
Ireland/ EIRSPAN	4	(Adey et al., 2014; TRANSPORT INFRASTRUCTURE IRELAND, 2017)
Italy/ (APTBMS)	2	(Adey et al., 2014)
Japan/ RPIBMS	1	(Adey et al., 2014; Hsien-Ke et al., 2017)
Poland/ SMOK	5	(Adey et al., 2014)
Portugal/ (GOA)	2	(Mendonça & Brito, 2014; Task Group GOA, 2007)
South Africa/ STRUMAN	5	(Committee of Transport Officials, 2018; Habeenzu et al., 2021)
South Korea/ KRMBS	4	(Jeong et al., 2018; Ministry of Land Infrastructure and Transport, 2012)
Switzerland/ KUBA	1	(Adey et al., 2014; Saback et al., 2021)
Taiwan/ (TBMS)	3	(Hsien-Ke et al., 2017; MOTC, 2015)
UK/ (SMIS)	6	(Habeenzu et al., 2021; Highways Agency, 2007)
USA/ AASHTOWare	8	(AASHTO, 2016; Adey et al., 2014; FHWA, 2012; Habeenzu et al., 2021)

In Brazil, there are two main inspection standards in force for bridges and similar infrastructures: ABNT NBR 9452 (NBR 9452, 2019) proposed by the Brazilian Technical Standards Association, and the DNIT 10/2004 – PRO (DNIT, 2004a), created by the National Department for Infrastructure and Transportation. Both standards share similar characteristics, differing mainly in the periodicity of inspections. Additionally, the DNIT standard has one more level than NBR 9452. Table 3 shows the types of inspections established by the DNIT.

Table 3 – Types of inspection according to DNIT (DNIT, 2004a)

Inspection	Description	Frequency
Cadastral Inspection	Inspection is carried out immediately after completion, installation, or as soon as it is integrated into a BMS.	Performed again when there are changes to the bridge configuration.
Routine Inspection	Periodic inspections to assess the progress of damages detected in previous inspections, or to list new defects and occurrences, such as repairs, reinforcements, recoveries, or any design changes made during the period.	Every two years.
Special Inspection	Special Inspections are detailed visual inspections led by a senior inspector. It may also be necessary to supplement conventional data gathering with deflections or deformations measurements carried out with precision instruments.	From five to eight years. Anticipated in the case of structures rated 1 and 2, or major alterations to the work.
Extraordinary Inspection	The extraordinary inspection must be presented in a specific report, describing the work, and identifying the anomalies, including mapping, photographic documentation, and recommended therapy.	When there is a need to evaluate an element or part of the bridge more carefully, and/or when accidents or natural events occur.
Intermediate Inspection	Inspection to monitor a suspected or already detected deficiency, such as a small foundation settlement, incipient erosion, a partially bare ridge, the condition of a particular structural element	For certain bridges, when recommended by previous inspections.

2.2 Bridge evaluation

Based on the inspection records, it is possible to assess the reinforced concrete structure, either element-by-element, component-by-component, or globally. Generally, the assessment of bridges can cover a variety of performance indicators, as well as different levels of analysis, which can be grouped into four distinct assessment categories: Condition State, Health Index, Structural Assessment, and Risk Analysis.

Visual inspection is widely recognized as the initial stage in bridge evaluation within the various Bridge Management Systems (BMS) worldwide. During this process, the bridge is submitted to a visual assessment of its structure, in which a condition state (CS) is assigned (Quirk et al., 2018). Generally, the condition state is estimated by the inspectors based on their engineering experience and rating guidelines, which include a detailed description of the damage and its corresponding ratings (AASHTO, 2016; Department of Transport Main Roads, 2016). It is worth noting that the definition and scale of condition states can vary for each BMS.

Although condition state is a primary indicator of infrastructure status and is widely adopted, some transportation agencies have developed bridge health indexesto quantify the damage present and its direct relevance to the components of the structures. These indexes can be derived from mapping the identified damage, abnormal responses, and deterioration calculated through structure health models, converting this data into discrete values (Wu et al., 2021). For example, in the United States, the Florida Department of Transportation uses the Bridge Health Index (BHI) as a metric when assessing the condition of bridges. The BHI is a weighted average of the condition states of bridge components and considers the cost of failures, the cost of repairs, and other weightings defined by the agency to summarize the overall condition of the bridge network (Inkoom et al., 2017).

Several countries have conducted studies to calculate bridge health indexes, such as the United Kingdom, South Africa, Australia, Austria, Germany, Japan, and Finland, which are discussed in detail in the FHWA document (FHWA, 2016). In addition, academic studies such as Wu et al. (2021), indicate a range of research that has developed indexes related to various areas of bridge assessment, covering indicators of safety, severity, and durability.

The performance indicators mentioned above reflect the condition or health of the structure based on the damage identified; however, they do not necessarily represent the actual behavior of the structure. Therefore, even if the condition states of the components are favorable, abrupt failures may happen (van Noortwijk & Frangopol, 2004). An example is a bridge that collapsed on the BR-319 highway, in Brazil, resulting in four deaths. Surprisingly, the last inspection report indicated a condition 4 on a 5-level scale, where 5 represented the best condition and 1 the worst (Sassine, 2022).

Detailed inspections can provide essential information for carrying out load capacity assessments. Such assessments estimate the probability of a load exceeding the bridge's design capacity, considering the permanent weight of the bridge's components and the live loads caused by traffic and environmental factors such as wind and temperature. Different causes and components can lead to distinct failure modes, such as force, and bending (Liu & Fan, 2020).

These load assessments can be applied in regular and extreme situations. The ordinary evaluations focus on the fatigue of the structure due to consistent loads, while the extreme assessment focuses on scenarios such as earthquakes (Guo et al., 2015), hurricanes (Mondoro et al., 2017), and exceptional heavy vehicles (Li et al., 2017). These evaluations consider the equivalent requirements that apply to conventional structural designs, although, due to the uncertainties arising from the lack of detailed design information, there is a further reduction in resistant properties and an increase in actions (Luechinger et al., 2015).

Within aBMS, risk assessment may also be conducted to estimate the probability of undesirable incidents occurring on bridges, aiding decision-making. There are two approaches to risk: event-based simulation and random field. In the former, risks (deterministic or stochastic) are hypothetically exposed on a network of bridges, and this technique is widely used for various types of hazards, such as earthquakes, floods, and overweight vehicles (Yang & Frangopol, 2020). In the second, random field theory is employed directly to approximate the spatial correlation of bridge failure (Bocchini & Frangopol, 2011; Zhang & Wang, 2016). Although random field models were developed primarily for specific disasters (e.g. earthquakes), they could also be applied to network deterioration.

2.3 Bridge deterioration

The DNIT Bridge Inspection Manual describes the deterioration processes that affect concrete and steel. Some pathological manifestations frequently found in reinforced concrete bridges are alkali-aggregate reaction, reinforcement corrosion, leaching, chloride and sulfate attack, carbonation, efflorescence, accumulation of organic matter, and the presence of living organisms (DNIT, 2010). According to Souza (2019), deterioration mechanisms can be categorized into three types: physical, biological, and chemical.

Physical deterioration, although not the principal agent of degradation in reinforced concrete, plays a crucial role in the damage since the most common type of pathological manifestation is concrete cracking. These cracks increase permeability and intensify the action of chemical agents, mainly related to the corrosion of the reinforcement (Souza, 2019). Another aspect of physical deterioration that deserves attention is cracks caused by loads not foreseen in standards and projects. Overloaded bridges can develop unforeseen cracks, impacting the structure (CEB, 1992; Miranda, 2006).

In addition to cracking, concrete can be physically affected by abrasion and erosion from vehicle or human traffic or the action of particles carried by water, affecting structural elements of bridges, such as pillars, sills, and channel walls (DNIT, 2010).

Biological deterioration is related to degradation caused by plants, microorganisms, and other living beings, which can penetrate the concrete through cracks and weak points, increasing stresses and contributing to increased cracking and deterioration (DNIT, 2004b). The presence of these organisms can increase water retention at specific points, increasing humidity and, consequently, the risk of reinforcement corrosion. Bacterias and other micro-organisms can contribute to the degradation of reinforced concrete by releasing acids that dissolve the cement paste and could corrode the reinforcement.

Chemical deterioration is the most important and damaging degradation for reinforced concrete structures, especially in bridges (Souza, 2019). The damages associated with this deterioration include attack by sulfates, acids, ammonium and magnesium salts, alkali-aggregate reactions, carbonation, and reinforcement corrosion. Due to the high humidity levels on the bridges, reinforcement corrosion is the most common pathology in these structures (CEB, 1992). Reinforcement corrosion is considered one of the most frequent damages and can cause cracks, concrete spalling, and crazing (Andrade et al., 2019; Bolar et al., 2013; Cadenazzi, 2020; fib Bulletin 59, 2011; Papadakis, 2013; Souza, 2019; Vishwanath & Banerjee, 2023).

A study conducted by (Miao, 2021) using artificial intelligence identified six factors that accelerate the deterioration of bridges, two of which are the concentration of carbon dioxide and the concentration of chloride ions, which are directly related to the corrosion of reinforcement. In Brazil, a study conducted by Martins et al. (2023) on a group of bridges revealed that 77% of the bridges showed concrete spalling with exposed reinforcement due to reinforcement corrosion.

The process of reinforcement corrosion occurs when the pH drops below 11 due to carbonation or when chlorides reach a critical level, destroying the protective film and stripping the reinforcement. It starts the process of corrosion propagation, generating damage that, if not repaired, can lead to the collapse of the structure (Andrade et al., 2019; Souza, 2019; Zambon et al., 2018). Reinforcement corrosion is an electrochemical process that results in highly expansive products that accumulate at the concrete-steel interface, generating a significant increase in volume and, consequently, cracks, delaminations, and detachment of the concrete (Costa, 1997; Souza, 2019).

2.4 Bridge interventions

Rehabilitation, repair, and reinforcement interventions are fundamental stages in the lifetime and management of bridges, as they guarantee the safety and good performance of these infrastructures in the country. Almeida (2013) identifies three types of interventions to be considered when managing bridges:

- Preventive Maintenance: Low-cost interventions, with minimal impact on the level of safety of the work, carried out periodically in a proactive manner, following defined time intervals.

- Essential Maintenance: Also, preventive interventions are implemented when a certain previously established level of performance is reached, within acceptable levels.
- Corrective Maintenance: Interventions carried out when a certain acceptable level is reached or exceeded following the criteria established in management.

The design selection of methods and materials to be used during the intervention are defined by the engineer in charge. The Portuguese Standard EN 1504-9 (2009) classifies 11 principles of protection and repair, each associated with a set of methods to be carried out, six of which are related to concrete and five to steel. In Appendix A and B, all 11 principles are presented with their respective methods and brief descriptions. It is important to note that although various methods are associated with different principles, the requirements and objectives may vary for each principle. In addition, several approaches can be applied jointly to rehabilitate a reinforced concrete structure, depending on the specific needs of each case.

In Brazil, a study by Martins et al. (2023) analyzed a set of bridges to identify and categorize common damages in reinforced concrete bridges, assigning to each damage a corresponding repair, as detailed in Table 4. The association between some of the damages and the adaptable repairs was established by considering both the elements affected by the damage and the extent of the reinforcement section loss. These associations were made using decision trees, as illustrated in the diagram in Appendix C.

Table 4 – Correlation between damages and repairs (adapted from Martins et al. (2023))

Damages	Repairs
Infiltration in concrete.	Repair 1: Removal of concrete by water jetting under very high pressure. Projected dry concrete fck = 30 MPa.
Thin deep crack or Deep open crack.	Repair 2: Mechanized epoxy adhesive injection.
Expansion joint damaged or missing or expelled.	Repair 3: Expansion joint replacement. Expansion joint cleaning.
Wheel guard or barrier destroyed.	Repair 4: Controlled demolition of concrete with a hammer. CA-50 steel reinforcement. Concrete drilling with electric hammer. Supply and application of structural adhesive based on epoxy resin. 10 mm plasticized plywood forms. Concrete fck = 30 MPa - made in a concrete mixer and cast by hand.
Guardrail destroyed.	Repair 5: Rebuilding guardrails.

3. Method

Two bridges on the BR-116 highway in the state of Ceará were selected for this study. These structures were chosen from a group of bridges inspected along kilometers 306 to 372 of the highway. The selection of the bridges was based on specific criteria, which included identifying bridges that would undergo repairs between 2020 and 2023 and that, during the inspection carried out in 2023, showed a recurrence of damage previously identified in the 2020 inspection before the repairs were carried out. Based on these parameters, the bridges selected were identified as the Curral Velho Brook Bridge and the Pitombeira River Bridge. Additional details on the characteristics of the bridges analyzed are shown in Table 5.

Table 5 – Characterization of the bridges analyzed in this study

Identification	Curral Velho Brook Bridge	Pitombeira River Bridge
Typology	Reinforced concrete beams	Reinforced concrete slab
Length/ Width (m)	21/ 9.1	59.2/ 10.1
Year built	1950	1960
ADT (average daily traffic)	2133	2133
Last inspection (year/ Condition State)	2020/ 3	2020/ 2
Aggressive class (NBR 6118, 2023)	I	I

The 2020inspection data was provided by the DNIT, while the 2023inspection data was collected by the authors of this article following the inspection methodology of the Bridge Inspection Manual and Standard DNIT 010/2004 - PRO (DNIT, 2004b, 2004a). In the routine inspections carried out in 2023, a photographic survey and cataloging of all pathological manifestations was carried out, after which the data was compared with the 2020 inspections taken from the BMS *Sistema de Gerenciamento de Obras de Arte (SGO)* to arrive at the results and conclusions of this article.

4. Results and discussions

4.1. Curral Velho Brook Bridge

The Curral Velho Brook Bridge was in good condition after the repairs carried out between 2020 and 2023, giving it a Condition State 4. The repairs focused mainly on the reinforcement's corrosion (Figure 1 a) and Figure 2 a)), resulting in a Condition State 3 during the inspection. In the visual observation of the structure, the repairs followed principles 3 and 7 of NP EN 1504-9: the first refers to the restoration of the concrete by manual application of concrete or mortar, and the second concerns to the restoration of passivity by replacing carbonated or contaminated concrete. According to the parameterization of Martins et al. (2023), the repairs carried out on the damages related to the corrosion of the reinforcement followed the first path of the decision tree in Appendix C, with a reinforcement loss of less than 20%, replacing the shotcrete with concrete or mortar applied manually. In addition to the above repairs, the bridge was cleaned and repainted. The asphalt sidewalk was repainted, while the reinforced concrete guardrails were only painted because the metal fencing installed before 2020 served as a guardrail. Figure 3 shows some of the repairs made to the reinforced concrete beams.

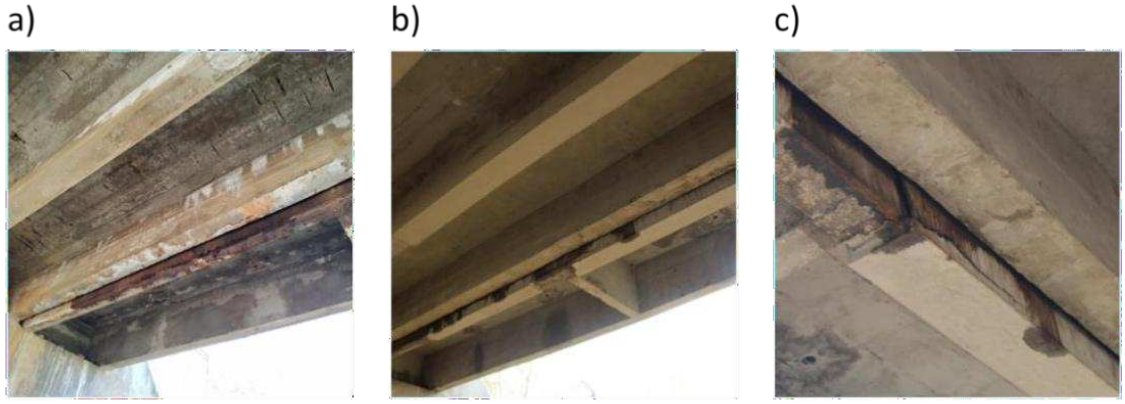


Figure 1 – Recurring bridge damage 02 in bridge; a) Damage at 2020 inspection; b) and c) Damage at 2023 inspection

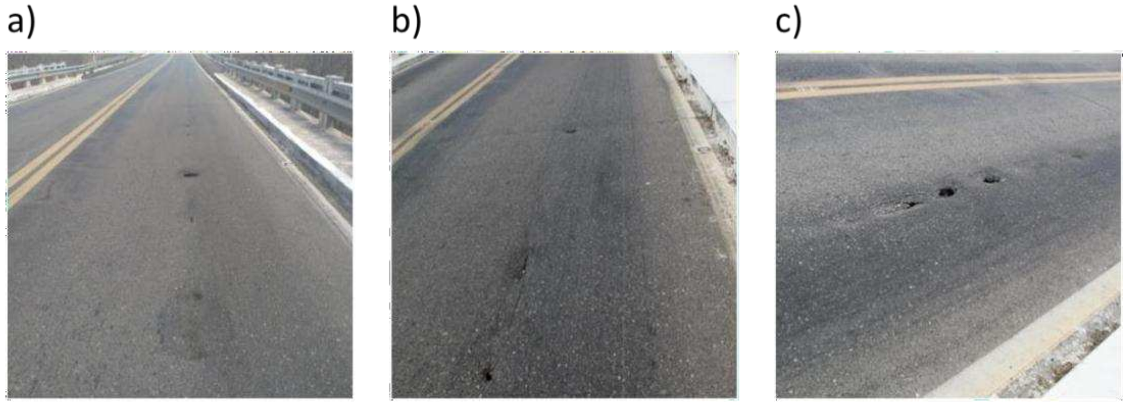
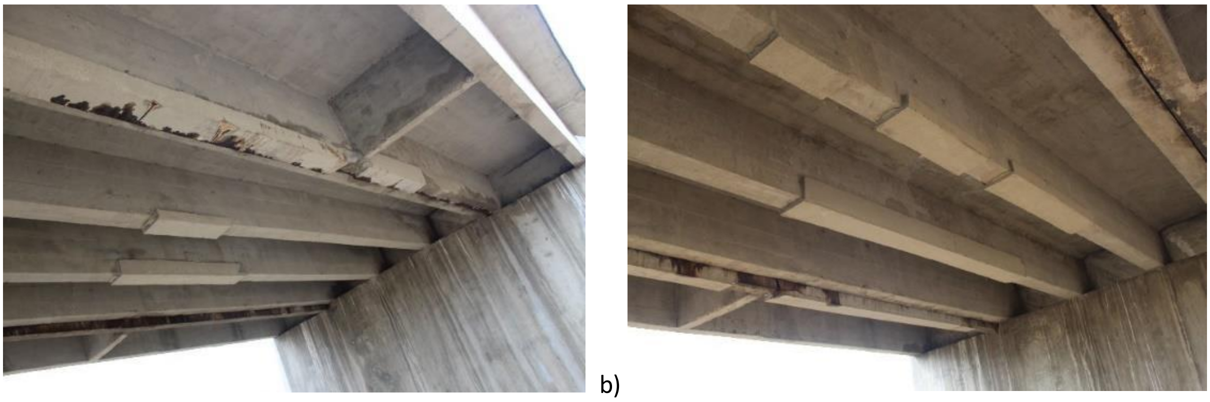


Figure 2 – Recurring bridge damage 03 in bridge; a) Damage at 2020 inspection; b) and c) Damage at 2023 inspection



a) b)

Figure 3 – Repairs to reinforced concrete beams; a) View of the 1st span; b) View of the 2nd span

Some damage identified during the 2020 inspection was not repaired. The principal damage observed included damaged or destroyed guardrails (see Figure 4 c)), as noted above, damage to the side plates of the slabs (Figure 4 a) and b)), and missing or inadequate expansion joints (Figure 4 d)). In addition to the unrepaired damage, some previously repaired damage to the beams recurred during the 2023 inspection. These include moisture stains, biological deterioration caused by bat droppings, cracking of the repair, evidence of reinforcement corrosion, and longitudinal cracks in the asphalt pavement. The most severe damage is shown in Figure 5, Figure 1, and Figure 2, where "a)" is the damage observed during the 2020 inspection, while "b)" and "c)" are the same damage observed during the 2023 inspection.

a) b) c) d)

Figure 4 – Unrepaired damage to the bridge: a) Damage to the left flange of the slab; b) Damage to the right flange of the slab; Damage to the reinforced concrete guardrail; d) Damage to the asphalt pavement due to missing or inadequate expansion joint

a) b) c)

Figure 5 – Recurring bridge damage 01 in bridge; a) Damage at 2020 inspection; b) and c) Damage at 2023 inspection

At some point during its service life, Curral Velho Brook Bridge was widened, and four new reinforced concrete beams were added. Figure 6 shows the original beams of the bridge in gray and the set of beams added after the widening in green. However, the connection between the old and new structures, represented in Figure 6 by the red circles, was made only through the asphalt pavement, resulting in a gap between the beams. It promoted the infiltration of water and pollutants and biological deterioration, as the opening served as a bat shelter. Consequently, the damage to the asphalt pavement and the beams was caused by this flaw in the widening project, which was not corrected during the repairs carried out between 2020 and 2023. It resulted in the recurrence of the identified damage.

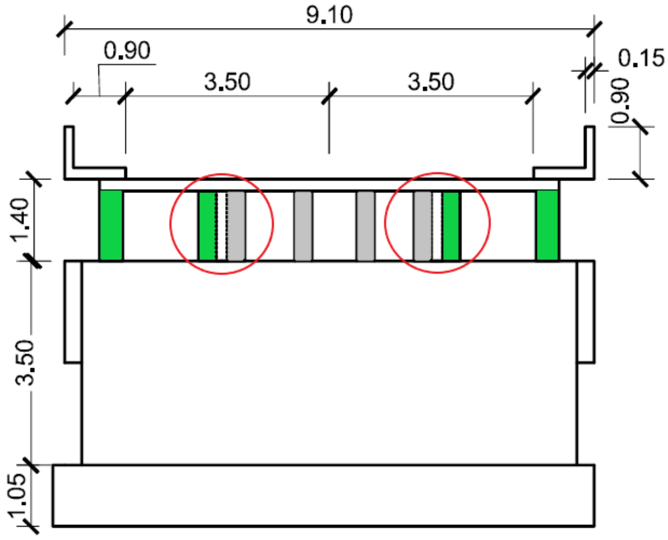


Figure 6 – Cross-section of the bridge; Grey: Original beams; Green: Widened beams

The solution to this problem would be to carry out the previous repairs and install longitudinal expansion joints between the beams in the circles highlighted in red. Concerning NP EN1504-9, the intervention would follow Principle 1, which aims to protect against the ingress of harmful agents by transforming cracks into expansion joints. About the methodology proposed by Martins et al. (2023), the repair would follow the same processes identified in the damaged or missing or expelled expansion joint, as described in Table 4, with the addition of an initial process to prepare the crack for the installation of a longitudinal expansion joint.

In summary, it is possible to associate the principal damage found with the necessary repairs, according to NP EN 1504-9, and the parameterization proposed by Martins et al. (2023), as shown in Table 6[1].

Table 6 – Main damage to Bridge A associated with repairs according to NP EN 1504-9 and Martins et al. (2023)

Damage	**Repairs – NP EN 1504-9 (Appendix A and B)**	**Repairs – Martins et al. (2023) (Table 4)**
Longitudinal crack in the asphalt (Figure 2)	Principle 1: method 1.6.	Repair 3, adding preparation procedures for a new expansion joint.
Moisture spot and biological deterioration (Figure 5 and Figure 1)	Principle 2: method 2.3.	Repair 1
Cracking and splitting of the repair (Figure 5 and Figure 1)	Principle 3: method 3.3. Principle 7: method 7.2.	Repair 1
Guardrail destroyed (Figure 3 c))	Principle 3: method 3.4.	Repair 5
Missing or inefficient expansion joints (Figure 3 d))	Principle 1: method 1.6.	Repair 3
Slab side flaps destroyed at specific points (Figure 3 a) and b))	Principle 3: method 3.4. Principle 4: method 4.2.	Repair 4

4.2. Pitombeira River Bridge

The Pitombeira River Bridge was in good condition after the repairs carried out between 2020 and 2023, classified as Condition State 4. The repairs were aimed at correcting corrosion of the reinforcement and

[1] The repairs shown in Table 6 are summarized examples and it is up to the designer to provide a detailed description of all repair procedures and materials used.

erosion of the piers, as shown in Figure 7, and Figure 8 (a), resulting in a classification of Condition State 2 during the inspection.

On visual inspection of the structure, the repairs followed principles 3 and 7 of NP EN 1504-9. Principle 3 concerns the restoration of concrete by manual application of concrete or mortar, while Principle 7 concerns the restoration of passivity by replacement of carbonated or contaminated concrete. Referring to the parameterization of Martins et al. (2023), the repair of damage related to reinforcement corrosion followed the first path of the decision tree in Appendix C, with reinforcement loss of less than 20%, resulting in the replacement of shotcrete with manually applied concrete or mortar.

In addition to the repairs mentioned above, Bridge B was cleaned, and the structure was repainted, like Bridge A. The asphalt sidewalk was resurfaced, while the reinforced concrete guardrails were only painted because the metal fencing installed before 2020 served as a guardrail. Figure 9 shows some of the repairs made to the structure.

Figure 7 – Damage present at the 2020 inspection

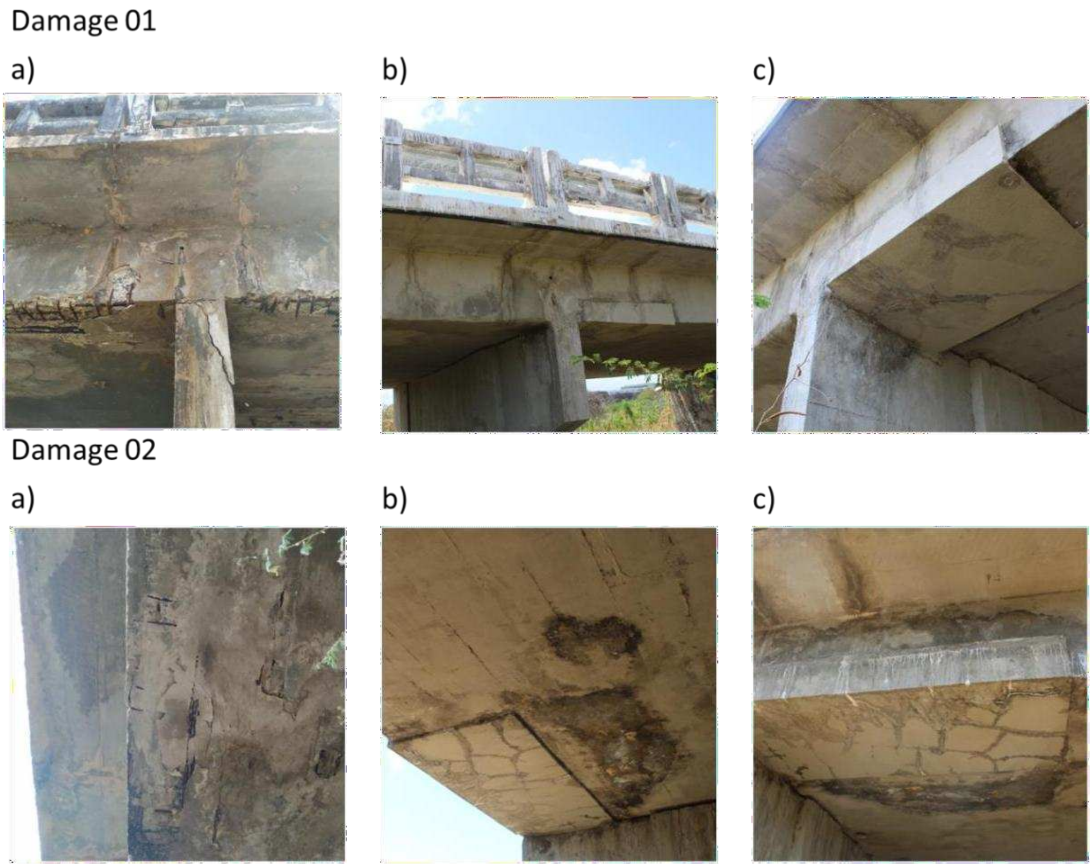


Figure 8 – Recurring bridge damage 01 and 02; a) Damage at 2020 inspection; b) and c) Damage in 2023 inspection

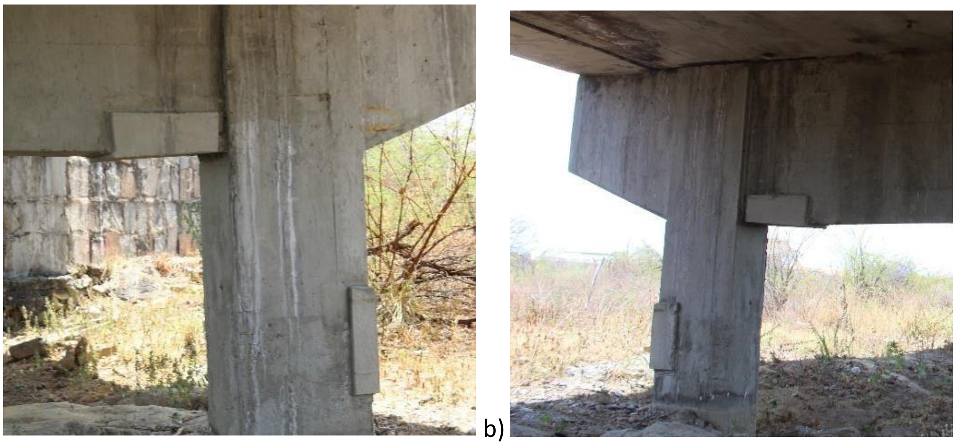


Figure 9 – Damage repaired to reinforced concrete pillars and crossbeams

Similarly, to the Curral Velho Brook Bridge, some damage observed on Pitombeira River Bridge during the 2020 inspection had not been repaired. The principal damage observed included damaged or destroyed guardrails (Figure 10 b)), as noted above, damage to the slab side tabs (Figure 10 a)), and the absence or deficiency of expansion joints (Figure 10 c)). In addition to the unrepaired damage, some previously repaired slab damage showed recurrence during the 2023 inspection. This recurring damage included concrete infiltration, moisture stains, efflorescence, cracking of the repair, and evidence of rebar corrosion. Figure 8 illustrates the damage with (a) the damage observed during the 2020 inspection and (b) and (c) the same damage observed during the 2023 inspection. Other repair locations also showed the same problem, as shown in Figure 12.

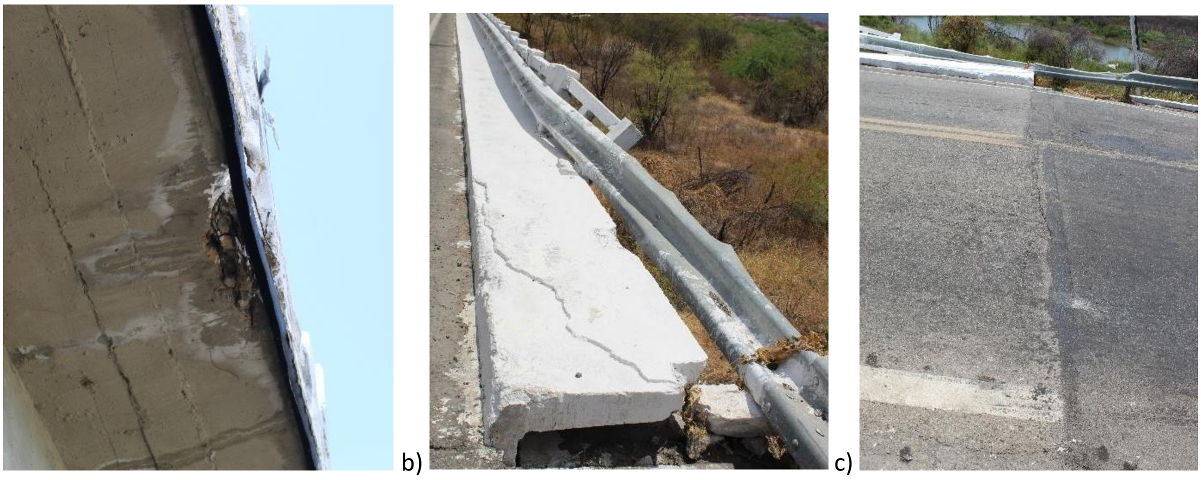


Figure 10 – Unrepaired damage: a) Damage to the right flange of the slab; b) Damage to the reinforced concrete guardrail; c) Damage to the asphalt pavement due to missing or inadequate expansion joint

The two main causes of recurring damage to the reinforced concrete slab are poor drainage and infiltration into unrepaired cracks. Figure 11 (a) shows a small hole for drainage, but it is inadequate, allowing water to seep into the structure and cause significant damage.

Another aspect of the drainage deficiency addressed in the repairs carried out previously was the absence of a drip rail. However, the cracks caused by water seeping into the concrete due to the lack of a drip rail were not repaired, as shown in Figure 11 (b). As a result, water seeps through the cracks and reaches the repair, causing the original damage to reappear, as shown in Figure 12.

Figure 11 – Drainage deficiencies on the bridge causing recurrence of damage; a) Side hole for insufficient drainage; b) Crack in the side flange of the bridge causing infiltration

Figure 12 – Recurring repair damage due to insufficient drainage and concrete infiltration

The solution to this problem would involve redoing the repairs made previously, repairing the damage that has not been repaired, and installing drainage mechanisms in the side flaps. Horns are often used for this purpose. In addition, it is crucial to seal the cracks and ensure that rainwater flows properly to the drainage mechanisms. This can be achieved by appropriately placing the drainage devices and providing a proper slope in the deck.

In summary, it is possible to associate the principal damage found with the necessary repairs, according to NP EN 1504-9, and the parameterization proposed by Martins et al. (2023), as shown in Table 7[2].

Table 7 – Main damage to Bridge B associated with repairs according to NP EN 1504-9 and Martins et al. (2023)

Damage	Repairs – NP EN 1504-9 (Appendix A and B)	Repairs – Martins et al. (2023) (Table 4)
Cracking in the slab (Figure 11 b)).	Principle 1: method 1.5.	Repair 2
Moisture spot and efflorescence (Figure 12, Figure 11 b) and Figure 8 a) and b)).	Principle 2: method 2.3.	Repair 1
Delamination and cracking of the repair (Figure 8 a) and b)).	Principle 3: method 3.3. Principle 7: method 7.2.	Repair 1
Guardrail destroyed (Figure 10 b)).	Principle 3: method 3.4.	Repair 5
Missing or inefficient expansion joints (Figure 10 c)).	Principle 1: method 1.6.	Repair 3

[2] The repairs shown in Table 7 are summarized examples and it is up to the designer to provide a detailed description of all repair procedures and materials used.

5. Conclusions

The drainage issue is of paramount importance in the context of reinforced concrete bridges. The absence or inefficiency of drainage can result in significant damage that, if left unrepaired, can cause structural instability. A critical aspect highlighted in this study is that even if the structure undergoes repair, if the original cause of the damage is not addressed, the problems are likely to recur.

In both Curral Velho Brook Bridge and Pitombeira River Bridge, problems related to water infiltration were identified as the primary cause of reinforcement corrosion in the slabs and beams. In the first case, an error in the widening project resulted in an opening between the girders that became a channel for water and shelter for bats, causing corrosion and biological deterioration of the girders. Failure to address this problem led to the recurrence of the damage. The principal solution proposed was the creation of a longitudinal expansion joint in addition to the necessary repairs to the existing damage.

In the second case, inadequate drainage on the bridge caused seepage into the concrete, resulting in reinforcement corrosion. The lack of efficient drainage channels and devices before the repair contributed to the problem. Although gutters were installed after the repair, the cracks resulting from their absence were not treated, resulting in seepage. In addition, efficient drainage devices were not installed, causing the damage to recur. The principal solution was the correct drainage device sizing, respecting the proper spacing, and ensuring the appropriate sag in the deck. This study provided an initial review of the inspection, evaluation, and repair of reinforced concrete bridges. The case study highlighted the importance of resolving the original problems of the bridge, in addition to simply repairing the existing damage, and provided a different perspective by relating the damage to two different repair approaches.

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Appendix

Appendix A. Intervention principles related to concrete deterioration (based on (NP EN 1504-9, 2009)).

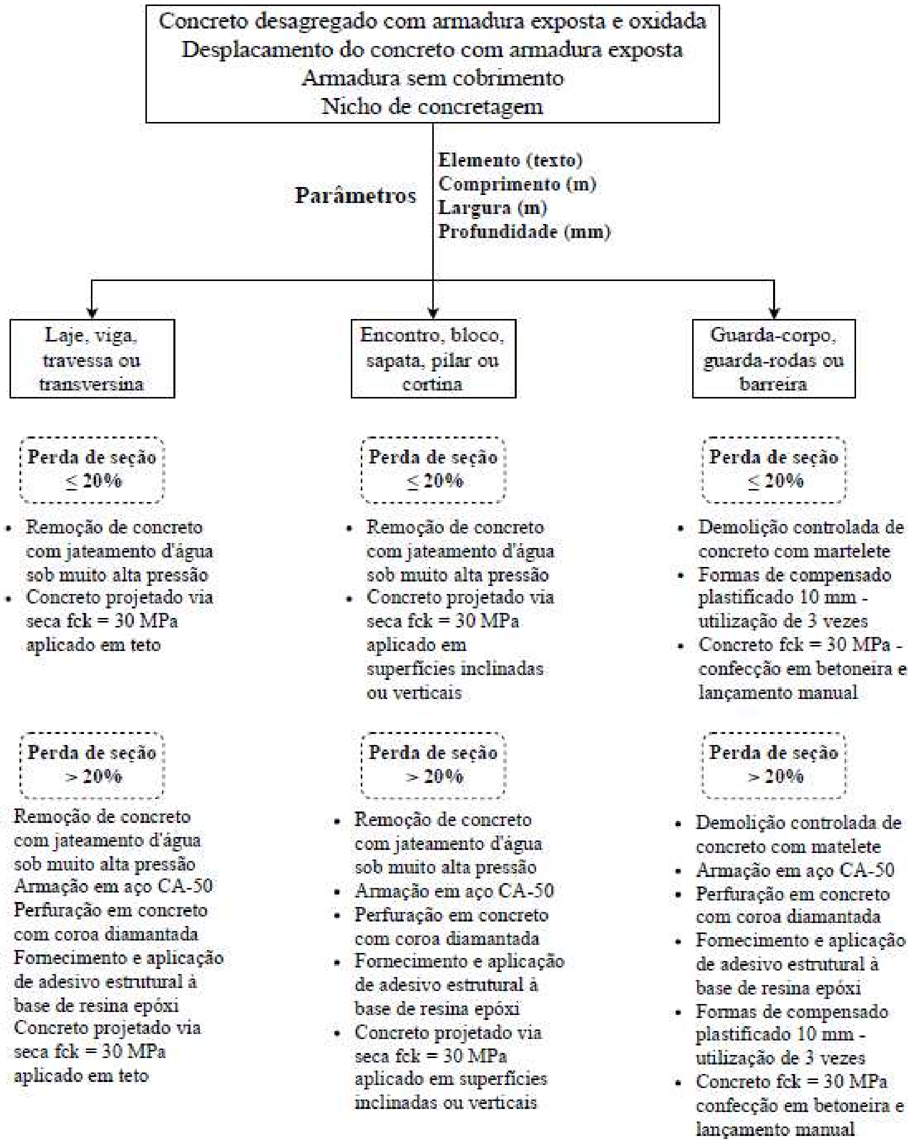
Principle	Method	Description
1. Protection against ingress: Principle 1 aims to reduce or eliminate the ingress of harmful agents into concrete, e.g. water, other liquids, steam, gas, chemical substances, or biological agents.	1.1 Hydrophobic impregnation	Hydrophobic impregnation aims to prevent the penetration of water through a treatment that makes the surface hydrophobic.
	1.2 Impregnation	Impregnations aim to fill the pores near the surface of the concrete to prevent the passage of liquids or gases. In addition, they generally create a thin film of the impregnating material on the outer surface of the concrete.
	1.3 Paint coating	Paint coating is a common technique for protecting and repairing concrete. It can include simple painting, sealing cracks and creating surfaces suitable for pedestrian or vehicular traffic, meeting specific requirements.
	1.4 Surface bonding of cracks	Surface bonding of cracks is a technique for sealing them and preventing the entry of harmful substances. It involves applying tapes, bandages, or flexible laminates over the cracks for protection.
	1.5 Filling cracks	Crack filling is an option to prevent harmful substances from entering the concrete through the cracks. An appropriate material is used to fill the cracks, closing them, and preventing the penetration of water and other harmful substances dissolved in them.
	1.6 Transformation of cracks into joints	To prevent the penetration of harmful agents, the treatment of cracks can involve turning them into joints. This is done by widening the crack with a diamond blade saw and filling it with sealing material using a joint sealing technique.
	1.7 Erection of external panels	Exterior panels can be used to protect concrete surfaces from harmful agents, especially on facades.
	1.8 Application of membranes	The method aims to protect concrete from the penetration of harmful agents by means of flexible and highly ductile membranes, such as bituminous membranes and screens.
Principle 2, Humidity Control in Concrete, aims to adjust and maintain the humidity level within a specific range to control the development of harmful reactions.	2.1 Hydrophobic impregnation	Humidity control can be achieved through hydrophobic impregnation, not only by preventing water penetration, but also by allowing evaporation through the impregnation process.
	2.2 Impregnation	Humidity control can also be achieved by impregnating the concrete (non-hydrophobic), the main function of which is to fill the voids near the surface of the concrete.
	2.3 Paint coating	Paint coating systems can also be used to control humidity in concrete.
	2.4 Erection of external panels	To reduce the humidity content in the concrete, external panels can be built in front of the surface of the concrete elements.
	2.5 Electrochemical treatment	The details of electrochemical treatment are not covered in the NP EN 1504 series.
Principle 3, Concrete Restoration, aims to restore the original form and functions of concrete in a structure,	3.1 Hand-applied mortar	Restoring the concrete in a structure by replacing defective concrete or mortar using hand-applied mortar is commonly done in relatively small areas.
	3.2 Shaped concrete or mortar	Applying concrete or mortar by molding is an alternative to applying it by hand or by projection. It is generally used for specific repairs that require molding to achieve the desired effect.

including the possibility of replacing some of its components.	3.3 Projected concrete or mortar	Projecting concrete or mortar is an effective method for repairing vertical surfaces or the underside of horizontal elements.
	3.4 Replacing elements	When replacing structural elements, other materials can be used in addition to reinforced concrete. It is crucial to consider the possible structural consequences during and after replacement.
Principle 4, Structural Reinforcement, aims to restore or increase the resilient capacity of a structural element by means of structural reinforcement.	4.1 Adding or replacing embedded or external reinforcement	Method 4.1 consists of replacing rebar or inserting it into holes previously formed or drilled in the concrete. It can also involve adding rebar to the outside of the existing structure, embedded in a new layer of concrete.
	4.2 Adding reinforcement in preformed or drilled holes	In Method 4.2, the connection of the new rebars to the concrete is achieved by anchoring the rebars in holes previously formed or drilled in the hardened concrete.
	4.3 Reinforcement with bonded plates	Method 4.3 is intended to reinforce a structure by applying laminates or composite fiber mats, or in exceptional circumstances, by means of steel plates.
	4.4 Adding mortar or concrete	In Method 4.4, the existing structure is reinforced by adding mortar or concrete, increasing the thickness of the element and, consequently, its resistance capacity.
	4.5 Injection of cracks, voids, or interstices	The most common method for reinforcing concrete with cracks, voids or interstices is the injection of filler materials capable of transferring stresses.
	4.6 Filling cracks, voids, or interstices	In Method 4.6, reinforcement does not involve pressure; the material is poured into the cracks, voids, or interstices. The aim is to achieve as complete a filling of the cracks as possible, since the purpose is to reinforce the structure.
	4.7 Reinforcement with prestressing	In Method 4.7, Reinforcement with prestressing, there is a complex intervention that radically modifies the structural system. Using prestressed cables or bars, it is possible to modify the static system to significantly increase the structure's resistance capacity.
Principle 5, Increasing physical resistance, aims to increase resistance against physical or mechanical damage.	5.1 Paint coating	In Method 5.1, Coating, the surface of the concrete is coated to increase its physical resistance, such as to abrasion or impact.
	5.2 Impregnation	In Method 5.2, Impregnation, the surface of the concrete is impregnated to increase its physical surface resistance.
	5.3 Adding mortar or concrete	In Method 5.3, to increase the mechanical or physical surface resistance of concrete, a layer of mortar or concrete is added to its surface.
Principle 6, Chemical Resistance, aims to increase resistance to deterioration of the concrete surface due to the action of chemically aggressive substances.	6.1 Coating	In Method 6.1, the surface of the concrete element is coated to increase its resistance to chemical attack.
	6.2 Impregnation	In Method 6.2, resistance to chemical products is enhanced by impregnation.
	6.3 Adding mortar or concrete	Method 6.3 aims to increase resistance to severe chemical attack by adding a layer of mortar or concrete with a higher strength than the existing concrete.

Appendix B. Principles of intervention related to steel deterioration (based on (NP EN 1504-9, 2009)).

Principle	Method	Description
Principle 7, Preservation, or restoration of passivity aims to create chemical conditions to maintain or re-establish a passive condition on the surface of the reinforcement. Thus, it can be applied as a preventive measure before corrosion begins or as a corrective measure to repair already damaged reinforcement elements.	7.1 Increasing coverage by adding mortar or concrete	In Method 7.1, the cover value is increased before the corrosion process begins. This method is preventative, postponing the onset of corrosion and thus extending the service life of the structure.
	7.2 Replacing contaminated or carbonated concrete	The most common method for repairing reinforced concrete involves removing all carbonated or contaminated concrete that contains a chloride content above the critical level. After cleaning the reinforcement, new concrete is placed to restore the integrity of the structure.
	7.3 Electrochemical re-alkalization of carbonated concrete	Regardless of whether the reinforcement is passivated or not, electrochemical realkalinization can offer additional protection against corrosion. This is achieved by increasing the alkalinity of carbonated concrete and ensuring the passivation of the reinforcement.
	7.4 Re-alkalization of carbonated concrete by diffusion	In Method 7.4, there are several possible approaches. One is to apply a highly alkaline hydraulic concrete or mortar to the surface of the carbonated concrete to promote realkalization.
	7.5 Electrochemical extraction of chlorides	The electrochemical extraction of chlorides provides extra protection against corrosion, regardless of the state of the reinforcement. Reduces chloride levels in concrete to maintain or restore reinforcement passivity.
Principle 8, Increased resistivity, aims to increase the electrical resistivity of the concrete to a point where the corrosion rate of the reinforcement becomes insignificant	8.1 Hydrophobic impregnation	In hydrophobic impregnation, several principles are addressed. In Method 8.1, moisture control is used to reduce steel corrosion.
	8.2 Impregnation	Impregnations can be used to increase the electrical resistivity of concrete. This helps to reduce the rate of reinforcement corrosion to an acceptable level.
	8.3 Coating	In addition to impregnations and hydrophobic impregnations, painting systems can be used to protect the reinforcement, reducing the resistivity of the concrete.
Principle 9, Cathodic Control, seeks to limit oxygen in the regions of the armor that can be cathodic, preventing its chemical activity and neutralizing the corrosion cells.	9.1 Limiting the oxygen content in the cathode by saturation or paint coating	One method based on this principle is to saturate the concrete element in water, thus reducing O_2 access. Another approach would be to apply a surface coating to the structure with a reduced O_2 diffusion rate.
Principle 10, Cathodic Protection, aims to reduce the electrochemical potential in the armor to below its natural corrosion potential.	10.1 Application of electric potential	The application of electric potential can be achieved in two ways: (i) by applying an electric current to the armature from an external source; or (ii) through the sacrificial anode method (galvanic action), which involves connecting a metal with greater chemical reactivity to the armature.
Principle 11, Control of Anodic Areas, aims to prevent the formation of incipient anodes in the armor to prevent corrosion, using coatings or other techniques.	11.1 Active reinforcement coating	In Method 11.1, an electrically active coating is applied to the reinforcement, which can provide cathodic protection or act as a corrosion inhibitor.
	11.2 Barrier coating on reinforcement	Barrier or watertight coatings are electrical insulators that prevent the anodic dissolution of iron and the cathodic reduction of oxygen due to their high resistivity, resulting in an extremely reduced flow of electric current under the influence of an electric field.
	11.3 Application of corrosion inhibitors in or on concrete	Method 11.3 addresses two ways of applying corrosion inhibitors to reinforced concrete: on the outer surface of the concrete or mixed into the mortar or repair concrete.

Appendix C. Decision tree to correlate damage and repairs (Martins et al., 2023).



Appendix D. Book chapter at the "*Bridge Maintenance, Safety, Digitalization and Sustainability*", ISBN 978-1-032-77040-6 and DOI: 10.1201/9781003483755-235.

Bridge Maintenance, Safety, Management, Digitalization and Sustainability –
Jensen, Frangopol & Schmidt (eds)

Bridge deterioration prediction models: A review of management systems in the world

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ABSTRACT: Predicting bridge deterioration is essential to an effective bridge management. Understanding the evolution of bridge performance in specific periods is fundamental to anticipating future needs and planning appropriate interventions. In this context, this paper aims to analyze Bridge Management Systems (BMS) that use deterioration prediction models and the methods employed. To perform this analysis, 12 BMSs from 12 countries were selected, considering the number of publications and citations related to the subject of "Bridge Management System" in each country. When examining the information from these systems, the significant importance of predictive models is evident. More than half of the systems (67%) use some type of deterioration prediction model, 25% do not use prediction models, and 8% did not obtain any information. Moreover, it is common to observe the countries that collaborate the most in BMS research adopt these models in their systems. Among the systems that employ deterioration prediction models, three main types were identified: physical, deterministic, and probabilistic models. In analyzing the bridge prediction models, it was found that 67% of them are based on probabilistic approaches using Markov chains, 11% are deterministic, 11% are physical models, and in 11% of the cases it was impossible to obtain information. These results highlight the preference for probabilistic approaches in modeling bridge deterioration, considering the uncertainty associated with the process. Such predictive models perform a crucial role in effectively managing bridges, enabling the anticipation of maintenance needs and the proper allocation of resources. In summary, the implementation of bridge deterioration prediction models is widely adopted in management systems worldwide, with probabilistic models based on Markov matrices being the most widely used. Understanding these models and their application can provide valuable insights for developing efficient and sustainable management strategies for bridge maintenance.

Keywords: Bridge, Deterioration Prediction Model, Bridge Management System, Physical Model, Deterministic Model, Probabilistic Model

1 INTRODUCTION

Effective bridge management plays a crucial role in maintaining the long-term performance, safety, and operational efficiency of these structures. Achieving this involves meticulous planning and execution of interventions. The core goal of bridge management is to optimize these interventions, seeking to attain optimal performance while minimizing associated risks. This process forms a solid foundation for informed investment choices. A fundamental component of this procedure involves the capability to forecast bridge deterioration as time progresses. Gaining insights into how the performance of structures evolves within specific timeframes is vital for enhancing the efficiency of intervention planning. Aiming to understand the processes underlying deterioration prediction and to identify the methods prevalent in bridge

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management systems globally, this paper conducts a review covering a detailed analysis of the models employed to predict bridge degradation in management systems worldwide.

2 METHOD

To perform the bibliometric review, we used the Scopus database platform. The search was carried out in August 2023, using the term "Bridge Management System" in "Titles, Abstracts and Keywords". Only documents in English published in the 21st century (2001-2023) were considered. A total of 686 documents were found and analyzed. VOSViewer, Bibliometrics, and the Scopus platform tools were used in the analysis. After a thorough review of existing methods to predict deterioration in BMS, the three methods employed by the selected systems were chosen for the analytical review of this paper.

The bibliometric review identified the main countries producing studies on BMS and the most relevant areas of concentration in the academic products. The selection of the countries analyzed was based on two clearly defined criteria: the presence of at least twelve documents and a minimum of 200 citations for each country. Based on this analysis, the twelve countries with the highest academic outputs and citations were chosen for a more detailed analysis. For this review, selection criteria for the BMSs were established based on the following aspects: the current use of the system, and the choice of only one system per country (giving priority to the first system developed and the number of structures).

3 BIBLIOMETRIC REVIEW

Table 1 lists, the 12 largest most collaborative countries regarding scientific production in the area, considering the minimum criterion of 12 documents and 200 citations.

Table 1. List of selected countries, number of documents and citations.

Country	N° documents	Citations
Australia	42	406
Canada	79	654
Germany	12	223
Ireland	13	323
Italy	33	303
Japan	57	337
Portugal	36	297
South Korea	44	474
Switzerland	24	294
Taiwan	25	237
United Kingdom	28	324
United States of America	157	2501

Figure 1(a) illustrates the substantial impact of the United States in this domain, evidenced by its extensive document count and network connections. This dominance can also be attributed to its pioneering role in spearheading research in this field. Upon analyzing the keywords, we extract the primary research domains within BMS, with two focal points emerging in relation to deterioration prediction: "Life Cycle" and "Deterioration," as depicted in Figure 1(b).

During the early 21st century, research within the realm of bridge management systems underwent a substantial surge. This upswing can be attributed primarily to the establishment of numerous systems in the 1990s and 2000s (Adey et al., 2014). While the output of related documents has since reached a steady state, the topic remains pertinent on a global scale. The annual distribution of research papers is illustrated in Figure 2.

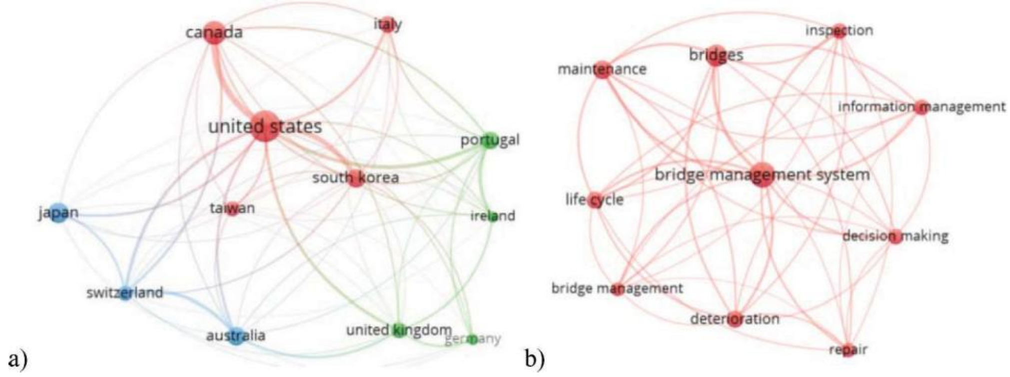


Figure 1. a) Connection between the selected countries; b) Keywords Analysis.

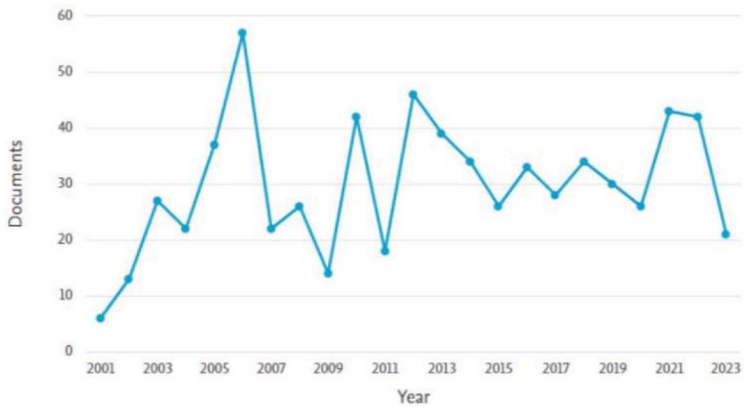


Figure 2. Documents by year.

In 2006, Figure 2 displays a pronounced peak, which can be ascribed to the occurrence of the 3rd International Conference on Bridge Maintenance, Safety, and Management (IABMAS). This event encompassed 34 publications dedicated to BMS, thus emerging as the primary contributor of papers for that year and century. Furthermore, it's noteworthy that the IABMAS congress, taking place biennially, instigated several publication spikes during even-numbered years such as 2006, 2010, and 2012.

In the realm of journals, notable contributions within the BMS domain encompass the Journal of Bridge Engineering, Journal of Infrastructure Systems, Structure and Infrastructure Engineering, and Transportation Research Record, as delineated in Table 2. Among these, the Structure and Infrastructure Engineering journal stands out with the highest number of publications (32), while the Journal of Bridge Engineering takes the lead in terms of citations (805).

Table 2. Journals with more publications.

Journal	Doc.	Citations
Journal of bridge engineering	22	805
Journal of infrastructure systems	15	357
Structure and infrastructure engineering	32	687
Transportation research record	30	291

4 ANALYTICAL REVIEW

4.1 *Bridge management system*

The foundation for a bridge to maintain its performance over its lifespan, ensuring a specific degree of safety and functionality, lies in how interventions are meticulously planned and executed. Bridge management seeks to optimize these interventions, aiming to ensure optimal performance while minimizing associated risks. This approach significantly contributes to the foundation of investment decisions (Oliveira, 2019).

A Bridge Management System (BMS) is structured into three primary categories: database management, data analysis, and decision support. The initial category pertains to data encompassing inventory details, evaluations of the bridge through inspections, cost-related information, and records of enhancement and preservation activities. These evaluations form a fundamental bedrock for data analysis, supplying vital inputs required for efficient information processing. Following this processing stage, the definition of analysis parameters follows, wherein each system must process and prioritize the most pertinent factors. Deterioration prediction and cost models constitute the most employed factors within this context (Adey et al., 2014). Lastly, decision support amalgamates insights derived from data analysis to serve as a bedrock and assist in making decisions and carrying out tasks, in a consistent and technically proficient manner.

Among the systems under scrutiny, the pioneering development and implementation transpired with KUBA, the Swiss Bridge Management System, in 1989. Shortly thereafter, in 1992, the USA introduced Pontis, which is currently known as AASHTOWare BrM. Subsequent instances emerged between 1996 and 2006 for the remaining systems, as detailed in Table 3.

Table 3. Selected BMS from each country (Adey et al., 2014; Habeenzu et al., 2021; Hsien-Ke et al., 2017; Mendonça et al., 2016).

Country	BMS	First Version
Australia	NSW	1996
Canada	OBMS	2002
Germany	GBMS	-
Ireland	EIRSPAN	2001
Italy	APTBMS	2004
Japan	RPIBMS	2006
Portugal	GOA	1999
South Korea	KRMBS	2005
Switzerland	KUBA	1989
Taiwan	TBMS	1999
United Kingdom	SMIS	1999
United States of America	AASHTOWare BrM	1992

Among the systems examined, AASHTOWare BrM in the United States is particularly noteworthy, covering a total of 750,908 structures, show in Figure 3. This predominance is justified by the adoption of this system by most states for the management of their structures. In 2021, 41 of the 50 asset management agencies in the United States used AASHTOWare BrM as part of their operations (AASHTOWare Bridge Management, 2021).

4.2 *Bridge deterioration prediction models*

The ability to anticipate the progressive decline of bridges over time plays a crucial role in the effective management of these structures. Understanding the performance trajectory of these constructions at defined intervals is essential to anticipate future requirements and plan appropriate medium to long-term interventions.

When examining the data from the twelve BMSs covered in this study, the significant importance of predictive models becomes evident. Over half of the systems (67%) employ some form of

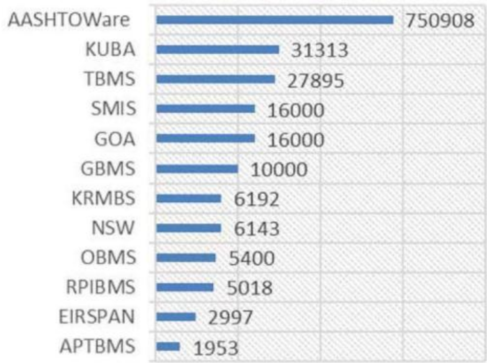


Figure 3. Number of structures in the selected BMSs (Adey et al., 2014; Habeenzu et al., 2021; Hsien-Ke et al., 2017; Mendonça et al., 2016).[1]

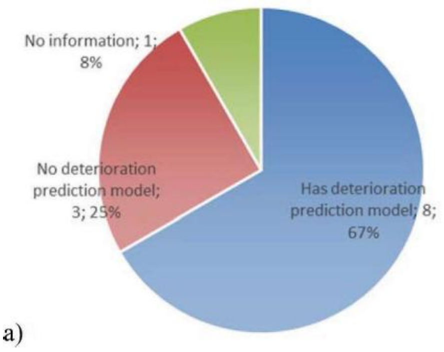
deterioration prediction model. These models are particularly prevalent in countries that stand out for their advanced research in BMS. Notably, the five countries leading in research in the field of bridge management systems generally incorporate deterioration prediction models in their respective systems. Of the systems investigated, eight BMSs adopt some form of deterioration prediction model (67%), while three do not make use of this feature (25%). For one of the systems, no information on the presence of such models was accessible (8%), as illustrated in Figure 4(a). All data collected are thoroughly presented in Table 4.

Table 4. Predicting deterioration in BMSs (Adey et al., 2014; Liao & Yau, 2011; Mendonça & Brito, 2014; Roelfstra et al., 2004).

BMS	Deterioration prediction models
NSW	Probabilistic deterioration prediction model in a system separates from the BMS
OBMS	Probabilistic deterioration prediction models by Markov chains
GBMS	Physical models for predicting deterioration (chlorides, carbonation and corrosion)
EIRSPAN	No deterioration prediction model
APTBMS	Probabilistic deterioration prediction models by Markov chains
RPIBMS	Probabilistic deterioration prediction models by Markov chains
GOA	No deterioration prediction model
KRMBS	Deterministic deterioration prediction model
KUBA	Probabilistic deterioration prediction models by Markov chains
TBMS	No deterioration prediction model
SMIS	-
AASHTOWare BrM	Probabilistic deterioration prediction models by Markov chains

Among the systems that adopt deterioration prediction models, three main models developed for integration into management systems are identified: physical models, deterministic models and, finally, probabilistic models that make use of Markov chains. In the examination of the prediction models applied to bridges, it is evident that 67% of them adopt a probabilistic approach based on Markov matrices, 11% are deterministic in nature, 11% are physical modeling and in 11% of the cases it was not possible to access detailed information on the elaboration of the model, as illustrated in Figure 4(b).

1. Data taken from the references may not correspond to the actual number of bridges in each system.



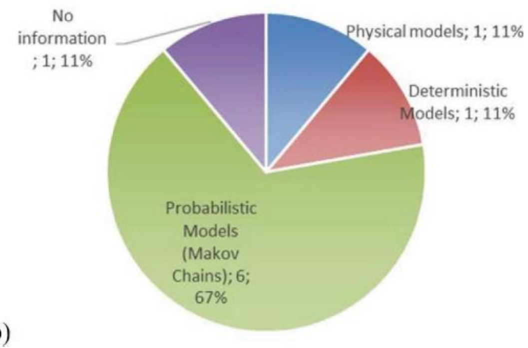


Figure 4. a) Predicting deterioration in BMSs; b) Type of deterioration prediction models used in BMSs.

4.2.1 *Physical models*

The deterioration of a structure emerges from the complex interaction of several physical processes within the system, interrelated with the materials used and the specific environmental conditions. To represent these degradation processes, either in the mechanical or chemical aspect, physical models have been developed to depict structure deterioration (Papadakis, 2013; Santamaria et al., 2019; Zambon et al., 2018).

Physical models addressing corrosion and carbonation are often preferred as they can clearly identify the main causes of deterioration in transportation infrastructure (Papadakis, 2013; Zambon et al., 2018). There are several models available for predicting the service life of reinforced concrete structures, considering factors such as chloride depassivation of reinforcement. The predominant formulations assume that the process is governed by diffusion (Andrade et al., 2019).

Some physical models that have not been implemented in the studied management systems can be explored in more detail in works such as Vieira et al. (2018) and Zambon et al. (2018). It is noteworthy that only the German GBMS system adopts physical models, which include chloride-induced corrosion and carbonation, for degradation prediction purposes.

4.2.2 *Deterministic models*

Based on mathematical or statistical equations, deterministic models establish connections between historical condition states and the service life of bridges. These structures may also incorporate additional factors that influence degradation. The main methods employed for the formulation of these models comprise projection curve fits, regressions, and the linear approach (García-Sánchez, 2016; Moscoso, 2017; Souza et al., 2023).

Among the most elaborate deterministic models today are regressions, which include both linear and non-linear regressions. In this context, the aim is to establish an empirical relationship between one or more variables, in which one of the variables is considered dependent on the others, which act as independent variables, if they are relevant. Regression analysis, in its essence, explores the interdependence between a variable of interest Y_i and one or multiple explanatory or predictor variables $X^{(j)}$.

Numerous researchers have been actively involved in crafting deterministic methodologies utilizing regression analyses to appraise the deterioration of bridges. Illustratively, notable references include the works of Jeong et al. (2017); Kim et al. (2019); Lu et al. (2019) and Souza et al. (2023). The KRMBS originating in South Korea stands as the singular management system that adopts a deterministic approach for the prediction of deterioration.

4.2.3 *Probabilistic models*

The process of deterioration in bridges, a synergistic interplay of multiple agents occurs, rendering the analysis of their individual influence rates unfeasible, as such, the phenomenon of deterioration takes on a probabilistic bias, where probabilistic deterioration models consider that deterioration over time is unknown, but there exists a probability for deterioration to unfold according to a certain law (Almeida, 2013; Oliveira, 2019).

The probabilistic degradation forecasting model predominantly employs Markov matrices, formed, for instance, by annual transition probabilities between different levels of condition states. This approach enables the prediction of the evolution of this performance parameter over time. This model finds common use in contemporary bridge management systems, primarily due to the relative ease in assembling data that allows for the identification of transition probabilities between different levels of this performance parameter.

Predicting bridge deterioration through Markov matrices involves stochastic processes, implying random processes that govern the behavior of a system over time, based on probabilistic considerations. These processes are categorized according to both Condition State and time, into discrete or continuous (Mishalani & Madanat, 2002).

Models classified by their state as discrete can be further divided into time-based or Condition State-based models. According to Mishalani & Madanat (2002), time-based models predict the probability of the time interval required for a change in the condition state of a bridge to occur. On the other hand, state-based models are models of deterioration that, within a chain Markovian process, predict the probability of a given bridge maintaining its condition state or changing its state within a fixed time span. State-based models can still consider the timing between discrete-time Markov processes and continuous-time Markov processes.

Various authors also have developed other models, including Calvert et al. (2020); L. Li et al. (2014); Manafpour et al. (2018); Santos et al. (2022) and Wellalage et al. (2015).

Eight management systems employ probabilistic models based on Markov matrices, as detailed in Table 4. Roelfstra et al. (2004) proposed a Condition State (CS) prediction of reinforced concrete highway bridges, using matrices calculated from simulated data, based on a model of chloride-induced reinforcement corrosion, to implement it in the Swiss KUBA system.

5 DISCUSSION AND CONCLUSION

In a comprehensive examination centered on a New York bridge, the work conducted by Xu & Azhari (2022) harnessed a predictive deterioration model to forge a bridge management strategy founded upon risk assessment. The findings revealed a substantial reduction in annual and overall costs when juxtaposed with conventional management methodologies, boasting an impressive 29% decrease in total expenses compared to the standard protocol. This underscores the effectiveness of a model-driven approach to bridge management. This aspect substantiates the adoption of bridge prediction models within the majority of analyzed systems, thereby enhancing safety, cost efficiency, and efficacy in managing these transportation infrastructures.

The most basic model is the physical one, but its applicability is often limited by the complex interaction of deterioration processes on bridges. This model is characterized by high uncertainty, stemming from a phenomenon-based approach rather than inspection data, which in turn restricts its capacity for updates. Both deterministic and probabilistic methods seek to strike a balance between the intricacies of development and the quality of the resulting model. While the deterministic model is easier to construct, it lacks precision and usefulness without complete information. For example, the absence of construction year data affects the accuracy of condition-age relationships. On the other hand, the probabilistic model requires more data but can have this data simulated, offering flexibility and precision. Unlike the deterministic approach, it's not bound by construction year or interventions. The deterioration curve in this model is anchored in time, not age, which makes it more dependable with an increased dataset.

These considerations steer bridge management systems toward the development of probabilistic models, particularly those rooted in Markov processes. It is worth noting that while not yet widely adopted in bridge management systems, deterioration prediction models utilizing artificial intelligence are steadily gaining ground and proving to be a viable alternative. This is evidenced by studies conducted by researchers such as Carvalho et al. (2019); Li et al. (2023); Miao et al. (2022); Santamaria Ariza et al. (2020) and Santos et al. (2022).

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Appendix E - Conference paper at the *"Congresso Brasileiro de Concreto 2024 (CBC2024)"*, ISBN 21758182.

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SPECIAL INSPECTION OF REINFORCED CONCRETE BRIDGES: A COMPARATIVE APPROACH TO BRIDGES FROM DIFFERENT PERIODS

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Abstract

This article presents a comprehensive special inspection study carried out on a series of reinforced concrete bridges in northeastern Brazil, built in different periods. The inspection was performed in accordance with the Bridge Inspection Manual of the National Department of Infrastructure and Transport (DNIT), using a variety of methods such as visual inspection and non-destructive tests such as ultrasound and sclerometer. The results were analyzed with a focus on the type of bridge in each construction period, highlighting variations in width, changes in the lateral protection systems (guardrails) and elements of the mesostructure that support the girders. The visual inspection revealed significant damage to all the bridges, two of which were in critical condition and required urgent intervention. The non-destructive tests were effective in estimating the strength and analyzing the quality of the concrete. However, it is crucial to complement them with detailed structural analysis and reconstruction of the original design for a more accurate assessment. This integrated approach will ensure appropriate and effective interventions, prolonging the life of the structures and ensuring the safety of the users. In summary, this study contributes to the understanding of the characteristics and condition of reinforced concrete bridges and highlights the continuing importance of monitoring and evaluating structures to ensure their long-term safety and durability.

keyword: Inspection; Bridge, Concrete; Non-destructive testing; Structures

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1. Introduction

Bridge infrastructure not only facilitates the mobility of people and the transportation of goods, but also plays a vital role in the economic and social growth of the regions they serve. In urban areas, bridges are essential for ensuring the continuous flow of traffic, while in rural regions, they connect communities and enable access to essential services such as health and education. However, these structures face ongoing challenges due to natural wear and tear over time, adverse climatic influences and ever-increasing traffic demands.
The aging process is inevitable for all structures, and bridges are no exception. Exposure to extreme weather conditions, such as heavy rain, strong winds and temperature variations, can cause gradual damage to concrete and steel, compromising structural integrity over time. In addition, increasing traffic volumes and changing load patterns can lead to accelerated wear and tear on bridges, requiring constant monitoring and timely interventions to ensure user safety. In this scenario, specialized inspections are essential to assess the condition of existing bridges and identify any potential problems before they become a threat to safety. DNIT's Bridge Inspection Manual establishes strict guidelines for conducting these inspections, ensuring uniformity and quality of procedures throughout the country. Methods such as visual inspection and non-destructive tests, such as ultrasound and sclerometers, are used to assess different aspects of the structure, from the integrity of the concrete to the presence of cracks and deformations.
Therefore, this article sets out to present the results of special inspections carried out on a series of reinforced concrete bridges in northeastern Brazil, offering valuable insights into the current state of these structures and highlighting the ongoing importance of monitoring and maintaining bridge infrastructure to ensure long-term safety and connectivity

2. Literature review

To better understand the results and discussions of this study, it is essential to conduct a literature review that addresses several important aspects. First, it is necessary to analyze the methods used to inspect and evaluate bridges and the characterization of bridges in different periods in Brazil, especially the Bridge and Viaduct Inspection Manual of the National Department of Infrastructure and Transport (DNIT). In addition, it is important to understand the deterioration processes of bridges to understand their structural behavior over time and to identify the pathological manifestations present in each bridge and their possible causes. Finally, a topic on structural assessment will be covered, focusing on non-destructive testing and methods for estimating the compressive strength of concrete. These topics will be discussed in more detail in the following sections of this text, providing a complete overview of the evaluation and inspection of reinforced concrete bridges.

2.1. DNIT Inspection Manual

The "Manual de Inspeção de Pontes e Viadutos" (DNIT, 2004b) was developed with two main objectives: to train engineers and professionals to perform bridge inspections, and to establish standardized procedures and practices in this area. This study covers three main topics: types of inspection, evaluation, and characterization of bridges.

2.1.1. Inspection types

The inspection types described in the Inspection Manual are detailed based on the guidelines established in Norma 10/2004 - PRO (DNIT, 2004a). This standard defines five different types of inspection, as specified in Table 1.

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Table 1. Types of inspection according to DNIT (DNIT, 2004a)

Inspections	Frequency
Cadastral Inspection	Performed again when there are changes to the bridge configuration.
Routine Inspection	Every two years.
Special Inspection	From five to eight years. Anticipated in the case of structures rated 1 and 2, or major alterations to the work.
Extraordinary Inspection	When there is a need to evaluate an element or part of the bridge more carefully, and/or when accidents or natural events occur.
Intermediate Inspection	For certain bridges, when recommended by previous inspections.

Cadastral inspection requires extensive documentation that includes data on the geometric, structural, functional, and material characteristics of the project, compared with reports and tests performed during construction. Routine inspection checks the progress of previously identified damage and reports any new damage, being mainly visual but sometimes requiring a special inspection. The special inspection is a more detailed version of the routine inspection, focusing on detecting previously unnoticed defects by mapping and quantifying anomalies in all visible and accessible elements of the bridge to formulate diagnoses and prognoses of the structure. Extraordinary inspection is conducted only when necessary to assess structural damage that compromises the bridge's safety and functionality due to events like car accidents, boat collisions, or natural disasters such as earthquakes or floods. Intermediate inspection monitors damage to the structure identified during previous inspections.

2.1.2. Bridge evaluation

During bridge inspections, the records obtained are more than mere data collection; they form the basis for a comprehensive assessment of the reinforced concrete structure. This assessment is crucial as it not only reveals the current condition of the bridge but also identifies areas needing immediate attention or future maintenance. The approach to this assessment can vary from detailed analysis of each structural element to an overall evaluation of the entire infrastructure.
The Bridge Inspection Manual outlines various pathologies and provides guidance on assessing each element. To simplify the process, a condition state is assigned to groups of elements, with the overall condition state of the bridge determined by the lowest value among these structural elements. This classification categorizes conditions into five levels, as detailed in Table 2.

Table 2. Condition States in Brazil (DNIT, 2004b).

State	Condition	Bridge Condition Classification
5	Excellent	No problem with the bridge
4	Good	Bridge without major problems
3	Regular	Potentially problematic bridge: It is recommended to follow the evolution of the problems through routine inspections.
2	Poor	Problematic bridge: Postponing the recovery of the bridge too long can lead it to a critical state, also implying a serious compromise of the structure's service life.
1	Critical	Critical bridge: In some cases, it can configure an emergency, and special preventive measures can accompany the bridge recovery

2.1.3. Characterization of bridges by period

According to the DNIT bridge inspection manual (DNIT, 2004b), bridges built between 1950 and 1960 had a total width of 8.3 meters with a deck span of 7.2 meters. These bridges were equipped with paired guardrails, each measuring 0.55 meters, and railings that were 0.15 meters wide and 0.6 meters high. Design loads at that time included a 24-ton

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compressor, a 12-ton truck per lane (excluding the lane with the compressor), and an evenly distributed load of approximately 500 kgf/m², collectively referred to as the Class 24 design vehicle. From 1960 to 1975, the bridges were widened to 10.00 meters with a lane width of 8.20 meters. They retained the double guardrail and railing, now 0.90 meters and 0.15 meters wide, respectively, with a raised railing of 0.90 meters. Design loads for this period consisted of a 36-ton vehicle and distributed loads of 0.5 tf/m² on the deck and 0.3 tf/m² on the sidewalks, designated as Class 36. Between 1975 and 1985, bridge widths exceeded 10.80 meters, and the roadway width exceeded 10 meters. Notably, the safety barriers changed from reinforced concrete to two New Jersey barriers. Load specifications mirrored those of the previous era. The post-1985 bridges were widened to 12.80 meters with a deck width of 12 meters. The New Jersey barrier configuration was retained. Design loads remained like Class 36, but with an increased vehicle load from 36 ft to 45 ft, resulting in the designation of Class 45.

2.2. Bridge deterioration

The DNIT Bridge Inspection Manual provides a thorough examination of various deterioration processes affecting reinforced concrete bridges, categorized into physical, biological, and chemical factors. Physical deterioration, primarily through crack formation from unexpected loads, significantly impacts bridge integrity by increasing concrete permeability and facilitating chemical agent actions like reinforcement corrosion (Miranda, 2006; Souza, 2019). Additionally, abrasion and erosion caused by vehicle traffic or waterborne particles can affect bridge structural elements (DNIT, 2010).

Biological deterioration involves plants, microorganisms, and other organisms infiltrating cracks and weak areas, increasing structural stresses and accelerating deterioration processes such as rebar corrosion (DNIT, 2004b). Microorganisms, including bacteria, exacerbate concrete degradation by releasing acids that dissolve cement paste and corrode reinforcement.

Chemical degradation poses the greatest threat to reinforced concrete structures, particularly in bridges (Souza, 2019). This includes attacks from sulfates, acids, chlorides, ammonium salts, magnesium salts, carbonation, and alkali-aggregate reactions, all of which are exacerbated by bridge humidity and contribute to common pathologies such as reinforcement corrosion (J. Andrade et al., 2019; Cadenazzi, 2020).

A study by Miao (2021) using artificial intelligence identified six factors accelerating bridge deterioration, including carbon dioxide concentration and chloride ion concentration, both directly linked to reinforcement corrosion. Reinforcement corrosion begins when concrete pH drops below 11 due to carbonation or critical chloride levels, compromising protective films and exposing reinforcement, leading to structural damage such as cracking, delamination, and spalling (J. Andrade et al., 2019; Zambon et al., 2019).

In summary, understanding these deterioration mechanisms is crucial for effective bridge maintenance and management to mitigate risks and ensure long-term structural integrity and safety.

2.3. Structural Evaluation

Based on bridge inspection records, thorough assessments of reinforced concrete structures can be conducted element by element, component by component, or comprehensively for the entire infrastructure. These assessments typically encompass various performance indicators grouped into four categories: Condition, Health Index, Structural Assessment, and Risk Analysis.

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Visual inspection serves as the initial step in bridge assessment within Bridge Management Systems (BMS) worldwide. Inspectors assign a Condition State (CS) based on engineering experience and rating guidelines, detailing observed damage (AASHTO, 2016; Quirk et al., 2018). However, definitions and scales of CS may vary among different BMS.

While Condition is widely used, some agencies have developed Bridge Health Indices (BHI) to quantify existing damage more directly in terms of structural components. For instance, the Florida Department of Transportation uses BHI, a weighted average considering repair costs and other factors (Inkoom et al., 2017). Similar studies globally have developed indices focusing on safety, severity, and durability (FHWA, 2016; Wu et al., 2021).

Detailed inspections are crucial for load capacity assessments, considering permanent and traffic loads, wind, and temperature effects, analyzing various failure modes (Liu & Fan, 2020). Assessments cover normal and extreme scenarios, from fatigue under regular loads to seismic events, hurricanes, and heavy vehicles (Guo et al., 2015; Li et al., 2017; Mondoro et al., 2017).

Risk assessments in bridge management systems analyze the probability of undesirable events, using event-based simulations for hazards like earthquakes and floods, or random field theory for spatial correlation of failures (Bocchini & Frangopol, 2011; Yang & Frangopol, 2018; Zhang & Wang, 2016). Random field models, initially for earthquakes, are applicable to network degradation and disaster-specific scenarios.

2.3.1. Non-destructive test

The evaluation of bridges involves non-destructive testing (NDT), design recomposition, and computer modeling. Non-destructive testing, such as the sclerometer and ultrasonic pulse velocity test, provides critical information about the structure's condition. The sclerometer measures concrete surface hardness, but its reliability in assessing concrete strength is debated due to varying results (M. Andrade et al., 2023). Similarly, the ultrasonic pulse velocity test evaluates concrete condition based on sound wave propagation speed, but its correlation with concrete strength varies significantly based on concrete composition and environmental factors (Santini et al., 2020).

An integrated approach like SonReb combines sclerometer and ultrasonic data to estimate concrete strength, while pacometer readings help account for reinforcement effects (Breccolotti et al., 2013; Breysse, 2012; Masi & Chiauzzi, 2013). Besides NDT, reconstructing bridge designs according to contemporary standards and using advanced modeling software are crucial for structural assessment and dimensioning.

2.3.2. Methods for Estimating Concrete Strength

There are two primary non-destructive methods to estimate material strength in bridges without conducting destructive or load tests:

- Strength estimation based on historical construction standards:

This method involves examining the standards and technical specifications that were in place at the time of the bridge's construction. By referencing these standards, it is possible to infer the strength characteristics of the materials used in building the bridge. This approach assumes that if the bridge was designed and constructed according to the standards of its time, its strength properties should align with those established standards. It is particularly useful when specific documentation detailing the materials used is unavailable. However, it may not accurately reflect the actual strength used in the project, as standards typically specify minimum required values rather than the precise strength employed. In Brazil, two main standards have governed the design of concrete strength in bridges: NB1, which was introduced in 1940 and utilized the Allowable Stress Method until 1980, when it was replaced by ABNT 6118, employing the Limit State Method. Analyzing these standards reveals the evolution of minimum concrete compressive strength values over the years, as detailed in Table 3.

Table 3. Minimum compressive strength of concrete per period.

Period	Current standard	Concrete's minimum compressive strength
1940 – 1960	(NB1, 1940)	$\sigma_{c,28} \geq 12{,}5\ MPa$
1960 – 1978	(NB1, 1960)	$\sigma_r \geq 11\ MPa$
1978 – 2003	(NB1, 1978) and (ABNT NBR 6118, 1980)	$f_{ck} \geq 9\ MPa$
2003 – Now	(ABNT NBR 6118, 2003, 2014, 2019, 2023)	$f_{ck} \geq 25\ MPa$*

*Value adopted for Environmental Aggressiveness Class (EAC) II. For other EACs, consult the standard.

In addition to the minimum values required by the standards, the original design can be reconstructed, considering the loads applied at the time and the dimensions of the structural elements. This provides a more realistic estimate of the resistance.

- Methods for estimating concrete strength based on non-destructive testing:

Methods for estimating concrete strength through non-destructive testing (NDT) offer a non-invasive approach to evaluate bridge materials effectively. One integrated method, SonReb, combines sclerometer and ultrasonic tests to provide a more reliable estimation of concrete strength. This method utilizes surface hardness measurements and the speed of sound wave propagation to calculate material strength, considering variables like concrete composition and environmental conditions.

Several models have been developed to estimate concrete strength based on sclerometer and ultrasonic pulse testing. Two major studies will be discussed here. The study by Andrade et al. (2022) correlated indirect ultrasonic pulse measurements with sclerometer tests to develop an equation for estimating the compressive strength of concrete. This model was calibrated using specimens taken from three bridges in the state of Minas Gerais and tested in the laboratory. The resulting equation was $\sqrt{f_c} = 0{,}003166 * V - 0{,}00265 * Ir - 2{,}85$, where V is the ultrasonic pulse velocity in m/s and Ir is the sclerometer index. On the other hand, Cristofaro et al. (2020) considered the correlation of direct ultrasonic pulse measurements with sclerometer tests to develop linear, polynomial, potential, exponential, and logarithmic models. This study was calibrated with data from 263 bridges in Italy, including 860 concrete strength measurements, 860 sclerometer readings, and 860 ultrasonic pulse readings. The linear equation developed was $f_c = 0{,}83 * (0{,}01174.V + 0{,}370\,Ir - 28{,}44)$, where V is the ultrasonic pulse velocity in m/s and IR is the sclerometer index. In summary, both code-based analysis and non-destructive testing provide valuable tools for estimating bridge material strength without invasive methods. These techniques facilitate safe and efficient assessment of structural integrity.

3. Methodology

The study focused on four bridges located in northeastern Brazil, specifically in Rio Grande do Norte and Paraíba. These bridges were selected based on specific criteria, including their prior inspection history and representation of different construction periods. The study aimed to conduct special inspections using NDT equipment, enabling a comprehensive comparative analysis of collected data. The selected bridges are detailed in Table 4.

Table 4. Bridges selected for the study.

Identification	Length/ Width (m)	Year built	Last inspection (year/ CS)
Zé Dias Brook Bridge	24.35/ 8.1	1955	2020/ 3
km 0,91 Bridge	19.5/ 10	1965	2020/ 1
Latadinha Brook Bridge	30/ 10.1	1970	2020/ 3
Peixe River Bridge	59.4/ 10.8	2015	2020/ 4

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Special inspections were conducted in two stages. Initially, visual inspections utilized damage forms and cameras to meticulously document all observed issues, ensuring inspector safety with protective gear such as footwear, vests, helmets, and sun hats. Detailed analysis of damages was facilitated using equipment like ladders, calipers, and laser tape measures.

In the second stage, NDT tests were performed to reconstruct bridge designs, evaluate load capacity, conduct structural analysis, and estimate material mechanical properties. Sclerometer tests assessed concrete surface hardness, while ultrasonic pulse tests analyzed wave propagation speed and material characteristics.

Two primary models were employed to estimate concrete compressive strength: the Andrade et al. (2022) model for indirect ultrasonic pulse readings, calibrated with Brazilian bridges, and the Cristofaro et al. (2020) model for direct ultrasonic pulse readings, validated extensively with a large dataset.

The study concludes by presenting inspection results and comparing the five analyzed bridges. It highlights design features, project histories, deterioration profiles, and concrete compressive strengths across different construction periods, offering a detailed overview of these structures' evolution and current conditions.

4. Result and discussions

4.1. Zé Dias Brook Bridge

The Zé Dias Brook Bridge, located in Paraíba, was built in 1955. It is a reinforced concrete beam bridge, consisting of two spans of 12.18 meters each, with a total length of 24.36 meters. Its characteristics are typical of the time, as indicated in the Bridge Inspection Manual: it has a width of 8.1 meters, two railings of 50 cm each, and two reinforced concrete guardrails above the railings.

The superstructure of the bridge consists of slabs, two beams, two curtain walls near the abutments, a slab stiffening beam and seven cross beams, all made of reinforced concrete. The mesostructure consists of two abutments and a stone wall column, materials commonly used in bridges of the 1950s and 1960s. There was no evidence of support devices. The bridge infrastructure was not visible to identify the foundation elements. Figure 1 shows a side view of the bridge.

Figure 1. Side view of Zé Dias Brook Bridge.

The visual inspection revealed several corrosion spots on all structural elements of the superstructure, as well as leaching and carbonation of the concrete. The combination of carbonation and high relative humidity has resulted in a generalized corrosion process. This damage is worrisome because carbonation lowers the pH of the concrete, leaving the reinforcement vulnerable to corrosion, while leaching indicates the loss of constituents from the concrete, weakening the structure.

Due to this damage, the bridge was classified as Condition 2, indicating the need for short-term intervention to prevent accelerated deterioration and ensure structural safety. Figure 2 highlights the most critical element, girder 02, which shows advanced signs of corrosion

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where the steel reinforcement is exposed and corroded, resulting in spalling of the cover concrete. The cracks observed are indicative of internal stresses and progressive deterioration that, if not addressed promptly, could develop into more severe damage and compromise the stability of the bridge.

Figure 2. Main damage to the bridge; Severe corrosion on beam 02.

In non-destructive testing (NDT), sclerometry and ultrasonic pulse tests were carried out on the two bridge beams. Due to the difficulty of access, only indirect readings of the ultrasonic pulse were possible, using the equation from the model by Andrade et al. (2022) to estimate the strength of the concrete. The sclerometry results, the average ultrasonic pulse velocity values and the estimated compressive strength of the concrete are shown in Table 5.

Table 5. NDT data for Zé Dias Brook Bridge.

Point	Sclerometer	Ultrasonic pulse test	Estimated strength
Beam 01	50.25	2589	16.12
Beam 02	55.30	2223.71	7.42

The estimated resistance results showed a significant variation, with one of the results not corresponding to the minimum values established by the standards of the time. This is due to the high degree of corrosion present in beam 02, which increases the reception time of the ultrasonic pulse and consequently reduces the propagation speed of the waves. This reduction in propagation speed indicates a reduction in the quality and integrity of the concrete. Because of this discrepancy, the readings for beam 02 were disregarded in the final strength estimate.

The compressive strength of the concrete for the bridge, based on the readings of beam 01, was estimated at 16.12 MPa, which is above the minimum established by the standards of the time, which was 12.5 MPa. Although this value is within the normative parameters, it is crucial to recognize that the results of non-destructive tests are influenced by the deterioration conditions of the material.

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4.2. km 0.91 Bridge

The km 0.91 bridge, located in Paraíba, was built in 1960. It is a reinforced concrete beam bridge made up of two 7.7-meter spans, totaling 19.5 meters in length. Its characteristics are typical of the time, as indicated in the bridge inspection manual: it has a width of 10 meters, two 90 cm railings each and two reinforced concrete guardrails over the railings.
The bridge's superstructure includes slabs, two beams, two curtain walls near the abutments and three crossbeams, all made of reinforced concrete. The mesostructure is made up of two stone masonry abutments, like the 1955 bridge, two column pillars and a column bracing beam, both in reinforced concrete. No support devices were identified. The bridge's infrastructure was not visible to identify the foundation elements. Figure 3 shows a side view of the bridge.

Figure 3. Side view of km 0.91 Bridge.

During the visual inspection, it was found that the bridge had undergone recent rehabilitation since the last inspection, as evidenced by the new paint job and repairs to the superstructure. However, significant damage was identified at the base of the two pillars due to corrosion of the reinforcement, which had not been repaired. On pillar 01, the situation was particularly critical, with spalling on two faces of the pillar. On one face, the reinforcement exhibited a marked degree of corrosion, resulting in substantial loss of material in one of the bars, as illustrated in Figure 4. On the other face, the condition was even more severe, with several exposed reinforcements and major section loss, including a broken bar, as shown in Figure 5.
This damage is particularly worrying for several reasons. Firstly, corrosion of the reinforcement reduces the load-bearing capacity of the abutment, compromising the structural integrity of the bridge. Exposure of the reinforcement further accelerates the corrosion process, since the steel is directly exposed to the corrosive agents present in the environment. Peeling concrete can indicate additional problems, such as loss of adhesion between steel and concrete, which reduces the effectiveness of reinforced concrete.
These conditions justified the assignment of condition 1 to the bridge, indicating the urgent need for intervention to ensure the safety of the structure.

a) b) c)

Figure 4. Main damage to the bridge; Severe corrosion on pillar 01 (face 1).

a)  b) 

Figure 5. Main damage to the bridge; Severe corrosion on pillar 01 (face 2).

To evaluate the propagation speed of the ultrasonic pulse in damaged concrete compared to undamaged concrete, specific tests were carried out in both regions of the two bridge pillars. The results of these tests are detailed in Table 6.

Table 6. NDT data for km 0.91 Bridge (pillars).

Point	1st reading	2nd reading	3rd reading	4th reading	Media
Pillar 01 not damaged	1842	2098	2096	3472	2377
Pillar 01 damaged	806	1505	1975	1546	1458
Pillar 02 not damaged	3419	3434	3063	3060	3244
Pillar 02 damaged	1991	2144	2656	-	2263.7

The data indicated that the readings in the damaged areas showed a reduction of approximately 30 to 40% compared to the undamaged areas. This discrepancy is attributable to several factors. Firstly, the cracks generated by the corrosion products, which are expansive, compromise the integrity of the concrete. In addition, processes such as carbonation, leaching, erosion and abrasion, which are common at the base of pillars, contribute significantly to increasing the permeability and porosity of the material.

These changes in the structure of the concrete hinder the propagation of ultrasonic waves, resulting in a longer arrival time at the ultrasound receiver. The greater porosity and cracks act as additional barriers, slowing down the transmission of sound waves. Consequently, the propagation speed of the ultrasonic waves is significantly reduced in the compromised regions, directly reflecting the increase in the time required for the waves to reach the receiver.

To estimate the strength of the concrete, the sclerometry and ultrasonic pulse results were considered for the bridge's pillar 02, which was in the best condition. Due to difficult access, it was not possible to obtain data from the beams, so the concrete strength was estimated based on the data from pillar 02, using the equation from the Cristofaro et al. (2020) model. The sclerometry results, the average ultrasonic pulse velocity values and the estimated concrete compressive strength are shown in Table 7. The compressive strength of the concrete for the bridge, based on the readings of column 02, was estimated at 23.21 MPa, which is above the minimum established by the standards of the time, which was 12.5 MPa.

Table 7. NDT data for km 0.91 Bridge.

Point	Sclerometer	Ultrasonic pulse test	Estimated strength
Pillar 02	49,5	3244	23,21

4.3. Latadinha Brook Bridge

The Latadinha brook Bridge, located in Rio Grande do Norte, was built around 1970. It is a bridge with reinforced concrete beams, made up of four spans: two of 12.10 meters and two overhangs of 2.90 meters, for a total length of 30 meters. Its characteristics are typical of

the time, as indicated in the bridge inspection manual: it has a width of 10.1 meters, two guardrails of 90 cm each and two reinforced concrete guardrails over the guardrails.
The bridge's superstructure includes slabs, two beams, two curtain walls near the abutments, and five crossbeams, all made of reinforced concrete. In terms of the mesostructure, unlike the other two bridges from previous decades, it did not have stone masonry abutments, opting instead for two balances at the beginning and end of the infrastructure. Regarding the pillars, the bridge was similar to the 1965 bridge, with pillars on columns and beams bracing the pillars, both in reinforced concrete; however, due to the greater width compared to the previous bridge, this bridge has six pillars and three bracing beams. No support devices were identified. The bridge's infrastructure was not visible to identify the foundation elements. Figure 6 shows a side view of the bridge.

Figure 6. Side view of Latadinha Brook Bridge.

During the visual inspection, several points of corrosion were identified in all the structural elements of the superstructure, especially in the slab, with reinforcements showing great loss of section and apparently some broken. This damage is worrying, as it could cause the slab to lose its resistance capacity, compromising its structural stability and potentially leading to a collapse of the structure.
Due to this damage, the bridge has been classified as condition 1, indicating the need for immediate intervention to guarantee structural safety. Figure 7 highlights the most critical element, slab 2, which shows severe corrosion, significant concrete spalling and large section losses in the reinforcements, possibly with some broken. These problems compromise the integrity of the slab.

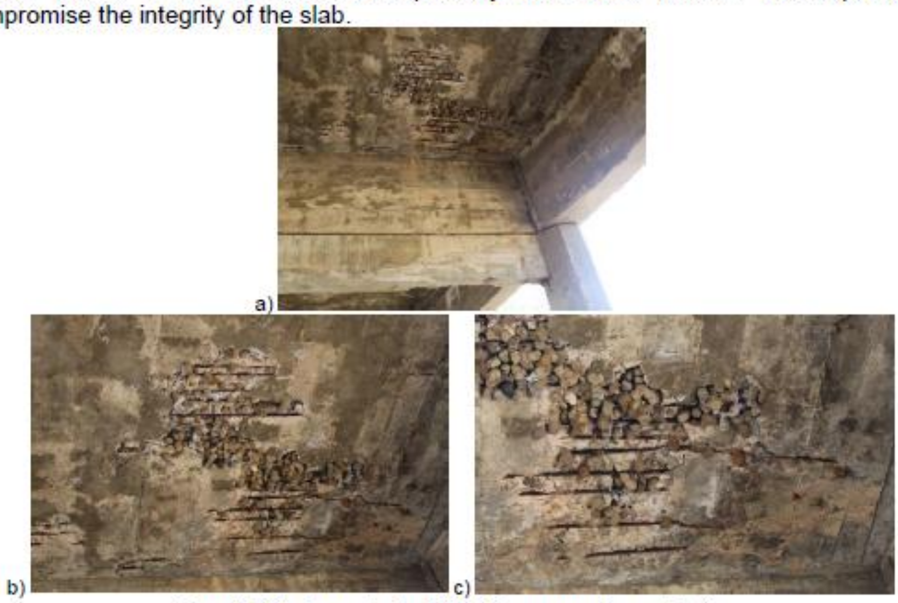

Figure 7. Main damage to the bridge; Severe corrosion on slab 02.

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In non-destructive testing (NDT), sclerometry and ultrasonic pulse tests were carried out on the two bridge beams and two of the six pillars. Due to the ease of access, all the readings were direct, using the Cristofaro et al. (2020) model equation to estimate the concrete strength. The sclerometry results, the average ultrasonic pulse velocity values and the estimated compressive strength of the concrete are shown in Table 8.

Table 8. NDT data for Latadinha Brook Bridge.

Point	Sclerometer	Ultrasonic pulse test	Estimated strength
Beam 01	58	3883,11	32,04
Beam 02	63,15	3941,11	34,19
Pillar 03	56,30	3752,44	30,25
Pillar 05	49,50	3261,89	23,38

The estimated strength results were significantly higher than the minimums established by the standards, but compatible with the type of infrastructure and type of bridge. There was also little variation in the estimated strength of each element, demonstrating a certain regularity in the quality of the concrete.

4.4. Peixe River Bridge

The Peixe River Bridge, located in Paraíba, was built in 1975 in the SGO, but local reports indicate that the current structure was built in 2015, replacing the previous bridge from 1975. This new bridge, made of reinforced concrete beams, has five spans: two of 4.20 meters, two of 16.10 meters and one of 18.70 meters, for a total length of 59.4 meters. Although replaced in 2015, the bridge retains typical 1975 characteristics, with a width of 10.8 meters and two New Jersey barriers.

The bridge's superstructure includes slabs, two beams, two curtain walls near the abutments, and 10 crossbeams, all made of reinforced concrete. The mesostructure was like the 1970 bridge, with columns and beams bracing the columns, both in reinforced concrete. However, due to the greater width compared to the previous bridge, this bridge had eight columns and four bracing beams. No support devices were identified. The bridge's infrastructure was not visible to identify the foundation elements. Figure 8 shows a lower view of the bridge.

Figure 8. Lower view of Peixe River Bridge.

During the visual inspection, some concreting faults and fire spots were observed in the upper part of one of the pillars. However, the most significant damage was the high level of cracking in the two beams due to shear, probably caused by the absence of skin reinforcement, required by the standard for beams with a height greater than 50 cm. Due to this high level of cracking, the bridge was classified as condition 3 and needs to be monitored more closely. Although cracking does not cause immediate structural instability, it can affect the durability of the infrastructure and users' perception of safety. Figure 9 shows one of the beams with high shear cracking, highlighted as the most critical damage on the bridge.

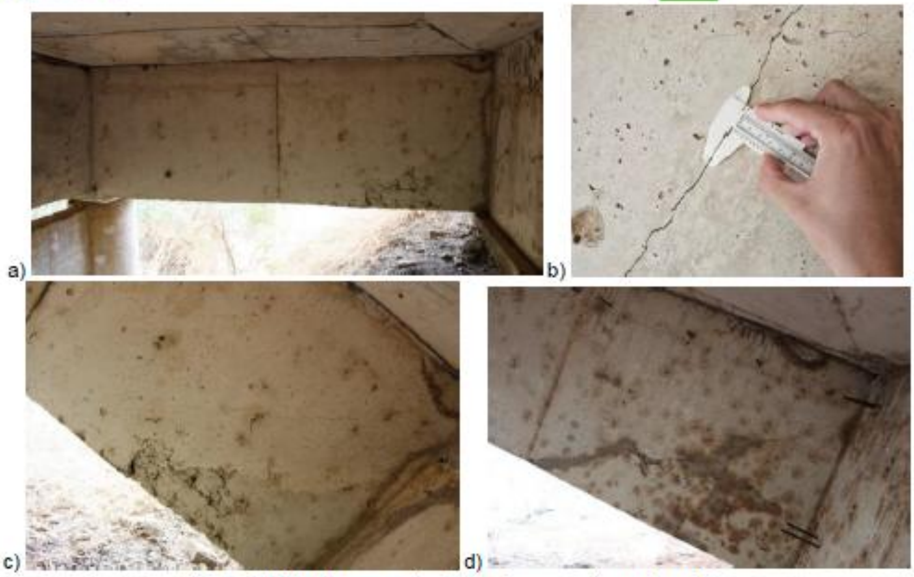

Figure 9. Main damage to the bridge; Severe cracks on beam 02.

Due to the ease of access, non-destructive tests were carried out on all the beams and columns of the structure, with direct readings in all cases, using the Cristofaro et al. (2020) equation to estimate the strength of the concrete. The sclerometry results, the average ultrasonic pulse velocity values and the estimated compressive strength of the concrete are shown in Table 9.

Table 9. NDT data for Peixe River Bridge.

Point	Sclerometer	Ultrasonic pulse test	Estimated strength
Beam 01	31,73	2477,3	10,28
Beam 02	32,14	2133,8	7,06
Pillar 01	53,20	3884,1	30,58
Pillar 02	43,10	4083,6	29,42
Pillar 03	41,80	4032,2	28,52
Pillar 04	54,38	4095,8	33
Pillar 05	51,85	4019,1	31,42
Pillar 06	47,57	4004,1	30,02
Pillar 07	46,92	3876,2	28,57
Pillar 08	53,77	4110	32,96

The estimated concrete compressive strength results for the beams were extremely low due to high shear cracking. This cracking increased the time it took to receive the ultrasonic pulse, demonstrating how non-destructive tests are influenced by damage to the infrastructure. For a more accurate estimate of the compressive strength of the bridge's concrete, only the values of the pillars were used, which showed good regularity and quality, with strengths in line with the normative values.

The visual inspection and non-destructive tests highlight the need for constant monitoring and possible interventions on the Peixe River Bridge. The high level of cracking in the beams requires special attention to ensure the durability of the infrastructure and the safety of users.

4.5. Discussions

After presenting the results, it is clear that, except for the Peixe River Bridge, all the bridges inspected had characteristics consistent with the time they were built. Peixe River Bridge

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deviates from this pattern due to the replacement of the original 1975 structure with a new bridge in 2015, which retained the typical characteristics of the 1975 bridge.
During the visual inspection, all the bridges showed some significant damage to their structural elements. The km 0.91 bridge and the Latadinha Brook bridge were in critical situations, requiring urgent intervention for repair and/or reinforcement. The Zé Dias Brook bridge requires short-term repairs but is in a slightly better condition than the other two most critical bridges. The Peixe River Bridge, on the other hand, although in need of repair, does not present any great urgency and should be monitored constantly with periodic inspections to observe the progress of the damage. Table 10, which accompanies this analysis, shows the state and condition of each bridge, highlighting its most critical elements.

Table 10. Condition state and most critical element of bridges.

Identification	Year Build	Critical element	CS
Zé Dias Brook Bridge	1955	Reinforcement concrete beam 02	2
km 0,91 Bridge	1965	Column in reinforcement concrete 01	1
Latadinha Brook Bridge	1970	Reinforcement concrete slab 02	1
Peixe River Bridge	2015	Reinforcement concrete beam 02	3

Non-destructive testing proved to be an effective tool for estimating concrete strength. Table 11 details the estimated results for each bridge, comparing them with the minimum values defined by the standards of the time. Although all the estimated values were within the normative parameters, it is important to recognize that the results of the non-destructive tests are influenced by the deterioration conditions of the material. This was evident in the results of girder 02 of the Zé Dias Brook bridge and the girders of the Peixe River bridge.

Table 11. Estimated strength and minimum standard strength of bridges.

Identification	Year Build	Beam strengths	Column strengths	Considered strength	Minimum strength according to standard
Zé Dias Brook Bridge	1955	16,12	-	16,12	12,5
km 0,91 Bridge	1965	-	23,21	23,21	11
Latadinha Brook Bridge	1970	33,12	26,81	29,97	11
Peixe River Bridge	2015	8,66	30,56	30,56	25

Although non-destructive tests provide a good indication of the condition of concrete, they should be considered as part of a more comprehensive and detailed analysis. Reconstitution of the original design and analysis in computer models are essential for a complete assessment. Reconstructing the original design allows for a better understanding of the applied loads and original design conditions, while computer analysis can simulate the behavior of the structure under various load conditions, identifying potential failure points.
Another point to consider is that the equations used in non-destructive testing have not been specifically calibrated for bridges in the region, which increases the uncertainty of the results. Local environmental and material characteristics can differ significantly from the parameters used in the model's original calibration, introducing additional variability into the results.
Therefore, although the results of non-destructive tests provide a good indication of the condition of the concrete, they must be complemented by a more detailed analysis. An integrated approach, combining non-destructive testing with detailed structural analysis and design reconstruction, will enable a more accurate and reliable assessment of the structural integrity of bridges. This will ensure appropriate and effective interventions for the maintenance and safety of these structures.

5. Conclusions

This study allows us to draw some important conclusions about the evaluation and maintenance of reinforced concrete bridges. In general, the bridges studied have characteristics typical of the period in which they were built, except for one bridge which, due to the replacement of its original structure, has inherited characteristics of a previous period. The visual inspection revealed any damage to the bridges, allowing them to be categorized in terms of their condition. Two of the bridges were found to be in critical condition, requiring immediate intervention to ensure structural safety. NDT has proven to be a valuable tool in the safety analysis of reinforced concrete bridges. These tests allow material properties and structural quality to be assessed without causing damage to the bridge. However, the results of non-destructive testing are affected by the presence of damage to the reinforced concrete elements, which can affect the accurate estimation of concrete strength. Although NDT provides a good indication of the condition of the concrete, it is essential to consider it as part of a more comprehensive and detailed analysis. Reconstruction of the original design and analysis in computer models should complement the tests to provide a more accurate and reliable assessment of the structural integrity of the bridges. This integrated approach will ensure appropriate and effective interventions, prolonging the life of the structures and ensuring the safety of the users.

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Appendix F - Scientific article accepted on 27 November 2024 in *"REM - International Engineering Journal"*, to be published in the second issue of 2025 in April, ISBN 0370-4467and DOI: http://dx.doi.org/10.1590/0370-44672024780062

Civil Engineering

Algorithm for estimating the construction year of Brazilian bridges between 1950 and 1980

http://dx.doi.org/10.1590/0370-44672024780062

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Abstract

The year of construction is an essential factor in assessing the condition of bridges, as it directly influences the prediction of their deterioration and the analysis of their load-bearing capacity over time. In addition, this data is fundamental for algorithms that deal with missing information, such as that related to design standards. This study proposes and validates an algorithm to estimate the year of construction of Brazilian bridges based on three main characteristics: design vehicle, barrier type and width. The aim of the algorithm is to fill this information gap and provide managers with information to manage these infrastructures. An analysis of 5,000 bridges in the Bridge Management System revealed that 41.7% of them had no record of the year of construction. During validation, the algorithm showed robust performance, achieving a hit rate of 87.82 percent and a mean absolute error (MAE) of 5.20 years. After adjustments, the MAE was reduced to 4.45 years, with accuracy rates of 99.46% (±10 years) and 79.62% (±5 years). In practice, the algorithm successfully estimated the year of construction in 81.87% of cases, with the majority of bridges built in the 1970s (64.16%). These results provide a solid basis for more accurate deterioration predictions and more reliable load capacity assessments, contributing to more efficient and safer bridge management.

Keywords: bridge management; missing data; construction year; algorithm; software.

1. Introduction

The effectiveness of decision-making processes in bridge management relies on the quality of data acquired throughout the stages within the structures' lifecycle. Data assumes a pivotal role in this context. With the rapid evolution of technologies associated with bridge management, inspection, evaluation, and analysis - particularly those aligned with computer processing and artificial intelligence - society has transitioned into the epoch of big data and intelligence. This transition has given rise to personalized, scientific, and intelligent services grounded in the framework of “data, information, knowledge, and wisdom” (Rowley, 2007). It is propelled by the vast amounts of data recognized as a domain of significant growth and relevance (Yang *et al*., 2022).

Jadhav *et al*. (2019) point out that missing data is a common challenge faced by researchers and data scientists. Invariably, missing data must be identified, cleaned and processed as a step for adequately applying statistical and data-driven approaches in managing bridges based on machine learning, for example (Sabellano; Bandpey; Shokouhian, 2023; Sein; Matos; Idnurm, 2017). Recently, there has been a push to deal more effectively with this problem. One approach is the suggestion of a simple step-by-step method to help identify missing data patterns (Madden *et al*., 2018). This method aims to make it easier for researchers and data scientists to handle missing data systematically.

In the realm of bridge studies, a significant concern revolves around inconsistent and missing data, particularly regarding the lack of structural health monitoring data. This absence is often attributed to equipment malfunctions or human errors during data collection (Chen *et al*., 2019; Gao *et al*., 2022; Li *et al*., 2021; Niu; Li; Li, 2022; Xu, 2023). In this context, some algorithms have been proposed and reported in literature (Sun *et al*., 2023).

The year of construction is a key factor in assessing a bridge's condition. It is not only valuable for evaluating its state but also serves as input for algorithms that handle missing data, such as those related to the design code used. This information is particularly important for predicting the bridge's load-carrying capacity, as proposed by Spinel *et al*. (Spinel *et al*., 2022).

Regarding the scarcity of data on construction years, there is limited literature available. Notably, Sovisoth *et al*. (2023) conducted a study where they successfully estimated the construction years of bridges in Cambodia using satellite data. In their research, they chose three pixels from satellite images: one positioned directly at the bridge's location and two others situated on similar terrain at a predetermined distance perpendicular to the bridge axis. Through the analysis of these images over time and by comparing pixel values, they managed to accurately estimate the construction years.

In the Brazilian context, there is a significant lack of data on federally managed bridges, with few inspection records, lack of construction projects, design vehicles, dimensions, and material properties, among other information. An extremely important missing piece of data on bridges is their construction year, since this information makes it possible to perform project reconstructions, durability analyses, historical records, mobile load analyses, create deterioration prediction models, and refine searches for other relevant information.

To address the gap in recording construction years, this study examined 5,000 bridges from the Brazilian Bridge Management System (Sistema de Gestão de Obras de Arte – SGO) (Silva *et al*., 2021). It found that 58.30% of these bridges had their construction years documented, while 41.70% did not. To fill this information gap, the study suggests an algorithm to estimate the construction year of bridges built between 1950 and 1980. This period was chosen due to significant changes in bridge characteristics during this time. Moreover, 53.44% of bridges with documented construction years were built within this timeframe. Most of these bridges date back to the 1970s, with an average construction year of 1973. Finally, the article describes the computational implementation (named YearBuild) and the validation by applying the algorithm to a sample of bridges obtained from the Brazilian Bridge Management System.

2. Background

The road bridge inspection manual (DNIT, 2004), published by DNIT, was conceived with two primary objectives: provide training to engineers and professionals in conducting bridge inspections, and to establish standardized procedures and practices within the field. In the scope of this study, discussed in the next sections are the characteristics of bridges across different historical periods that were examined as outlined in this manual.

2.1 Bridges constructed between 1950 and 1960

Bridges constructed between 1950 and 1960 typically feature a total width of 8.3 meters, with the roadway spanning 7.2 meters. Additionally, these bridges were equipped with two guardrails, each measuring 0.55 meters in width, as well as two railings, each measuring 0.15 meters in width and standing at a height of 0.6 meters, as shown in Figure 1. The guardrail described in the SGO is known as the “old DNER guardrail” (DNER is the acronym for the former National Department of Highways, Departamento Nacional de Estradas de Rodagem), which was responsible for bridges during that period but has since been replaced by DNIT. Figure 2 depicts a bridge featuring this type of barrier used between 1950 and 1960. The live load utilized for designing bridges during that era comprised a 24-tonne force (tf) compressor, a 12 tf truck for each lane (excluding the lane with the compressor), and a variable crowd load based on the segment and theoretical span, typically set at 500 kilograms force per square meter (kgf/m^2). This combination of loads is designated as a design vehicle, referred to as Class 24, illustrated in Figure 3.

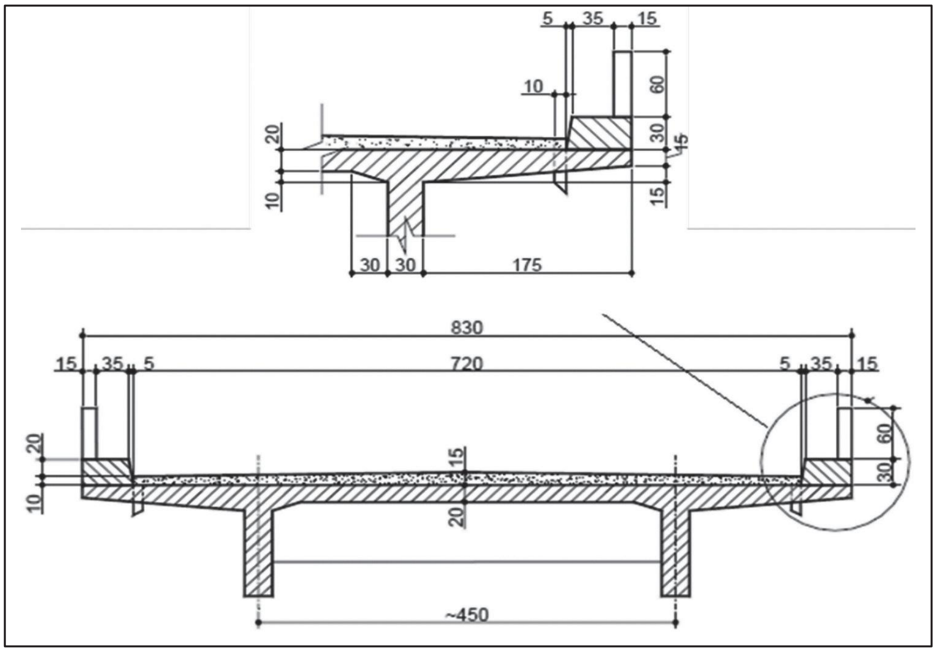

Figure 1 - Bridge typology for those built between 1950 and 1960 (DNIT, 2004).

Figure 2 - Example of the type of barrier used on bridges constructed between 1950 and 1960.

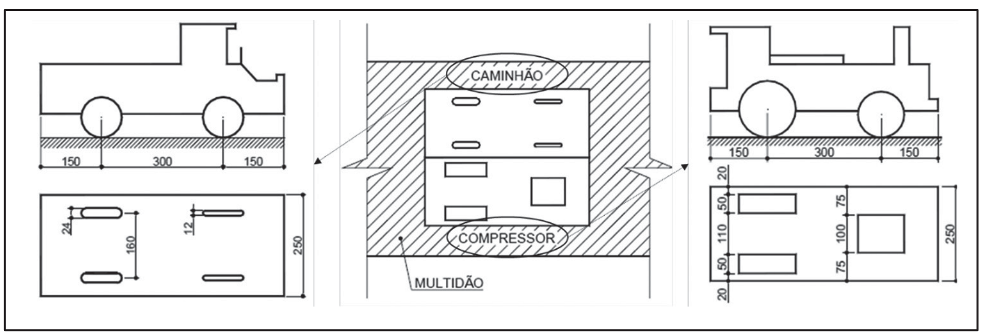

Figure 3 - Class 24 design Vehicle (DNIT, 2004).
Caption: "Caminhão" = Truck; "Compressor" = Compressor; "Multidão" =Crowd

2.2 Bridges constructed between 1960 and 1975

Bridges built between 1960 and 1975 typically have a total width of 10.00 meters, with a roadway width of 8.20 meters. Additionally, they were equipped with two guardrails, each 0.90 meters wide, and two railings, each measuring 0.15 meters wide and 0.90 meters high, as depicted in Figure 4. The guardrail specified in this period is also referred in the SGO as the "old DNER guardrail", or simply as any guardrail. Figure 5 illustrates a bridge with this type of barrier in use between 1960 and 1975. The live loads utilized for designing bridges during that period comprised a 36 tf vehicle and a distributed load of 500 kgf/m^2 on the roadway, along with 300 kgf/m^2 on the sidewalks. This combination of loads is designated as a design vehicle, referred to as Class 36, illustrated in Figure 6.

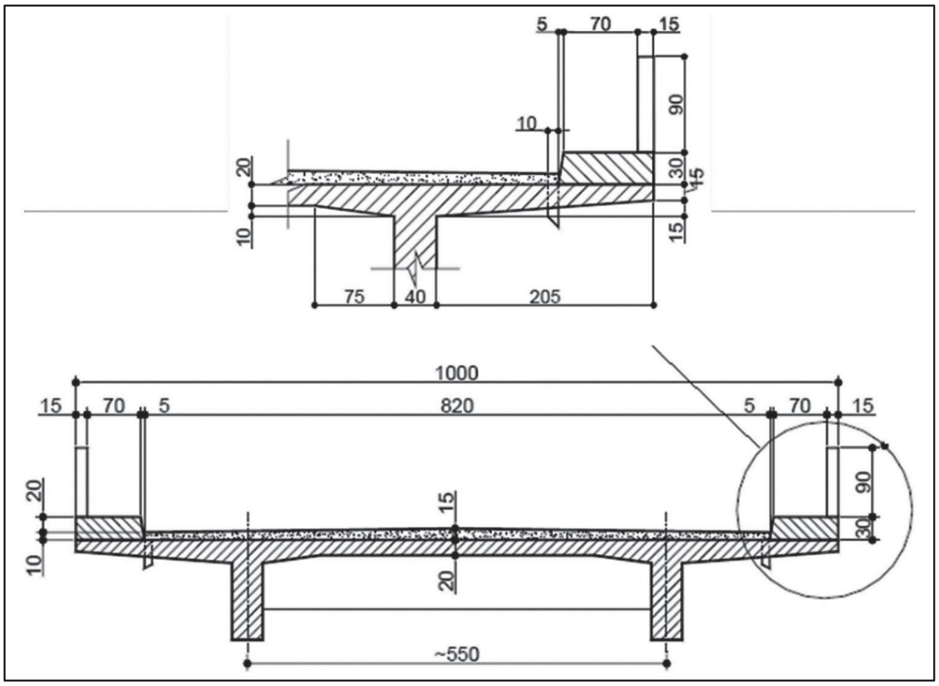

Figure 4 - Bridge typology for those built between 1960 and 1975 (DNIT, 2004).

Figure 5 - Example of the type of barrier used on bridges constructed between 1960 and 1975.

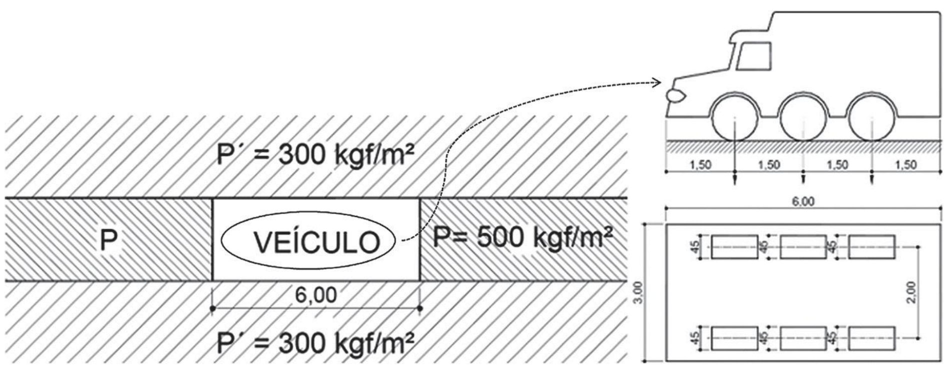

Figure 6 - Class 36 design Vehicle (DNIT, 2004).
Caption: "Veículo" = Vehicle

Bridges constructed between 1975 and 1985 typically feature a total width exceeding 10.80 meters, with a roadway width of over 10 meters. During this period, there was a shift in the configuration of the protection barriers, with reinforced concrete guardrails being replaced by two New Jersey barriers, as depicted in Figure 7 The New Jersey barrier remains a standard feature in bridge design today (Figure 8). The live loads used to design the bridges in this period were the same as those used for the bridges built between 1960 and 1975.

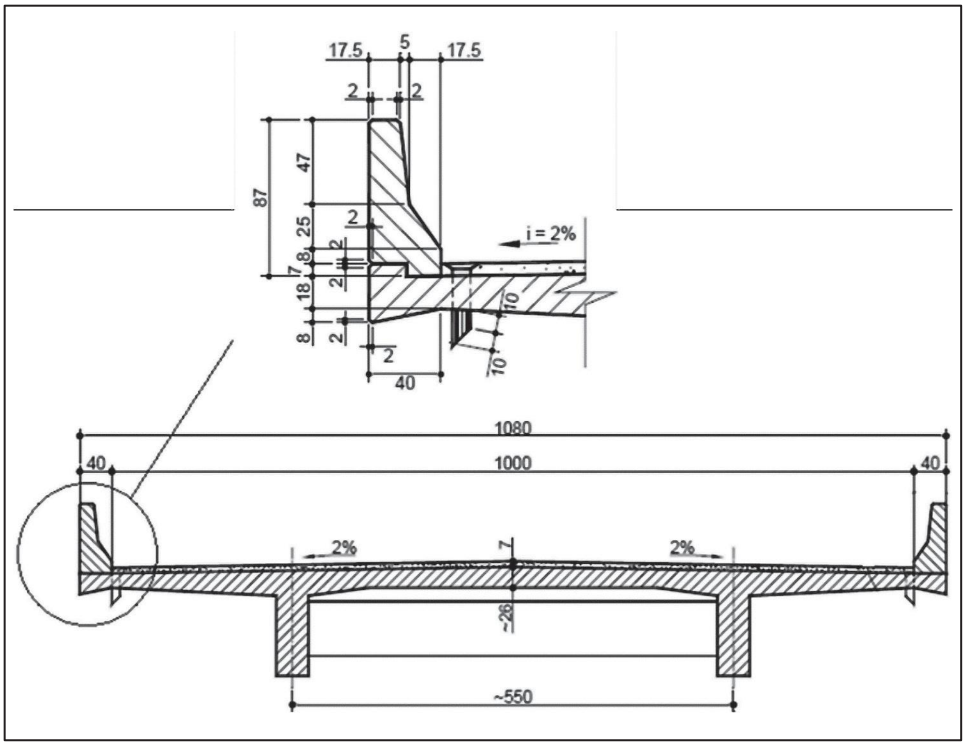

Figure 7 - Bridge typology for those built between 1975 and 1985 (DNIT, 2004).

Figure 8 - New Jersey Barrier.

2.3 Bridges constructed after 1985

Bridges constructed after 1985 typically have a total width of 12.80 meters, with a roadway width of 12 meters. The type of barrier adopted continued to be the use of two New Jersey barriers, as illustrated in Figure 9. The live loads utilized for designing bridges after 1985 followed the same typology as those for bridges built with the Class 36 design vehicle. The only modification was the vehicle load, which was increased from 36 tf to 45 tf, resulting in the design vehicle being renamed Class 45.

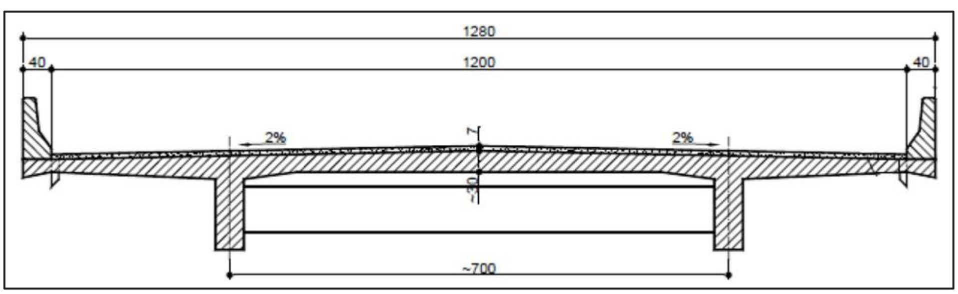

Figure 9 - Bridge typology for those built after 1985 (DNIT, 2004).

3. Method

The authors concentrated on three primary characteristics that are distinct and easily accessible: the design vehicle, the type of barrier, and the total width of the bridge. The chosen scope of the algorithm extends from 1950 to 1980, encompassing most Brazilian bridges and marked by notable changes in construction practices over time. Post-1985, bridges experienced fewer design modifications, making it more difficult to precisely ascertain the construction year.

The design vehicle was classified into four distinct categories:

- Class 24: Bridges constructed up to 1960, defining the range of the algorithm's estimates to the period between 1950 and 1960.
- Class 36: Bridges constructed between 1960 and 1985, limiting the estimates to the period between 1960 and 1980.
- Class 45: Bridges constructed after 1985, requiring the input of the construction year by the user, as it falls outside the defined scope.
- Not specified: Bridges lacking a specific classification, that must be analyzed based on other parameters.

The type of barrier was divided into four groups:

- Reinforced concrete railings and old DNER guardrail: Bridges built between 1950 and 1960.
- Reinforced concrete railings and/or any guardrail: Bridges built between 1960 and 1975.
- New Jersey barrier: Used on bridges built after 1975.
- Other: Bridges featuring barrier types not mentioned previously; these bridges are assessed in the same manner as those with reinforced concrete railings and any guardrail due to their broader coverage.

The width of the bridge was utilized to further refine the estimation of the construction year, adjusting according to the bridge's characteristics and adhering to the widths specified in the Road Bridge Inspection Manual.

The algorithm developed to estimate the year of bridge construction uses a structured decision tree to identify the likely construction period based on combinations of previously identified parameters. Figure 10 illustrates all potential pathways within the decision tree of the algorithm. In this figure, the year was adjusted in five-year intervals based on the specific characteristics of each bridge.

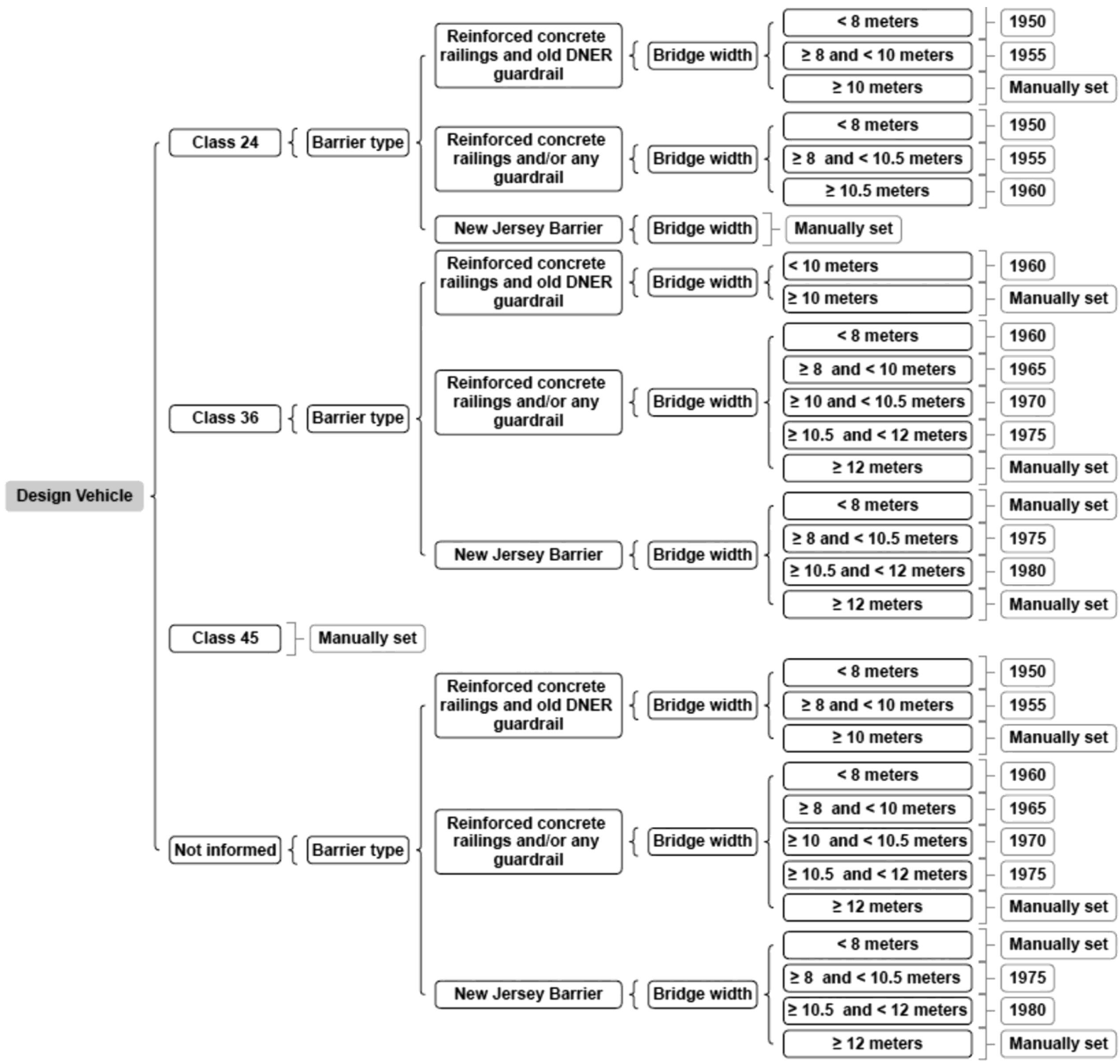

Figure 10 - Algorithm decision tree.

For Class 24 bridges, the use of reinforced concrete railings and guardrails indicates construction between 1950 and 1960, while the use of old DNER reinforced concrete railings and guardrails indicates construction between 1950 and 1955. For each combination of barrier type and width, the algorithm assigns a specific range of years, providing a more accurate construction estimate.

If the design vehicle is Class 24 and the barrier is of the New Jersey type, the algorithm prompts the user to specify the year of construction due to inconsistencies in the data, such as incorrect or incomplete information or changes in bridge characteristics over time. In this case, bridges classified as Class 24 should not normally have New Jersey barriers, since Class 24 was used until 1960, while the New Jersey barrier was introduced after 1975.

For Class 36, the process is similar, but the construction year estimates start in 1960 and go through 1980. This differentiation reflects changes in design specifications, as the Class 36 vehicle design was used from 1960 onwards. In these cases, the New Jersey barrier is already in the appropriate service life range.

For Class 45 bridges, the year of construction must be specified by the user because the design vehicle used was adopted after 1985, which is outside the scope of the study. This is due to the lack of clear correlations between the characteristics adopted, since after 1985 all the bridges had the same vehicle design, the same type of barrier (New Jersey) and the same width (12.80 m).

Finally, for bridges whose Design Vehicle Class has not been provided, the algorithm applies the same criteria as for Class 24, but requires he user's intervention in some cases, especially when the width and type of barrier do not follow traditional standards.

In addition, the width of the bridge caused difficulties in some situations. When the width was incompatible with other characteristics analyzed or outside the parameters defined by the algorithm, user intervention was required to check and adjust this data, ensuring a more aligned and coherent analysis with the actual conditions of the bridge.

The algorithm is efficient in estimating the approximate years of construction for most bridges, but in some cases an estimate is not possible due to inconsistencies in the data, modifications to the original structure (which may have changed the type of barrier or other characteristics), or bridges outside the scope of the algorithm. When an estimate is not possible, users must find other ways to obtain this information, such as consulting historical records, obtaining reports from local residents, or analyzing specific characteristics of the bridge.

The computer implementation utilized the Python language within the Visual Studio Code development environment. After creating and implementing the algorithm, the next step was to apply it to real bridges. For this purpose, data was selected and collected from 1003 SGO bridges. Among these, 468 bridges had a known construction year and were used to validate the algorithm's prediction range, while the remaining 535 bridges lacked this information and were used for application purposes. The selected bridges are part of a database for a more complete study, involving several research fronts.

When the algorithm was applied to bridges with a known construction year, the initial metrics were evaluated, followed by the identification of the largest errors and inconsistencies. Bridges with data inconsistencies were then removed, and the final metrics were calculated. Finally, all results and data were thoroughly analyzed. Figure 11 simplifies the process of validating and applying the algorithm, providing a clear and concise visualization of the procedure performed.

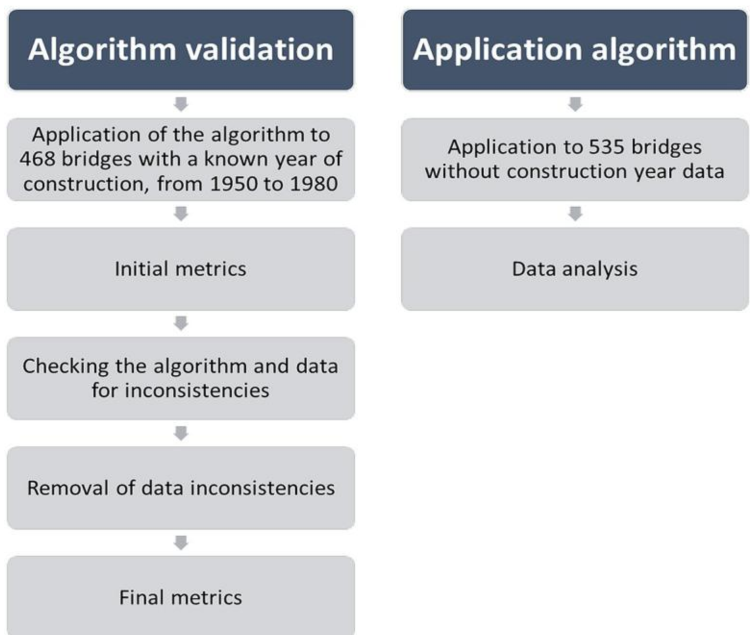

Figure 11 - Validation process and application of the algorithm.

4. Results

The results and discussions have been divided into two distinct groups. The first part deals with the validation study, while the second part deals with the application study. Each of these groups will be detailed in the following topics. At the end of this section, a brief description of the computational tool implemented as a result of this study is presented and discussed.

4.1 Validation

The algorithm was applied to a set of 468 bridges constructed between 1950 and 1980, for which the construction year was known. The algorithm successfully estimated the construction year 87.82% of cases. In 12.18% of cases, the algorithm's decision tree indicated the need for setting the construction year by the user due to inconsistencies in the data.

Out of the 57 bridges, where estimating the construction year was challenging, six exhibited inconsistent feature combinations. For example, some bridges featured the Class 24 design vehicle along with the New Jersey barrier, which contradicted the typical construction periods associated with these vehicle types and barriers. Specifically, the Class 24 design vehicle was phased out by 1960, while the New Jersey barrier was introduced after 1975. Additionally, one bridge had the Class 45 design vehicle, which doesn't align with the study's chosen timeframe, since bridges with this train type were typically built after 1985. The remaining bridges had widths that didn't correspond with other characteristics or the known construction period, either due to later widening or data inaccuracies. In these instances, the algorithm prompted users to manually specify the construction year.

Among the 411 bridges that the algorithm estimated the year of construction, statistical metrics were examined to evaluate the model's performance. Table 1 presents these metrics, with a mean absolute error (MAE) of 5.20 years, indicating that, on average, the algorithm's estimates deviated by ±5.20 years. Given that the estimated year of construction varied every five years, this result is considered satisfactory. While the coefficient of determination (R^2) is not close to 1, this was expected due to the discrete estimation in five-year intervals, potentially reducing this metric. Lastly, the root mean square error (RMSE) penalizes extreme errors more than smaller ones. The RMSE result of 6.42 suggests that the algorithm didn't make significant errors, which is a positive outcome for the study.

Table 1 - Initial metrics (author).

Me· ics	
Coefficient of determination (R²)	0.48
Mean absolute error (MAE)	5.20
Root Mean Square Error (RMSE)	6.42

Another approach to analyzing the model is by assessing its accuracy within acceptable margins of error. Figure 12 presents the analysis of three different scenarios: the accuracy rate within a ten-year margin of error, the accuracy rate within a five-year margin of error, and finally, the exact accuracy of the algorithm.

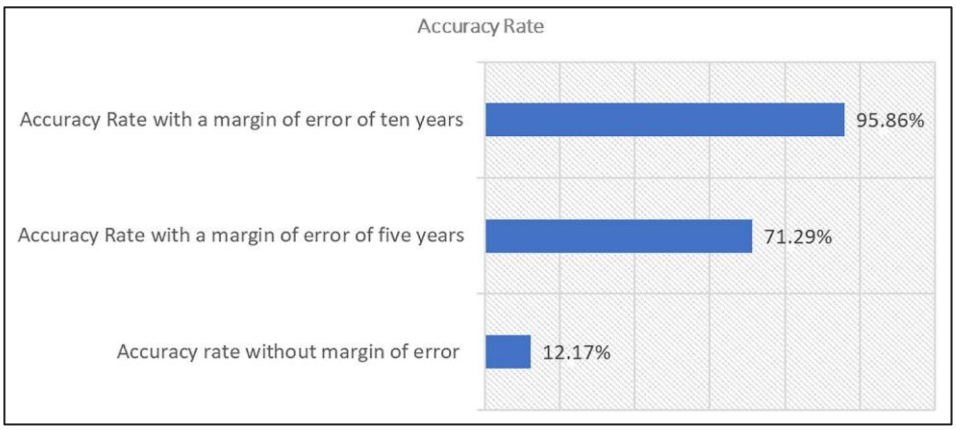

Figure 12 - Accuracy rate.

An accuracy rate of 95.86% with a 10-year margin of error aligns with what was observed in the RMSE, indicating that the model had few significant errors, with only 4.86% of cases having errors greater than 10 years. The five-year margin of error is particularly relevant in assessing the model's quality, considering that the estimated year varied every five years. In this case, the model achieved an accuracy rate of 71.29%, which is considered positive, given the challenge of estimating the construction year and the potential for inconsistencies in the SGO data.

To explore the algorithm's limitations further, bridges with discrepancies of more than five years were meticulously analyzed, one by one, to discern whether inconsistencies arose from the algorithm, or the data sourced from the SGO. The analysis revealed that in 63.56% of cases, errors exceeding five years stemmed from algorithmic inconsistencies. These errors were not due to inaccuracies but rather to an observed gap: bridges featuring a Class 36 design vehicle, reinforced concrete railings, any guardrail, and approximately 10 meters in width could have been constructed within a timeframe spanning up to 15 years, from 1960 to 1975, resulting in errors surpassing five years. In contrast, inconsistencies were detected in the data in 36.44% of the cases, suggesting that certain information did not align with the bridge's actual year of construction. Among these cases, 62.79% of the inconsistencies were related to width, 25.58% to barrier type, and 11.63% to design vehicle information.

Analysis of the bridges revealed that in 18.60% of the cases, discrepancies stemmed from incorrect data in the SGO. For example, three Class 24 bridges built before 1960 were listed with a construction date of 1968 or later in the SGO. In two other instances, bridges with reinforced concrete guardrails and old DNER railing barriers, typically built up to 1960, were recorded in the SGO as having been constructed in 1966 and 1978. Additionally, two bridges were indicated in the SGO as built in 1980 but lacked a New Jersey barrier installed by 1975, contrary to the expected type for the reported year of construction. Analysis of photos in the bridge report confirmed that the bridge typology was inconsistent with the recorded construction year.

In 37.21% of the cases, data inconsistencies were attributed to bridge rehabilitations, such as widening or changing the type of barrier. In 44.19% of the cases, it was not possible to confirm whether the inconsistency was due to rehabilitation or if the data in the SGO was incorrect.

Excluding the bridges where the error was related to data inconsistency led to an improvement in the statistical metrics, as demonstrated in Table 2. Specifically, there was an increase in the coefficient of determination (R^2) and a decrease in both the mean absolute error (MAE) and the root mean square error (RMSE).

Table 2 - Final metrics (author).

Metrics	
Coefficient of determination (R²)	0.61
Mean absolute error (MAE)	4.45
Root Mean Square Error (RMSE)	5.37

A mean absolute error (MAE) of less than 5 and a root mean square error (RMSE) close to 5 validate the efficiency of the algorithm in achieving its objectives, as these values align with the variation between the estimated years occurring every 5 years. Evaluating accuracy with margins of error of 10 years, 5 years, and exact hits reveals an increase in all hit rates. Nearly 100% accuracy with a 10-year margin of error suggests that, on average, the maximum error of the model is 10 years. There was an approximately 8% increase in accuracy with a 5-year margin of error and just over a 1% increase in exact hits, as illustrated in Figure 13.

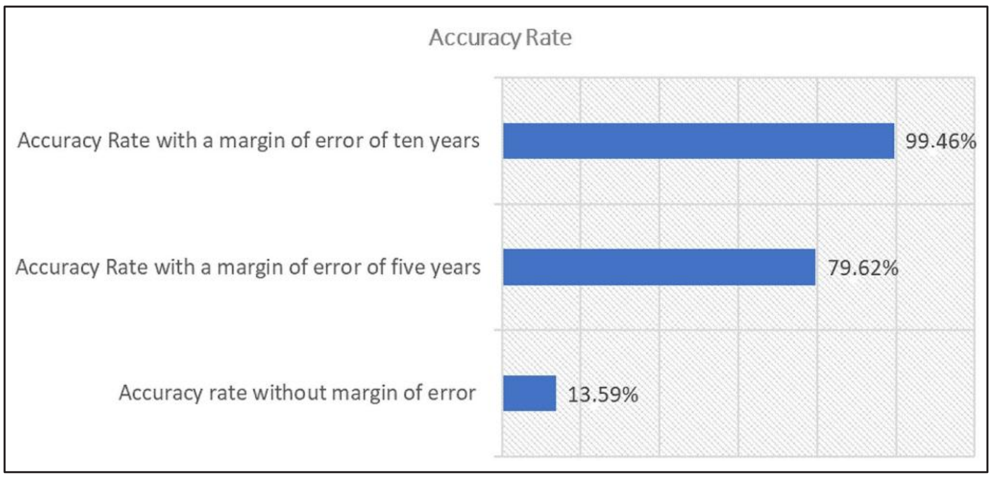

Figure 13 - Accuracy rate final.

4.2 Real-world application test

After validating the algorithm and obtaining satisfactory results, it was applied to a set of 535 bridges without information on the construction year. In 18.13% of the cases, estimating the construction year wasn't feasible, either due to data inconsistencies or because the bridges fell outside the period covered by the algorithm. This figure is slightly lower than the number of bridges estimated during validation. While the algorithm successfully estimated the year of construction in 87.82% of the cases during

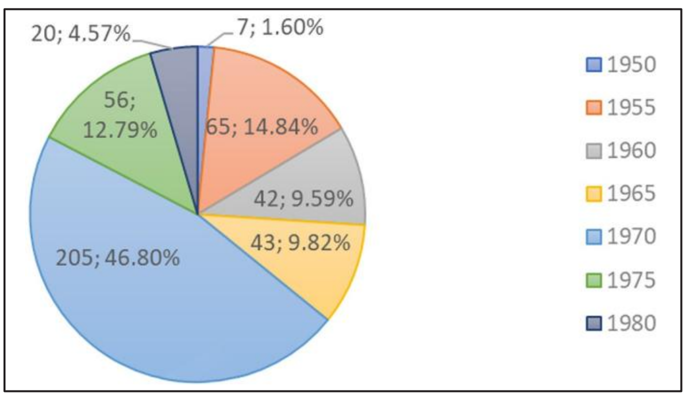

Figure 14 - Proportion of the estimated construction years obtained in the application test.

validation, this figure dropped to 81.87% in the application phase. This decrease can be attributed to the inclusion of bridges from other eras in the application phase, which are outside the scope of the algorithm.

Examining the estimated construction years, it was observed that most bridges are from the 1970s, as illustrated in Figure 14, with an average construction year of 1970. These findings align closely with the analysis conducted on 2758 SGO bridges with known construction years falling within the range of 1950-1980, where the average construction year was determined to be 1973.

4.3 Computational tool

The computer implementation was carried out in two main stages: the programming of the code in Python that would constitute the computational core of the software and the development of an interface that would allow any user to estimate the year of construction of the bridge by entering its characteristics.

During the first stage, the code was prepared, tested, and executed in the VisualStudio Code environment. It used both native Python operations and the Pandas library, the latter being responsible for reading the data from Excel. The code was then applied to all the bridges in the dataset. Finally, a function was developed to export the results in Excel format, including the estimated years of construction for all the bridges.

The second phase focused on developing the software interface using the native Python library called Tkinter. In the initial window of the interface, users can select the characteristics of the bridge for which they want to estimate the year of construction, such as the design vehicle, the type of barrier, and the width of the bridge in meters. To help the user, information buttons ("i") have been included to answer questions about the available design vehicle and barrier types. Figure 15 shows the initial window with the data already filled in.

Figure 15 - YearBuild interface.

After filling in the information and pressing the button to estimate the year of construction, two possible result windows may appear. One will display the estimated year of construction, as shown in Figure 16, with a margin of error of five years, according to the average absolute error observed during validation. The other window will display a message indicating that the algorithm was unable to estimate the year of construction due to inconsistencies in the data or construction after 1980 and will instruct the user to manually verify the year of construction. Figure 17 shows an example of this message.

Figure 16 - YearBuild interface with estimated year.

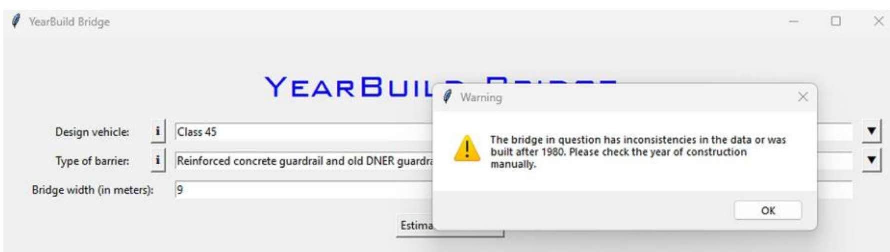

Figure 17 - YearBuild interface with a warning to set manually.

Finally, the YearBuild software has been registered with the National Institute of Intellectual Property (“*Instituto Nacional de Propriedade Intelectual – INPI*”) under registration number “BR512024002078-0” with a creation date of 08/04/2024 and issued on 25/06/2024.

5. Discussion

Despite its critical importance for formulating maintenance plans, estimating budgets, and predicting the soundness of such assets (Sovisoth *et al.*, 2023), recent studies focused on estimating the construction year of bridges are scarce in literature. While this might not seem to be a major issue in developed countries, it appears to be significant in developing countries, impacting the development and effectiveness of governmental administration procedures for infrastructure assets.

In this context, the establishment of the Brazilian DNIT BIM nucleus, spurred by the Brazilian presidency's Act 10306 mandating the use of BIM methodology in public administration construction projects, along with other initiatives, is paving the way for the creation of a new BMS (Bridge Management System) that can adapt to a BIM-based system and incorporate other technologies (Martins *et al.*, 2024). Such initiatives are putting pressure on improving the quality of available data to enable the development of more complex and robust tools for enhancing the decision-making process through statistical and other data-driven approaches.

Another important aspect of the proposed algorithm is its robustness in estimating data. A comparison with another method for estimating the year bridges were built, such as that used by Sovisoth *et al.*, shows greater applicability and accuracy. The Sovisoth *et al.* method requires both satellite data and an advanced understanding of the use of these images. In contrast, the current algorithm can estimate the year of construction using only the basic characteristics of the bridge. In addition, it is more accurate, with a coefficient of determination of 0.61, compared to the range of 0.3149 to 0.4095 of the Sovisoth *et al.* method.

6. Conclusion

This research underscores the critical importance of data in the efficient management of bridges and emphasizes the need to address data deficiencies, particularly concerning the construction years of bridges in the Brazilian context. The conducted analysis revealed a gap in construction year records for a significant portion of bridges under federal government jurisdiction, and the importance of developing innovative solutions to fill this gap. The main finds are listed as follows.

- An algorithm has been proposed, computationally implemented, validated, and applied for estimating the construction year of Brazilian reinforced concrete bridges constructed between 1960 and 1980, which lack such information.
- In the validation test, the algorithm successfully estimated the construction year in 87.82% of cases. When excluding data inconsistencies, the observed R^2 was 0.6, with a mean absolute error of 4.45 years, falling below the 5-year minimal interval set.
- The primary causes of identified failure regarding the data were a combination of features that didn't adhere to the design code of a particular era, often due to interventions over time or inaccuracies in the database. Notably, inconsistencies in the width of the bridge were the most significant, followed by discrepancies in information regarding the barrier type and design vehicle.
- In the real-world application test on bridges from the SGO database lacking the construction year information, the algorithm successfully estimated this data for 81.87% of cases. Notably, due to the impossibility of filtering the time interval between 1950-1980, the results showed a slightly inferior performance compared to the validation test.

The proposed algorithm, designed to estimate the construction years of bridges built between 1950 and 1980, is a valuable tool for addressing data deficiencies with sufficient accuracy. It enables the handling of missing data issues, permitting the application of statistical and other data-driven approaches in the management of Brazilian bridges. Demonstrating adequate accuracy and reliability, the algorithm provides a viable solution for estimating construction years for bridges lacking such data.

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