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Review article

Bridge management systems: A review on current practice in a digitizing world

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ABSTRACT

Bridges are subject to a plethora of deterioration phenomena, such as corrosion, fatigue, and damaging events (e.g., truck impacts and earthquakes) that can affect their performance and compromise functionality and safety. These challenges, along with the expansion of physical infrastructures and limited economic resources, underscore the need for effective management systems to enhance the efficiency of maintenance activities. To address this need, bridge operators have developed Bridge Management Systems (BMSs), which assist in ensuring safe operations while optimizing budget allocation and intervention strategies. Existing state-of-the-art studies on BMSs, dating back several years, primarily focus on specific aspects of BMSs and do not provide exhaustive insight into the implemented processes. Consequently, a comprehensive analysis of the entire process is currently lacking. This review organizes and discusses the key features of existing BMSs and introduces a novel definition of BMS modules—data management, diagnosis, prognosis, and decision-making—where consensus is currently lacking. The paper covers the historical and current practices of the most common BMSs, outlining the main principles of each phase along with their critical aspects and future trends.

1. Introduction

The rapid expansion of transportation infrastructure and the continuous advancements in technology have significantly transformed the landscape of bridge management [1]. As transportation networks grow more complex and the volume of collected data generated increases, there is a heightened demand for automated systems that can effectively manage and utilize this information for optimal bridge maintenance and decision-making [2,3].

Nevertheless, effective bridge management goes beyond addressing immediate maintenance needs; it also encompasses ensuring the long-term safety and cost-effectiveness of these critical assets [4]. Consequently, authorities and infrastructure managers are increasingly focused on developing and implementing policies that promote the sustainable operation of bridges throughout their entire life-cycle - from initial design to eventual replacement [5].

In response to these demands, Bridge Management Systems (BMSs) have been developed in the last decades. A BMS can encompass a compilation of codes and guidelines, as well as a specific software program. Typically, BMSs incorporate both elements, with the software serving as a digital implementation of the standards established over the years. BMSs can be utilized at two distinct levels: the individual bridge level and the network level. [6]. Recently, thanks to the developments in Information Technology (IT), BMSs benefit from information systems such as Bridge Information Modelling (BrIM) and Digital Twins [7,8]. All these aspects facilitate bridge management in a digitalizing world while meeting quality and performance standards [9].

Nevertheless, developing a custom BMS is a long-term commitment that involves the most advanced informatics skills, and high costs in terms of time, resources, and funds, both for initial development and subsequent maintenance due to the need for continuous and periodic updates.

This paper provides an updated and complete overview of the current state of the art of BMSs, with the fundamental goal of reviewing

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current procedures and identifying areas of further research and improvements. As discussed in the following section, despite the importance of the topic, the majority of state-of-the-art studies on BMSs are dated between 2000 and 2014. Post-2014, documents have predominantly focused on specific aspects of BMSs, often targeting a limited cluster of countries. In this work, the available literature, including state-of-the-art studies on this topic, is analyzed and the history and current practice of BMSs are presented. Despite considerable advancements in the field, there remains a lack of consensus on a standardized definition for these modules. Thus, based on a comprehensive review of the literature and the analysis of practices from numerous countries, this study proposes a novel definition for the modules of BMSs. The main techniques used in BMSs for data collection, acquisition, transmission, and storage are discussed. The current practices for condition assessment within a BMS framework are analyzed. The paper also identifies and analyses the principal deterioration models as well as decision ort tools adopted in existing BMSs. The procedures of very few infrastructure operators are publicly reported due to copyright reasons as well as the confidentiality of budget management. One such operator is the Autonomous Province of Trento with the BMS APTBMS, whose documents have been thoroughly analyzed in this paper as an illustrative example. Future trends in BMSs are discussed, followed by general conclusions that summarize the study's findings.

2. BMSs in the current literature

While the topic of BMS is recognized as an important aspect of bridge management, there is a notable scarcity of comprehensive studies dedicated to BMSs. However, there are a few noteworthy exceptions that merit discussion.

At the beginning of 2000, the European project "Bridge Management Europe" (BRIME) undertook the development of an overarching framework for an ideal BMS tailored to the European road network. This envisioned BMS aimed to facilitate rational bridge stock management, optimizing budgets while ensuring adequate structural performance. The final report [10] focused on a sample of 10 BMSs and identified six key modules. McGee et al. [11] conducted an analysis of 11 BMSs from various locations worldwide and compared them with BMSs in Australia and New Zealand. In addition to outlining the architecture of the reviewed BMSs, the study offers insights into the two fundamental approaches that govern bridge management: the top-down and bottom-up approaches. Furthermore, the report highlights potential future directions for BMS development, addressing emerging challenges and offering recommendations for advancements in the field. The International Association for Bridge Maintenance and Safety (IABMAS) compiled a comprehensive report on BMSs in 2008, gathering information from BMSs worldwide. Subsequently, the report was updated in 2010, 2012, and 2014 to ensure its relevance and incorporate new developments in the field of bridge management. The most recent version of the report [12] gathers data from 25 BMSs in 18 countries through questionnaires. The report provides an overview of global practices in BMSs, offering insights into their design, functionalities, and implementation approaches.

To the best of the authors' knowledge, no comprehensive state-of-the-art review on BMSs has been published in the past decade.

Nevertheless, numerous papers address specific aspects of BMSs. In December 2023, a preliminary literature review was carried out using the Scopus database using the keyword "Bridge Management Systems", which produced 844 results. Fig. 1 reports the number of publications on the topic per year.

The first publications in the field date back to 1985 and the scientific interest in the topic has had an increasing trend over the years with a significant peak in 2006, due to the large number of papers on BMS published in [13].

A "network visualization diagram" is created through VOSviewer software to highlight the most common keywords associated with BMSs, see Fig. 2. The different colors suggest the clusters of the words that are reported together in the analyzed documents. The concepts of "maintenance", "inspection", "deterioration", "life-cycle costs" and "optimization" are often studied in relation to BMSs. However, they are not generally integrated. These aspects are analyzed in the following sections.

3. BMSs in the world: history and current practice

The development of BMSs was initially fostered by tragedies such as the collapse of the Silver Bridge on December 15th, 1967, in the US. According to the authors' knowledge, the first developed BMS software is the Danish DANBRO BMS which was released in 1975 to support and implement the increasingly comprehensive and restrictive management regulations. Later, the BMS DISK was developed in the Netherlands in 1985, and it is still used along with the TISBO Infrastructure Maintenance Management System, a BMS that integrates inspection registration and maintenance management. In 1985, Serbia introduced a BMS, called BPM, with a system of prioritization that is still used nowadays [14]. Italy started using Oracle and SQL Server in 1986. Nowadays, in Italy, several BMSs exist, among which the Autonomous Province of Trento BMS (APTBMS) was developed in 2004 by Zonta et al. [15]. This BMS introduces reliability concepts for bridge management and includes sections for condition state evaluation based on visual inspections, safety assessment, and prioritization. Several Italian infrastructure operators are currently working on their own BMS, such as Autostrade per

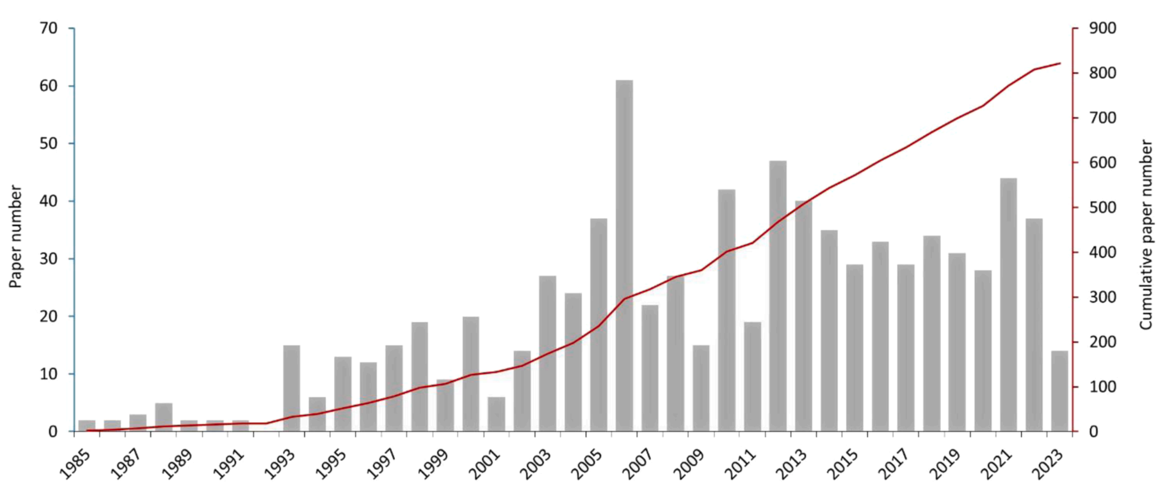

Fig. 1. Publications on BMSs.

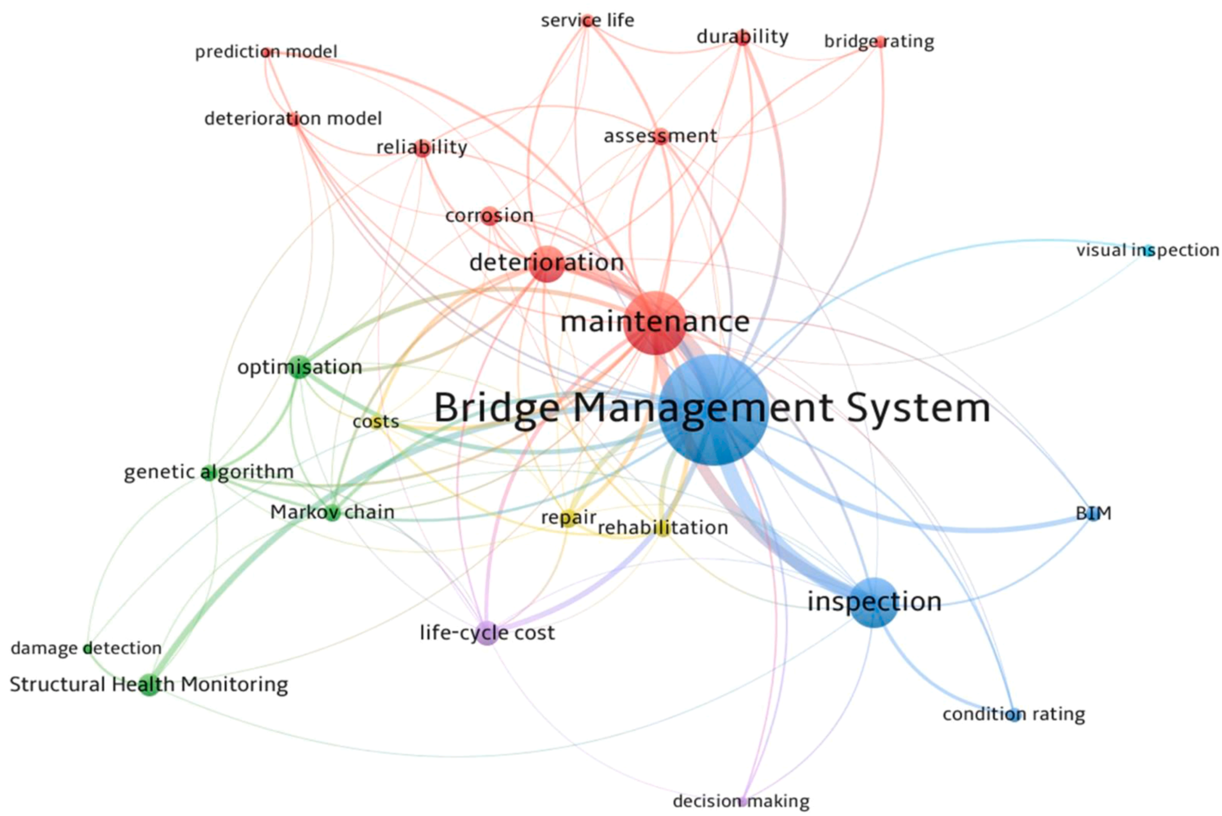

Fig. 2. Network visualization diagram related to the BMS literature.

l'Italia (Argo), Rete Ferroviaria Italiana (DOMUS) and Autovie Venete (Netkubed).

In 1987, Sweden implemented the software Bridge and Tunnel Management System (BaTMan). At the beginning of the 90 s′, several BMSs were created, such as the Finnish BMS (FBMS) in 1990, the KUBA BMS of Switzerland in 1991, and the well-known Pontis [16] and Bridgit [17] in the US, respectively in 1992 and 1993. Pontis was developed for the FHWA and became an AASHTO product renamed BrM in 1994 [18]. Although Pontis is the most well-known and widespread BMS in the US, other BMSs have been developed both by individual states [19–22] and at the Federal level [23,24] in recent years. In the late 90 s′, Hungary started using BMS software in 1996, France in 1999, and in 1997 Poland implemented SMOK which was then followed by the software SZOK in 2001.

Between 2000 and 2001, Germany created the Bauwerk Management System or SIB-Bauwerke (GBMS). In 2001, numerous countries developed their own BMS, namely Vietnam with Bridgeman, Ireland with Eirspan which was developed using DANBRO as a starting point, and England with Oracle. In the same year, Estonia started using Pontis. The following year, in 2002, Latvia implemented LT Brutus, Canada the Ontario BMS (OBMS), and the Czech Republic the IIS database + MS SQL Server. Later on, in 2003, Korea started using the Korea Road Maintenance Business System (KRBMS) [12], and between 2004 and 2005, Bulgaria developed Scanpoint-Freissinet, which was integrated in 2009 with a prioritization system. In 2005, Spain developed SPG. In 2006, Japan released the Regional Planning Institute of Osaka BMS (RPIBMS) [18,25]. During the same year, two more Canadian BMSs were implemented, namely EBMS and PEIBMMS, followed by Quebec BMS (QBMS), in 2008. More recently, between 2019 and 2020, Croatia also developed a BMS, called Oracle 10.G. Nowadays, within a single country, different road operators or administration entities might have their own management systems, due to the differences in bridge management practices [12]. These systems are usually developed internally by the operators, sometimes by consulting private companies. Other BMSs are BAUT (Austria), SIMS (United Kingdom) [26], SAMOA (Italy), and GOA (Portugal) [12], GNWT (Canada) [12], SGO (Brazil), Bridge-ASYST, MRWA and NSW(Australia) [12], MICHI (Japan) [12], T-BMS (Taiwan) [18,27], Slovenia BMS (Slovenia) [28], HiBris and Hanke-Shira (Finland) and Lagora (France) [29] and the North Carolina's BMS NCDOT [11].

4. The general architecture of a BMS

To effectively address diverse management objectives, BMSs must be adaptable and include various modules tailored to specific needs. The design of BMSs can vary significantly depending on the country or the requirements of the operator. In the context of the BRIME project [10], key requirements for a BMS were identified, along with essential modules, see Fig. 3.

The first four modules pertain to individual structures, covering (1) the inventory (database), (2) the collection of data on structural conditions, (3) the assessment of structural conditions, and (4) the comparison of different maintenance strategies. The remaining modules relate to the bridge network, encompassing (5) the optimization of interventions, and (6) the prioritization of interventions considering existing constraints.

Specifically, modules (1) and (2) are concerned with data management (in red), while module (3) pertains to both diagnosing the structural state and predicting future conditions (the yellow indicates diagnosis whereas the green indicates prognosis). Modules (4), (5) and (6) are focused on decision-making (in blue) regarding individual structures and the bridge portfolio.

Nevertheless, non-uniform definitions of BMS modules can be found in the literature (see Table 1). For instance, Lauridsen et al. [30] defined BMS components as: 1) Interrelated activities for handling bridges, 2) Set of codes and guidelines, 3) Organization to manage and carry out

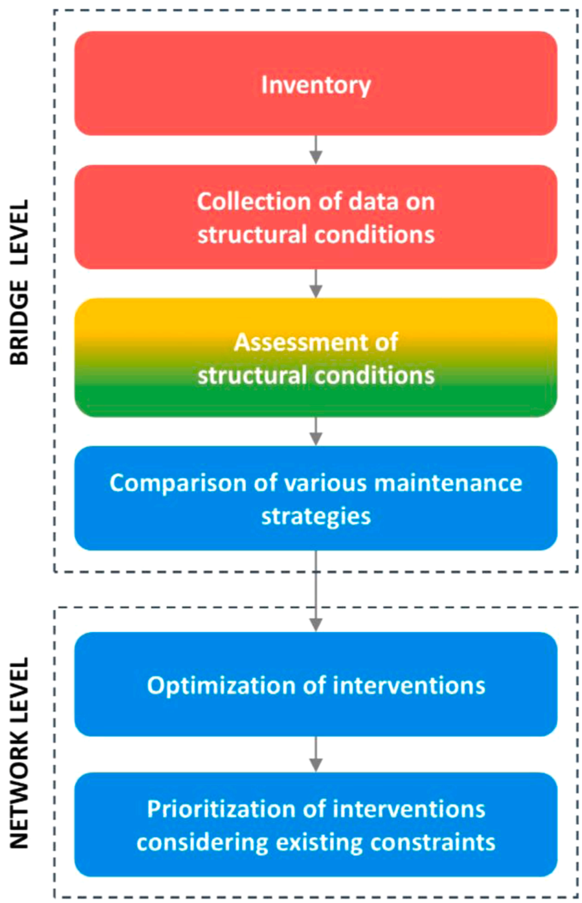

Fig. 3. BMS modules according to BRIME [10].

previous activities, 4) Database holding data resulting from previous activities, and 5) Set of computer tools for processing the data. Zonta et al. [15] detailed sections within the APTBMS as: 1) Database, 2) Inspection and evaluation module, 3) Maintenance degradation reliability and cost module, and 4) Decision tools module. Pellegrino et al. [31] considered: 1) Bridge Database, 2) Inspection System, 3) Structural capacity evaluation, 4) Lifetime prediction of the future condition of the structure, and 5) Cost evaluation system. Pregnolato [32] identified modules as: 1) Inventory, 2) Inspection, 3) Repair and Rehabilitation, and 4) Optimization.

The inventory module and inspection module are always present, though they may be referred to by different names, establishing them as fundamental components of BMSs. Often, BMSs limit their scope to these modules, guiding decisions based on engineering judgment. Discrepancies across the literature also emerge in modules dedicated to condition assessment and decision-making. Consequently, there is a pressing need to establish standardized categories. Defining uniform BMS modules is important for several reasons. A standardized definition ensures a common understanding within the industry, promoting clear communication among researchers, practitioners, and policymakers. Uniform definitions also facilitate comparisons and benchmarking across different BMSs, promoting best practices and continuous improvement. Furthermore, standardized modules provide a foundation for the development of interoperable and compatible BMSs. This interoperability is increasingly important in an era where data exchange and integration between different systems are vital for comprehensive and efficient bridge management. Hence, in this paper, BMS modules are defined as follows:

Table 1
BMS modules according to different authors.

Lauridsen et al. [30]	BRIME [10]	APTBMS [15]	Pellegrino et al. [31]	Pregnolato [32]
Interrelated activities for handling bridges	Inventory	Database	Bridge Database	Inventory
Set of codes and guidelines	Collection of data on structural conditions	Inspection and evaluation	Inspection System	Inspection
Organization to manage and carry out previous activities	Assessment of structural conditions	Maintenance degradation reliability and cost	Structural capacity evaluation	Repair and Rehabilitation
Database holding data resulting from previous activities	Comparison of various maintenance strategies	Decision tools	Lifetime prediction of the future condition of the structure	Optimization
Set of computer tools for processing the data	Optimization of interventions		Cost evaluation system	
	Prioritization of interventions considering existing constraints			

(i) *Data management*, dealing with data about bridges and the status of their components;
(ii) *Diagnosis*, consisting of condition rating and deteriorating assessment;
(iii) *Prognosis*, gathering all the activities connected to the prediction of future bridge conditions;
(iv) *Decision-making* identifying optimal management actions.

The proposed four modules are interconnected, as shown in Fig. 4. Diagnosis and prognosis rely on data pertaining to bridges and their components, while decision-making is influenced by the outcomes of diagnosis and prognosis and can also impact data management. The subsequent sections present and examine these four modules in detail.

5. Data management

Data management encompasses four stages, namely data collection, acquisition, transmission, and storage. The collection phase involves gathering data pertaining to the bridge inventory, such as observations or signals. Two primary approaches have emerged for data collection: inspections – including visual inspections, Non-Destructive Tests

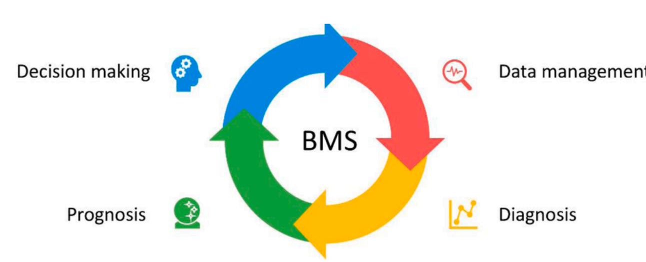

Fig. 4. Modules of a BMS.

(NDTs), and Destructive Tests (DTs) - and Structural Health Monitoring (SHM). The acquisition phase entails converting the collected data into a computer-readable format. Data transmission refers to the process of sending data to computing networks or electronic devices. Lastly, the storage phase involves saving and recording the data. These four phases are illustrated in Fig. 5. In the subsequent sections, these phases are discussed with reference to inspections and SHM. Visual inspections provide a direct, qualitative assessment of visible damage and structural conditions, while NDT and DT techniques offer quantitative data on material properties and hidden defects. Instead, SHM can reveal trends and anomalies that might not be apparent through inspections alone, serving as a valuable complement to inspections, particularly in critical or complex structures [33]. Inspections and SHM should not be seen as replacements but as complementary processes that allow operators to achieve a comprehensive understanding of a bridge's condition.

5.1. *Inspection data management*

Inspection methods involve technicians who assess structural and non-structural anomalies [34]. Different types of inspection exist with varying levels of detail based on their scope and frequency, such as inventory, routine, in-depth, and special inspections [35]. Inventory inspections provide baseline condition assessment when the bridge is first constructed or added to the management system. Routine inspections, conducted at regular intervals, ensure ongoing monitoring of the bridge's condition. In-depth inspections are more detailed and may involve accessing hard-to-reach areas to closely examine specific components. Special inspections are carried out in response to specific events, such as after a natural disaster or a vehicle impact, to assess any resulting damage [36].

Extensive research and documentation exist on inspection methods, see, e.g., [35,37]. Due to the importance of inspections in current practice, they are typically regulated by codes and guidelines at the national or regional level. However, operators typically have the flexibility to adopt internal procedures as long as they align with overarching regulations. Table 2 shows some examples of inspection codes and guidelines. In addition to the description of the procedures and of the instrumentation to use, these documents generally specify the requirements that must be met in terms of inspection competencies and expertise depending on the type of inspection.

While inspections are widely used and remain a cornerstone of bridge condition assessment, they come with several limitations. Accessing certain areas of a bridge, such as underwater pier foundations or bridge soffits on long-span bridges, can be challenging and often requires specialized equipment like bridge inspection trucks, boats, and drones. These logistical challenges can also necessitate traffic interruptions or restrictions, leading to additional costs and inconvenience. The periodic nature of inspections, typically scheduled at regular intervals or triggered by specific events, means they do not offer early warning signals for the occurrence of damage, limiting their effectiveness in proactive maintenance. Additionally, the costs associated with inspections can be substantial, particularly for bridges that are difficult to access.

Table 2
Inspection codes and guidelines.

Country	Regulation
US	American Association of State Highway and Transportation Officials, The Manual for Bridge Evaluation[24]
	Federal Highway Administration (FHWA), Bridge Inspector's Reference Manual[36]
	Massachusetts Department of Transportation, Bridge Inspection Handbook - Field Inspection, Data Collecting, Report Writing and Report Review[21]
	New York State Dept. of Transportation Office of Structures, Bridge Inspection Manual[22]
	Iowa Office of Bridges and Structures, Bridge Maintenance Manual[20]
Canada	Ontario Ministry of Transportation, Ontario Structure Inspection Manual [38]
	Alberta Transportation (AT), Bridge inspection and maintenance system: BIM Level 1 inspection manual. Version 4[39]
UK	Highway England, Requirements for Inspection and Management of Bridges, BD 62/94 and BD63/94[40]
Norway	Norwegian Public Roads Administration, Handbook for Bridge Inspection Part I[41]
China	Ministry of Transport of the People's Republic of China, Standards for Quality inspection and verification of highways.[42]
Australia	Main Roads Western Australia, Detailed Visual Bridge Inspection Guidelines[43].
Italy	Consiglio Superiore dei Lavori Pubblici, Linee Guida per la classificazione e gestione del rischio, la valutazione della sicurezza ed il monitoraggio dei ponti esistenti[44]
Spain	Ministerio de Fomento, Guia para la realizaciòn de inspecciones principales de obras de paso en la Red de Carreteras de Estado[45]
Ireland	Transport Infrastructure Ireland, EIRSPAN bridge management system principal inspection manual[46]

5.1.1. *Inspection data collection*

Procedures for bridge data collection include visual surveys, NDTs, and DTs. Visual inspections are a fundamental component of bridge management, typically carried out by trained technicians. The scope of these inspections varies based on the inspection type; for example, routine inspections may focus only on accessible elements, while more detailed inspections might include hard-to-reach areas. The primary purpose of visual inspections is to detect visible signs of deterioration, such as cracks, corrosion, spalling, and deformation, and to document these findings for further analysis [47]. Furthermore, visual inspections allow for the detection of a variety of issues beyond structural integrity, including hydraulic phenomena (e.g., presence of scour or debris accumulation on piers in water) and geotechnical phenomena (e.g., initiation of landslides). These aspects have been stressed by e.g., the recent Italian Guidelines for bridges [44] which suggest a multi-risk assessment of bridges based on archive data and visual inspections.

Visual inspections involve several steps. Inspectors use checklists and standardized forms to ensure consistency and comprehensiveness in their assessments. They often use tools such as binoculars, cameras, and drones to enhance their ability to inspect inaccessible areas [48]. Findings are recorded, often using digital platforms that facilitate data storage, analysis, and sharing among stakeholders. Visual inspections remain indispensable despite advancements in technology, as they provide a direct and immediate evaluation of a bridge's condition. Nevertheless, they are inherently subjective, as the outcomes can vary

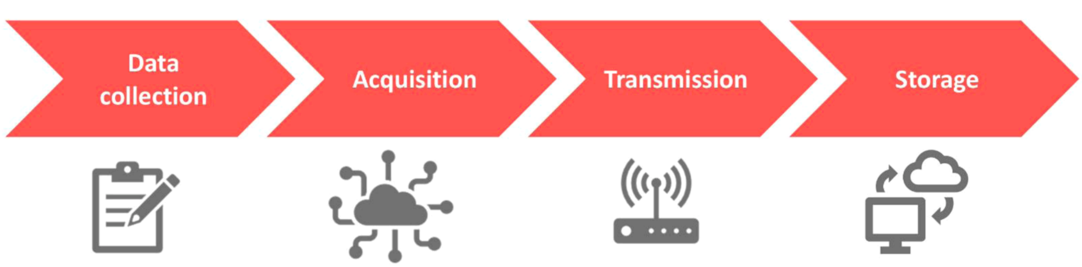

Fig. 5. Phases of data management.

based on the skills and expertise of individual inspectors. This subjectivity can lead to inconsistencies, especially when inspection codes and guidelines lack clarity on how to assign judgments to specific defects. Furthermore, visual inspections face challenges in identifying hidden defects.

In turn, NDTs can identify defects in structural elements that are not visible such as internal flaws and delamination. Ultrasonic testing, Eddy Cutting Testing (ECT), Acoustic Emission (AE), and Magnetic Flux Leakage (MFL) testing can be used to detect corrosion and fatigue on steel components [49–51]. Specifically, ultrasonic testing uses high-frequency sound waves to detect internal defects, such as flaws and irregularities, and measure material properties, like changes in microstructural or mechanical properties. ECT utilizes electromagnetic induction to detect surface or subsurface defects in conductive materials. AE techniques monitor the release of elastic stress waves from localized sources (such as cracks or other discontinuities) when a material deforms under stress. MFL testing detects corrosion, breaks, pitting, and breaks by inducing a magnetic field to the component and evaluating leakage in the material from its flux path. Further, NDTs such as impact echo and ground penetrating radar can detect corrosion in reinforced concrete. Impact echo is an ultrasonic method that is able to detect defects by measuring the velocity of propagation of elastic waves [52]. Ground-penetrating radar employs radar pulses to image subsurface anomalies. Thermography utilizes infrared imaging to detect variations in temperature that indicate potential defects like delamination, fatigue crack propagation, or moisture intrusion [53].

DTs involve controlled damage to a part of the bridge to evaluate its properties and performance [53]. Material properties might differ from design values. Also, as bridges age, uncertainties related to the structure increase due to deterioration mechanisms and real-life conditions. Therefore, reliable prediction of bridge capacity and behavior often requires DTs of material samples for calibrating models and evaluating the performance of existing bridges [54,55]. Common DTs include core drillings to extract material samples for analysis, cutting and removing portions of the structure for detailed examination, chemical testing to assess material composition and degradation, and accelerated aging tests to simulate long-term wear and environmental impacts [56].

5.1.2. Acquisition, transmission, and storage of inspection data

Inspections generate a variety of data types. In consideration of visual inspections, outputs include photographs, videos, sketches, and written reports that describe observed conditions and defects. NDTs and DTs of material specimens generate another layer of critical data for bridge assessments. The acquisition of NDT and DT data involves using specialized equipment to collect measurements, that are then converted into digital formats for analysis. These data need to be collected, transmitted, and stored for effective use in BMSs [57].

The results of inspections are typically collected in a database, either by the operator who performed the inspection or by the technical office based on the submitted inspection record, in paper format, or through the interfaces of the software. To this end, smartphones and tablets have been rapidly developing in the inspection field in recent years. Smartphones, which embed a mini personal computer integrated with sensors, operating systems, and communication systems, proved to be an effective tool for data acquisition and particularly for the improvement of inspection both in terms of immediacy and accuracy [58,59].

Transmission of inspection data can rely on wireless communication technologies and cellular networks to transfer images and videos to central databases. In the case of high-resolution and complex outputs, a stable internet connection is essential to prevent data loss and ensure accuracy. Both for visual inspection and NDT and DT data, the storage solution must accommodate the large file sizes and diverse formats generated during inspections. Cloud-based storage systems offer scalability and remote access, allowing multiple users to view and analyze data concurrently [60]. These systems also support robust data management practices, including version control, metadata tagging, and secure access protocols, ensuring that inspection data remains organized and easily retrievable. Storage systems must also ensure data security and integrity, supporting features like encryption, blockchains, backup, and recovery protocols [61,62]. Smartphones allow not only for direct cloud communication with databases but also the ability to associate increasingly high-quality photographs with inspection judgments in an immediate way thanks to the possibility of having BMS software on the field. Similarly, the use of drones connected to BMS software for inspections is also gaining popularity [63]. Field software, particularly when connected to the BrIM of the structures, can offer significant advantages. The possibility of updating in real-time the condition of the structure brings significant savings in terms of time for acquisition, transmission, and storage [64].

The acquisition of inspection data can be enhanced with digital tools that allow inspectors to annotate images, create 3D models, and integrate findings into centralized databases. Advanced software platforms facilitate real-time data entry during inspections, enabling inspectors to upload images and notes directly from the field using mobile devices, in order to process and analyze findings in an immediate way facilitating quick identification of critical issues [65]. The rapid digitization of inspection data not only streamlines the documentation process but also ensures that critical information is promptly available for analysis [66].

5.2. SHM data management

In recent decades, the limitations of inspections have driven operators to explore SHM systems, which automate data collection and provide continuous updates on structural conditions. National and international initiatives and organizations have played a crucial role in advancing SHM technologies and practices, promoting best practices and collaborative research across countries, and underscoring the global impact and potential of SHM advancements. Associations such as the International Society for Structural Health Monitoring of Intelligent Infrastructure (ISHMII) [67] and the International Association for Experimental Vibration Analysis for Civil Engineering Structures (EVACES IA) [68], foster research about SHM. Furthermore, numerous international conferences bring together researchers and practitioners periodically, such as SMAR [69], EVACES [70], EWSHM [71], IWSHM [72], IOMAC [73], EUROSTRUCT [74], IABMAS [75], and EURODYN [76]. As for research projects, it is worth mentioning the COST Action TU1402, active from 2014 to 2019, which involved representatives from academia, industry, infrastructure owners, operators, and authorities. Its primary objective was to advance the management of structures and infrastructure systems through optimized SHM systems based on the Value of Information (VoI) [77,78].

Following the tragic collapse of the Morandi bridge in Genoa in 2018 [79], Italy has made significant investments in bridge instrumentation with monitoring systems. For instance, ANAS, the operator of most Italian roads, has launched a "Structural Health Monitoring Program" funded with 275 million euros [80,81]. From the academic point of view, the Italian national FABRE consortium exemplifies collaborative scientific endeavors aimed at enhancing bridge management and monitoring practices [82]. Additionally, the ReLUIS (Rete dei Laboratori Universitari di Ingegneria Sismica e Strutturale) network focuses on seismic engineering and structural monitoring, contributing significantly to the development of SHM practices in Italy [83].

Nevertheless, it is important to acknowledge the current limitations of SHM. First, SHM techniques – especially the vibration-based ones – are generally not sensible to superficial and small damages, which instead can be directly detected by visual inspections. Also, SHM systems degrade in time and require continuous maintenance, making it difficult to distinguish between anomalous data caused by out-of-service systems, malfunctioning sensors, or actual structural damage [84]. There is no widely accepted procedure to demonstrate the Return On Investment (ROI) in an SHM system, which represents maybe the greatest limitation to the extensive employment of SHM technology

[78]. Additionally, permanent SHM systems collect huge amounts of data that have to be adequately managed and post-processed, and there are no general rules regarding the choices of technologies to use. Another significant barrier is the shortage of experts proficient in the proper analysis of SHM processes [85]. This lack of expertise leads to a preference among managers for more familiar data collection methods, such as visual inspections.

To address these challenges, several guidelines have been published starting from 2001 with the aim of standardizing SHM practices. The objective is to enhance understanding and knowledge of the SHM process, highlight its value, and develop rules and protocols [86]. These documents also provide recommendations for data processing in structural diagnosis applications. Fig. 7 illustrates a chronological compilation of significant documents. It showcases the purpose of SHM as defined in each specific document, indicating a current trend of integrating SHM data into BMSs.

5.2.1. SHM data collection

SHM systems consist of several components, including sensors, data acquisition devices, data transmission systems, databases for storage, and processing units for analysis and modeling [87]. This hardware converts physical measurements into damage-sensitive features, providing insights into structural health over time. A wide range of sensors has been introduced over the last decades [88]. Widely used sensing technologies in SHM include contact sensors such as fiber optics, piezoelectric sensors, global navigation satellite systems, and magnetostrictive sensors [89]. Microelectromechanical Systems (MEMS) sensors are gaining widespread popularity [90], [91] due to their reliability, efficiency, and compact size, making them highly suitable for a wide range of applications [92].

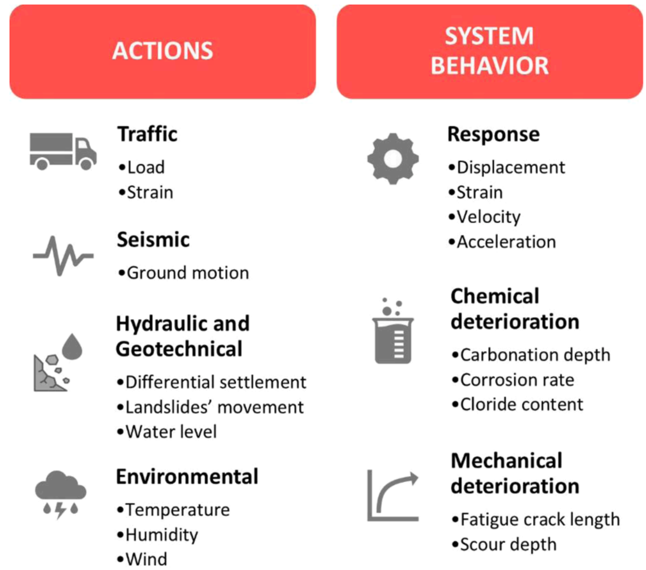

Fig. 7. Non exhaustive list of SHM monitorable parameters.

Sensors have been exploited to measure different types of quantities relating not only to structural behavior but also to external actions and environmental factors. Fig. 7 shows a non-exhaustive list of monitorable parameters in SHM.

SHM strategies are typically categorized as local or global approaches. Local SHM provides detailed information about specific

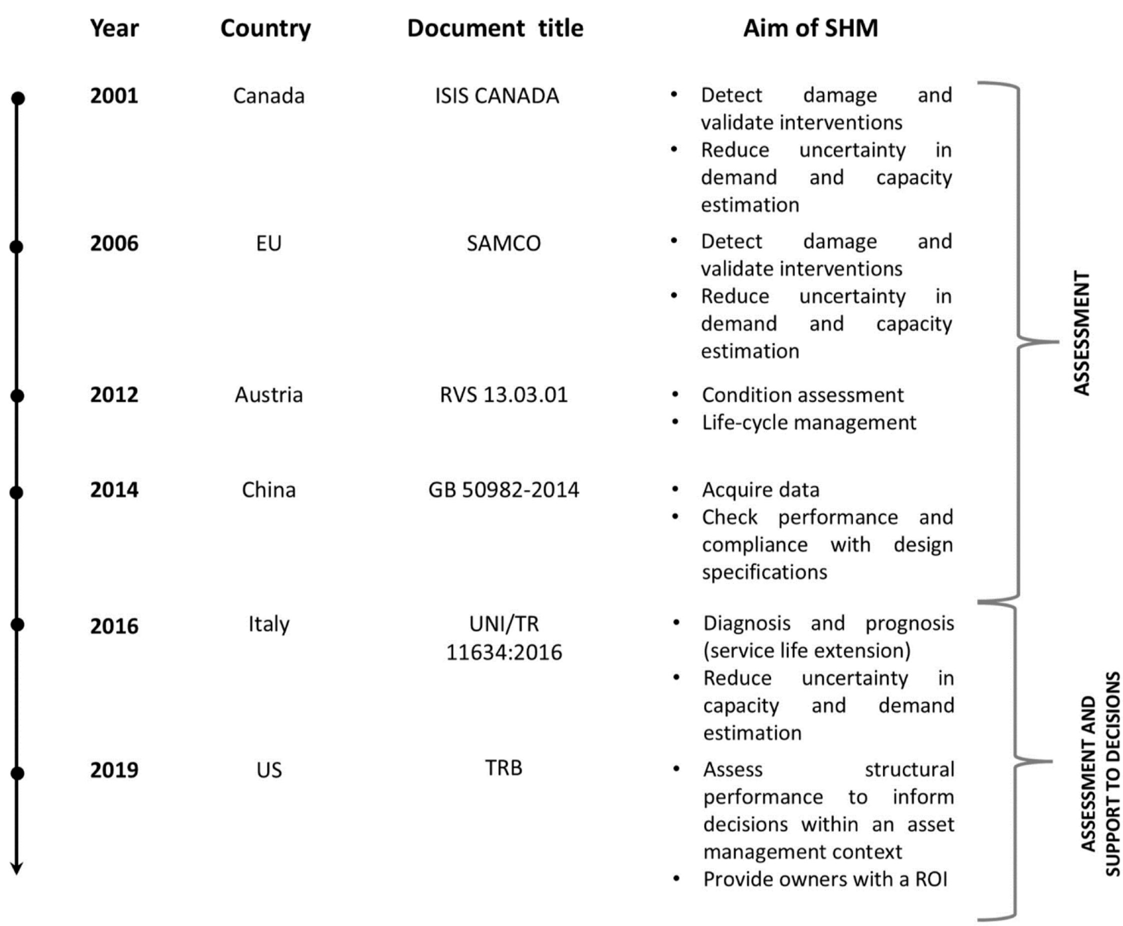

Fig. 6. Documents for the standardization of SHM.

locations within the structure where sensors are deployed [93], [94], often focusing on monitoring slow-varying parameters such as pier tilt and strain. In contrast, global SHM focuses on dynamic structural properties such as modal parameters to assess overall structural integrity, even without sensors positioned directly at potential damage sites [95], [96].

Critical phenomena such as corrosion, fatigue, and scour, in principle, can be identified by both local and global monitoring systems.

Recent advancements in local fatigue crack and corrosion detection include the development of high-sensitivity vibration and acoustic emission sensors [97], as well as large-area strain sensing technologies [98] and ultrasonic guided waves [99]. On a global scale, tracking modal parameters from acceleration records, such as natural frequencies, can also be effective in identifying corrosion and fatigue cracks, particularly when these phenomena cause significant changes in structural stiffness [100], [101]. Data acquisition methods can be combined with signal processing algorithms and machine learning techniques for damage identification, facilitating timely interventions. Ongoing research focuses for example, on refining fatigue and corrosion models through neural-network [102], [103] as opposed to more classical analytical probabilistic formulations [104].

Digital Image Correlation (DIC) has shown promising results as an advanced technique for detecting and quantifying both in-plane and out-of-plane fatigue cracks, which are common in steel bridge components [105], [106]. As a noncontact, vision-based sensing technology, DIC tracks the surface deformation of materials by analyzing changes in a speckle pattern applied to the structure's surface. This method is particularly advantageous for inspecting fatigue-prone regions because it provides high-resolution, real-time data on crack initiation and growth without the need for direct physical contact or extensive on-site monitoring.

Scour is considered one of the major causes of bridge failure worldwide [107]. A variety of sensors have been developed to monitor scour occurrence and progression [108], such as float-out devices, radar and sound-based systems, and buried rod systems. These technologies are based on the detection of changes in scour hole depth and therefore are able to provide information about specific locations. Alternatively, Vibration-based SHM systems have become increasingly popular in recent years. These systems monitor changes in the natural frequency of a bridge structure caused by scour, which affects the structural boundary conditions and consequently the global modal behavior [109].

5.2.2. *Acquisition, transmission, and storage of SHM data*

The process of acquisition, transmission, and storage of SHM data is generally digitalized and automated. When the sensor receives an input, an acquisition system converts an analog signal into a digital one by an analog-to-digital converter, to make the signal readable by a computer [110]. Despite future direction aims at the employment of sensors that do not necessarily require converters, e.g., most of the aforementioned MEMS sensors, the great majority of sensors on the market still employ acquisition systems that include these elements. An acquisition system generally consists of three main elements: sensors, signal conditioning circuits, and the aforementioned analog-to-digital converter. When a sensor converts a physical phenomenon into an electrical signal, the data often requires signal conditioning to be useful for SHM. This process may involve filtering to remove noise, buffering to stabilize the signal, amplification to enhance weak signals, and potentially compensations or linearization to correct for any distortions or non-linearities, depending on the quality and characteristics of the original signal.

Regarding transmission, traditional SHM systems are mainly wired-based. Wired systems transmit data through coaxial wires to process them afterward with the system [110], [111]. Lately, there has been great progress in wireless-based solutions [112], [113]. Wireless Sensor Networks (WSN) often consist of many sensor nodes, connected with sensors, which contact each other via a wireless network and send data directly toward the base station [88]. The newest mobile communication technology, 5 G, has introduced innovative network paradigms capable of offering an unprecedented level of reliability, low latency, higher connectivity, and higher data rates [114].

Given the escalating data acquisition rates in emerging technologies, the volume of data and the available memory are critical parameters for data storage, especially in long-term monitoring. Internet of Things (IoT) systems and cloud-based architectures have become prevalent due to their numerous advantages [115], [116]. These benefits include large data flow and storage capacities without the significant physical footprint of traditional solid storage, as well as the capability for wireless communication with remotely connected devices, such as sensors, smartphones, and tablets. The goal is to store data files in a more compact form while retaining sufficient information for future use, processing, and analysis, aided by increasingly performant databases.

6. Diagnosis

The objective of the diagnosis module is to evaluate the condition of individual bridge components, single bridges, or infrastructure networks. This requires the identification of appropriate Performance Indicators (PIs), thresholds, or goals at various levels (component, system, and network). The research community has made significant strides in this field in recent years. For instance, the COST TU 1406 Action has played a key role in developing a guideline for quality control plans in roadway bridges, with a focus on standardizing and harmonizing PIs, thresholds, and goals across different countries [117], [118]. The following sections describe methodologies and approaches for assessing bridge conditions via PIs.

6.1. *Performance Indicators*

Different types of PIs exist to address and describe different aspects concerning the structure of interest. In general terms, PIs can be classified into technical PIs and non-technical PIs [119], see Fig. 8. At different levels, decision-making is then guided by the integration of both types of PIs [118].

Technical PIs capture the mechanical properties and/or the degradation of structures and can characterize their ultimate capacity as well as serviceability conditions. Additionally, technical PIs can also encompass aspects related to the surrounding conditions of the structure, addressing e.g., geotechnical, and hydraulic aspects.

Herein, technical PIs are classified into (i) PIs based on the results of inspections (including visual inspections and tests), (ii) PIs obtained from SHM, and (iii) PIs dealing with structural reliability and risk.

Bridge Condition Indicators (BCIs) are quantified by combining the condition rates of individual bridge components assigned during visual

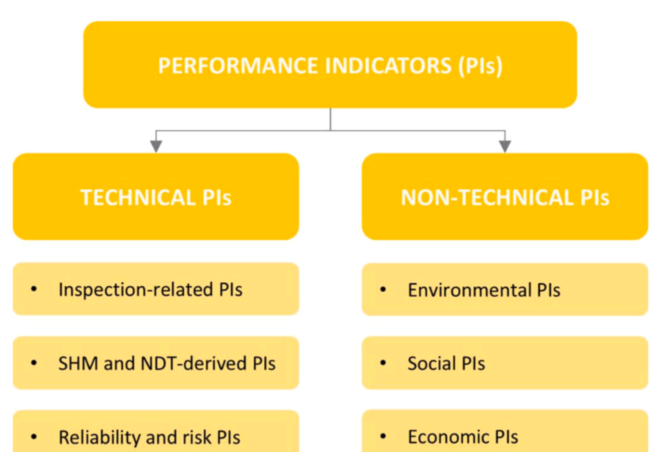

Fig. 8. Classification of performance indicators.

inspections [120]. The evaluation of the BCI for a stock of bridges can lead to a priority repair ranking within the network [29], [121]. BCIs are commonly used in practice by road agencies and their computation is implemented in BMSs worldwide, although the quantification methods can differ. Nevertheless, often the optimum repair or rehabilitation strategy is not obvious based only on such information. BCIs alone cannot provide a clear structural safety judgment since no quantitative evaluation is done from both the resistance and the loading sides.

Different types of damage-sensitive features can be extracted from SHM data according to the type of sensors, the type of structure, and the goal of the monitoring. In general, an SHM-derived PI that can be correlated to the presence of damage is defined as *Damage Indicator* or *Index* (DI) [122]. Overall, the implementation of DIs in BMS software is still at an early stage of development.

More recently, the interest in PIs taking into account reliability and risk considerations has increased [117]. They include structural reliability and risk, cumulative probability of failure, survivor function, hazard rate function, structural redundancy, structural robustness, structural resilience, and load rating factor [119], [123], [124]. Reliability is an important PIs, which is linked to the probability of failure for a bridge component with respect to a given limit state function, considering both load and resistance characteristics [2], [125], [126]. It is often used to forecast structure performance over time: combining the reliability of different failure modes with a deterioration model, a reliability profile for the observed bridge can be obtained [127]. However, reliability by itself does not enable accounting for the consequences related to failure which in turn may be a decisive factor in prioritizing maintenance interventions, especially under budget constraints. Risk provides a more comprehensive assessment by considering both the probability and consequences of potential failures [128].

Economic, social, and environmental indicators complement technical integrators [119] even though they are not systematically implemented in BMSs [117]. Non-technical PIs include economic, social, and sustainability PIs.

Economic PIs relate to construction and maintenance costs. One of the most important economic indicators is the Life-Cycle Cost (LCC), which consists of the sum of all costs related to a bridge during its service life, e.g., reconstruction costs, inspection costs, preventive maintenance costs, repair costs, out-of-service costs, user costs [129–131]. At the component level, a widely used economic indicator is the ratio between the total cost of repairing individual damages and the price of a new component. Components with a ratio exceeding 1.0 are typically recommended for replacement [118]. The APTBMS (Italy) [15] includes the calculation of a cost indicator, which is directly used for the priority ranking of the stock.

Social PIs are related to road users' satisfaction and safety to assess the social performance of a bridge. They encompass factors such as increased travel times for users.

Sustainability PIs characterize the environmental impact of a structure in the course of its life-cycle. They consider aspects such as cumulative energy demand during a bridge life-cycle, the use of renewable or non-renewable resources, durability, solid waste production, and the emissions measured in kg of CO_2 equivalents [119].

6.2. Condition assessment using technical indicators

Technical indicators play a crucial role in BMSs by providing quantifiable measures of structural damage and its severity. The first part of this section addresses technical performance indicators derived from inspection results, which are extensively utilized in BMSs worldwide. The second part focuses on technical performance indicators obtained from SHM data.

6.2.1. Condition assessment based on BCIs

BCIs are generally calculated based on the condition ratings of structural components and, in some cases, the service provided by the bridge (i.e., the importance of the bridge within the network). Four main approaches for the evaluation of the BCI are identified [120], [132], as follows:

Weighted average approach. The BCI is estimated by combining condition ratings of all individual bridge components weighted by the importance of the component in terms of functionality and safety, by the gravity of the damages identified during the inspection, or by the bridge's importance within the network.
Qualitative approach. The BCI is assigned based on numeric rating scales (e.g.,1-5) and linguistic expressions such as excellent, good, fair, and poor, based on the condition state and importance of the investigated components.
Worst-conditioned component approach. The BCI corresponds to the rating of the component in the worst condition.
Ratio-based approach. The BCI is assigned based on the ratio of the current condition to the condition of the structure when it is new.

Table 3 reports, for each condition rating approach, examples of BMS software adopting that particular approach and the country in which the BMS has been implemented.

In general, BCIs provide a rating of the bridge condition and generally enables owners and operators to rank the interventions within the bridge inventory. Ranking procedures are suitable for implementation in BMS frameworks since they can be easily linked with recommendations about follow-up actions, maintenance and rehabilitation plans, and costs [133].

Numerous frameworks have been proposed for BCI evaluation, addressing both gradual deterioration [119], [134], [135] and the effects of natural hazards [136], [137]. Some studies employ probabilistic approaches to account for uncertainties in BCI evaluations, particularly through visual inspections, investigating the link between the probability of damage detection and condition ratings [131], [138]. Fuzzy logic tools [139], evidential reasoning approaches [140], and machine learning [141] were explored to enhance the accuracy and reliability of bridge condition assessments.

6.2.2. Condition assessment based on SHM

Traditionally, four levels of damage identification are contemplated [142], namely: damage detection (i.e., identify or not the presence of damage), damage localization (i.e., find the location of damage), damage assessment (i.e., quantify the level of damage), and prognosis (i.e., forecast the evolution of damage).

Damage-sensitive features often do not provide information about damage by themselves, unless with reference to their value in a baseline state. This calls for the need to define the DI, which might not have a clear and direct physical meaning but allows for expressing variations of damage features with respect to the baseline. The extraction of DIs can be performed based on two different approaches: physics-based, and data-based.

The physics-based approach utilizes the inverse problem technique to deduce the state of a structure based on the selected DI. Inverse problems involve inferring the values of the chosen DI and other related parameters that describe the system using measured data obtained from

Table 3
BCI in existing BMSs.

Condition rating approach	BMS	Country
Weighted average approach	HiBris, Hanke-Siha	Finland
	SMIS	UK
	STRUMAN	South Africa
Qualitative approach	LAGORA	France
	BaTMan	Sweden
Worst conditioned component approach	SIB-Bauwerke	Germany
	APTBMS	Italy
Ratio-based approach	Pontis/BrM	US

monitoring. The interpretation models establish the connection between the DI under investigation, which represents the state of the structure, and the observations from monitoring. These models can take the form of analytical or numerical functions, such as Finite Element (FE) models. Model updating techniques are crucial in physics-based approaches and are employed to refine and improve the accuracy of the models [143].

The data-based (or data-driven) approach uses a variety of algorithms to learn structural behavior from collected data. This approach does not rely on the use of a predefined physical interpretation model. Different machine learning algorithms have been developed and used to distinguish patterns in SHM data [144], [145]. The common final goal of machine learning algorithms is the extraction of DIs from monitoring data and the detection of outliers lying at an abnormal distance from the population of the damage-sensitive feature.

Ideally, the DIs should be sensitive to the specific phenomena to monitor, and they should be robust with respect to other sources of variability so that they would vary consistently only with the level of damage. Nevertheless, a critical problem for damage identification in SHM is the impact of operational and environmental effects on the quantities measured by sensors and, in turn, DIs. Live loads as well as temperature changes (both daily and seasonal) can significantly influence the structural response and increase the uncertainty in the detection of damage [51], [146]. Environmental effects can hide the presence of damage or be misinterpreted and result in a false indication of damage and must therefore be removed. Such an issue is common to both physics-based and data-based approaches.

Damage indicators are typically compared to predefined thresholds in order to classify the structural condition. The choice of a specific threshold is closely linked to the uncertainty inherent in the damage detection process. The selected threshold needs to strike a balance: it must be strict enough to prevent false identification of damage due to uncertainty, while still allowing for the identification of outliers caused by structural damage.

In the simplest scenario, the classification of structural conditions based on the DI value involves two possibilities: damaged and undamaged, constituting a binary classification. When comparing the DI with a particular threshold, there are four possible outcomes: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). To determine the probabilities associated with these outcomes, the Probability Density Function (PDF) of the damage indicator in both undamaged and damaged conditions can be considered, as depicted in Fig. 9.

Analyzing these PDFs provides a means to assess the likelihood of different outcomes when comparing the DI value with a specific threshold. In binary classification problems, the choice of a threshold should be based on the minimization of the odds of false damage detection (false positives and false negatives). A statistical tool that enables the evaluation of the desired results (true positives and negatives) and unwanted results (false positives and negatives) is the Receiver Operating Characteristic (ROC) curve. A ROC curve is a graphical tool that allows for quantifying the performance of classifiers, varying the threshold position, and statistically evaluating the erroneous predictions related to false detection [147].

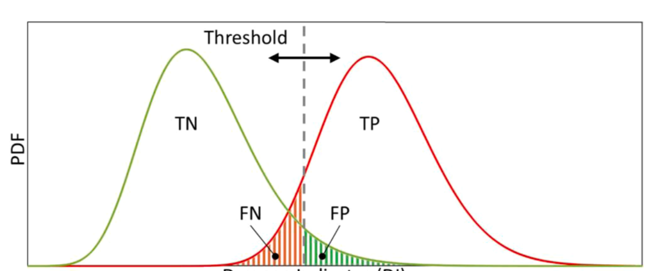

Fig. 9. Binary classification of damage indicators.

In most cases, however, it is not convenient to decide among thresholds based solely on ROC curves (i.e., based on true positive-false positive pairs). In decision problems, possible different consequences and expected costs related to the different outcomes should be considered. This problem has been tackled using the principles of the Expected Utility Theory (EUT) [148], [149].

7. Prognosis

The prognosis module relies on deterioration models and incorporates information about the current conditions of bridges and their components to forecast their future states. The diverse characteristics of bridge components—varying in importance, size, age, position, and material—coupled with their exposure to various loading and environmental conditions, result in a significant variability in the rate of deterioration among these components. The literature on degradation models spans various applications, addressing both structural and nonstructural components, different materials, degradation mechanisms, and environmental factors [150].

However, the literature provides limited details on the implementation of deterioration models in existing BMSs, which hinders the expansion of this section. Following a thorough examination, information about twenty BMSs was found and is reported in Table 4. These BMSs predominantly incorporate two types of deterioration models: stochastic and deterministic. BaTMan, Slovenia BMS, STRUMAN, and NCDOT BMS, utilize deterministic deterioration models. However, the majority of BMSs, including APTBMS, Bridgit, KUBA, Ontario BMS, Pontis, and BAUT, use stochastic deterioration models.

Subsequent sections introducing these types of deterioration models do not aim to explain them, as models adopted in existing BMSs are well-established and widely known. Readers are directed to the provided reference for further details [155], [158].

The limited knowledge regarding the prognosis module remains a key focal point in this study, providing an avenue for discussing crucial aspects and future directions within the dedicated sections.

Table 4
Deterioration models used in BMSs.

BMS name	Country	Deterioration Model
AASHTOWare	United States of America	Stochastic[12]
APTBMS	Italy	Stochastic: Markov Chain[151]
BaTMan	Sweden	Deterministic: Regression[152]
BAUT	Austria	Stochastic: Markov chains[153]
Bridgit	United States of America	Stochastic: Markov Chain[11]
Disk	Netherlands	Stochastic[12]
EBMS	United States of America	Stochastic: Markov Chain[12]
Florida DOT	United States of America	Stochastic: Semi-Markov Chain[154], [155]
GNWT	Canada	Stochastic: Markov Chain[12]
KRMBS	Korea	Stochastic[12]
KUBA	Switzerland	Stochastic: Markov Chains[156]
Lat Brutus	Latvia	Stochastic[12]
NCDOT BMS	United States of America	Deterministic: Regression[11]
NSW	Australia	Stochastic[12]
Ontario BMS	United States of America	Stochastic: Markov Chain[11]
PEI BMS	Canada	Stochastic: Markov Chain[12]
Pontis	United States of America	Stochastic: Markov Chain[11]
QBMS	Canada	Stochastic: Markov Chain[12]
RPIBMS	Japan	Stochastic[12]
Slovenia BMS	Slovenia	Deterministic: Regression[28]
STRUMAN	South Africa	Deterministic: Regression[157]

7.1. Deterministic models

Deterministic models provide a single, definite solution for a given set of model parameters and inputs. Essentially, the outcomes of deterministic models are entirely determined by their inputs and the model's structure devoid of any consideration for uncertainty. These models assume well-defined and predictable cause-and-effect relationships.

Among deterministic models, regression models find application in BMSs. They can be either linear or non-linear depending on the type of function used to fit the data. Linear regression models, consisting of first-order functions, describe the deterioration process as linearly dependent on time. Instead, nonlinear regression models utilize nonlinear functions, such as multiple-order polynomial functions. These models can be more accurate in long-term predictions than linear ones [11].

According to Table 4, regression models are applied into the Swedish BaTMan [152], the NCDOT BMS [11], the Slovenia BMS [28], and the South African STRUMAN [157].

In particular, NCDOT BMS [11] employs linear regression models, allowing, for instance, the prediction of material condition ratings by assuming a constant traffic load over time and regular maintenance.

The recent Slovenia BMS [28] implements piece-wise linear functions to approximate the deterioration state of bridge components. Such deterioration model accounts for material characteristics (reinforced concrete, steel, or stone), year of construction (before or after 1995, year of implementation of the current design code), and damage degree (negligible, low average, high, or severe). The inclusion of these parameters in the definition of the linear functions was determined by analyzing 25 years of recorded inspection data and has proven to be accurate in short/medium-term predictions.

Similarly, the deterioration model adopted in STRUMAN consists of a piece-wise linear function. In addition to the parameters considered by the Slovenia BMS, it accounts for traffic volume as well as environmental and climatic factors [157].

The Swedish BaTMan system differs from other BMSs by not implementing linear regression models at the level of bridge components. Instead, it forecasts the evolution of network performance [12]. The evaluation of bridge component deterioration is left to the judgment of expert engineers [152].

Deterministic models are used in BMSs because of their simplicity and practicality. The main disadvantages include neglecting the stochastic nature of bridge deterioration and the need to recalibrate the deterioration model when new data are acquired.

7.2. Stochastic models

Stochastic models are essential tools for predicting the deterioration of bridge components, incorporating inherent uncertainties through the use of random variables. These models diverge into two primary approaches: state-based models, exemplified by Markov Chain models, and time-based models, also known as duration models [155].

Markov Chain models represent a fundamental state-based approach to deterioration modeling within BMSs. These models operate under the assumption of the memoryless property, where future states depend solely on the current state and not on the historical condition of the component. They describe the progression of bridge condition states over discrete time intervals using fixed transition probabilities organized into transition matrices. Markov Chain models can be either time-homogeneous, with constant transition probabilities (the transition matrix is thereby defined as stationary), or time-inhomogeneous, where these probabilities vary over time based on external factors such as environmental changes or maintenance interventions. Expert opinions, bridge type, current condition, environmental factors, and historical maintenance data inform the determination of these transition probabilities [159]. The simplicity and ability to integrate expert knowledge make Markov Chain models popular in BMS applications, such as the implementation detailed in the APTBMS.

Time-based or duration models offer an alternative stochastic approach to deterioration prediction, focusing on the time a bridge component remains in a particular condition state. These models utilize statistical distributions such as Weibull or Gamma to describe the variability in the duration until the component transits to a new condition state. Unlike Markov Chain models that emphasize discrete states and transitions, duration models provide insights into the expected lifespan of components under varying conditions. Factors influencing duration models include environmental conditions, structural design, and the effectiveness of maintenance and rehabilitation efforts.

An example of a stochastic deterioration model that integrates a duration model is documented in the Florida DOT BMS [154]. In this model, the likelihood of a structure maintaining its initial condition state is characterized using a Weibull survival function, while transitions between subsequent condition states are governed by a Markov Chain. This combined approach is known as Semi-Markov chain model, offering a nuanced depiction of deterioration over time.

Stochastic deterioration models represent an active research area in academia as evidenced by recent studies [160].

However, there are some critical aspects to consider when using these models. First, the assumptions underlying Markov chain models are hardly satisfied in practice. For instance, it is often difficult to estimate accurately the probabilities of transition between different states of the structure due to the lack of reliable data. Additionally, most common deterioration models are not always reliable, especially for bridges that have been subjected to unusual or extreme loading conditions or that have experienced environmental or geological hazards. Current deterioration models can grasp generalized deterioration processes at the bridge component level. However, the failure of a component is often due to localized deterioration phenomena. This fact represents a limitation to the application of deterioration models and must be taken into account when performing maintenance schedules [177].

8. Decision-making

Bridge management accounts for three different scales, namely: network, element, and component scale. The network scale refers to a set of bridges sharing some common characteristics, e.g., position, static scheme, and length. The element scale focuses on an individual bridge whereas the component scale encompasses both structural components (e.g., deck, girders, piers) and non-structural components (e.g., road accessories, road surfaces, drainage systems) of individual bridges.

At the level of single bridges, an important aspect of bridge management relates to the optimization of maintenance activities at the component level. Maintenance corresponds to the sequence of actions to be taken to preserve the initial performance of a bridge and maximize life expectancy [161]. Still, managers usually handle large portfolios of bridges and account for unavoidable constraints in economic, material, and personnel resources. For this reason, managers need to prioritize maintenance activities identifying a priority ranking between different structures. Two primary approaches for decision-making are identified: the top-down approach, which focuses on network-level optimization, and the bottom-up approach, which concentrates on individual bridge maintenance optimization. The selection of the best approach generally depends on the size of the network and also on the optimization method employed.

These aspects are addressed in this section considering the recent literature on these aspects.

8.1. Maintenance Strategies

Four different maintenance strategies exist, namely corrective, preventive, condition-based, and predictive maintenance, each with different characteristics and increasing complexity [161–163], see Fig. 10.

The corrective (or reactive) maintenance strategy includes the set of

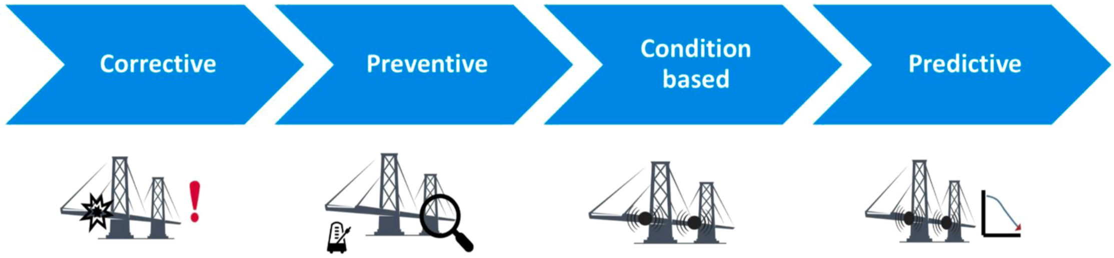

Fig. 10. Maintenance strategies.

actions that are performed to repair or replace faulty components and equipment. These failures are typically identified during routine inspections. Interventions can be carried out immediately after the detection of failure or deferred in time, in the case the failure does not significantly affect the bridge functionality. The corrective strategy is implemented in case the costs sustained for downtime and repair are lower than the investment required for a scheduled maintenance program or data collection. This strategy is generally considered cost-effective for non-structural bridge components.

Preventive strategies imply periodic activities performed on predetermined schedules or according to prescribed rules (e.g., use-based), aiming at reducing the risk of failure or severe performance degradation of bridges. Preventive strategies can be applied both for structural and non-structural bridge components. For example, APTBMS utilizes a preventive maintenance strategy for certain categories of bridge components, such as components positioned on the road planes (joints, road slabs, etc.) and accessories (guardrails, etc.) with a time frame of one year [151]. Similarly, STRUMAN implements preventive plans for non-structural bridge components such as drainage systems [157].

Condition-based maintenance uses new data from visual inspections, tests, and SHM systems to identify and track deterioration. It follows specific condition criteria, e.g., reliability thresholds, to decide when maintenance is needed. This method cuts long-term maintenance costs, reducing the chances of major failures. Condition-based maintenance strategies are used for instance, by DANBRO, MRWA, and Bridgeman BMSs, which do not include a prognosis module for maintenance optimization [12].

Predictive maintenance exploits information about deterioration models to assess current conditions and forecast future failures before they occur. This strategy is used to determine the optimal inspection and intervention scheduling and prevent system failures.

Predictive maintenance involves utilizing inspection, test, and SHM data coupled with deterioration models to forecast bridge failures before they occur. By monitoring key parameters and analyzing trends, predictive maintenance enables timely interventions and minimizes downtime. Predictive maintenance strategies are implemented by several BMSs, such as APTBMS, KUBA, and BatMan, as reported in [12].

8.2. *The Top-down and the Bottom-up approaches*

The literature traditionally distinguishes two main approaches to deal with bridge management optimization, namely the Top-down and the Bottom-up approaches [11], see Fig. 11.

The top-down approach operates at the network level considering the mutual relations and common features among bridges. This approach includes the optimization of the network maintenance planning, minimizing the total costs of maintenance and delay of interventions, and maximizing the road network performance [164]. The network topology and network roles are analyzed to find relations and determine the most critical bridges that, if closed, would result in the highest indirect costs (social and environmental). The identification of bridge clusters with similar properties allows for more efficient planning of inspections and interventions [1]. However, applying the top-down approach to large networks becomes computationally challenging due to the need to assess network relations and clusters in the road network.

The bottom-up approach focuses on identifying the optimal maintenance strategy for an individual bridge. This approach establishes minimum performance standards for the bridge and determines the most suitable inspections and intervention schedule. However, unlike the top-down approach, the bottom-up approach does not consider the role of the bridge within the network. As a result, the bottom-up approach potentially results in adverse traffic conditions and a lack of coordination in implementing maintenance activities among neighboring bridges [11].

The US Pontis [16] and Ontario BMS [165], the South African STRUMAN [157], and the Slovenian BMS [28], implement a top-down

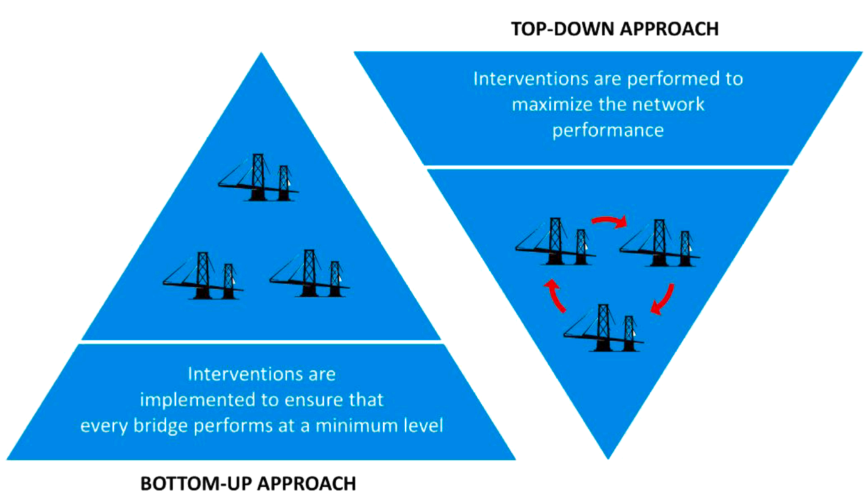

Fig. 11. The Bottom-up and the Top-down approaches for bridge management.

approach in the planning of interventions. STRUMAN provides a ranking of the bridge at the network level based on the indirect consequences of the loss of functionality taking into consideration the relevant average daily traffic [157]. The US Bridgit and the US NCDOT [11] implement a bottom-up approach prioritizing maintenance activities based upon a minimum bridge condition standard and within the budget. Information about budget optimization approaches used in current BMSs is shown in Table 5.

8.3. Optimization methods

Optimization methods adopted in existing BMSs include single-objective optimization procedures to allocate resources and prioritize maintenance interventions [168]. Specifically, BMSs implement two main optimization methods: priority index ranking and cost-benefit analyses [12].

The calculation of a priority index is a rather simple approach the majority of BMSs adopt to evaluate and rank interventions both at an element and at a network level. At the element level, priority indexes can be used to compare different interventions and select the optimal one. At a network level, priority indexes can be used to prioritize interventions among different bridges [15]. As anticipated in the diagnosis section, both technical and non-technical PIs can be used for decision-making. For instance, reliability and risk PIs can be used in prioritizing repair and maintenance interventions. Cerema in France and more recently the Ministry of Transportation of Italy developed multi-level assessment procedures with increasing complexity for network scale risk management for bridge portfolios. Both procedures are characterized by a multi-level approach that begins with a qualitative risk assessment of the entire bridge portfolio and concludes with a detailed analysis of fewer critical bridges. Specifically, the Italian guidelines address multiple types of hazards, including earthquakes, landslides, structural issues, and hydraulic actions. In contrast, the French guidelines are divided into different volumes, each focusing on a single hazard. Maintenance interventions are ordered by a priority ranking and implemented consequently according to budget constraints.

BMSs typically integrate a cost model. The descriptions of the most common interventions on the numerous bridge components are standardized into BMSs (in terms of cost, time, and effect) and utilized in the maintenance optimization [12]. The APTBMS [151] utilizes a priority index both to compare different alternatives (repair or substitute) and to prioritize interventions within the network. This is detailed in the next section.

Life-cycle cost analysis is typically employed in BMSs to assess different intervention strategies. The optimal strategy is determined based on the life-cycle cost minimization considering either the bridge or the network. Life-cycle cost analysis at the bridge or the network level is implemented in numerous BMSs such as the Austrian BAUT, the Swiss KUBA BMS, the US Pontis, Ontario, and Bridgit BMS. These BMSs use a standardized forecast model that considers the costs of the bridge through its entire life span (from construction to demolition) accounting for interventions, development of future budgets for inspections and interventions and cost transparency through the life-cycle of the structure. An example of life cost analysis can be found in the Austrian national guidelines for bridge management [169].

Furthermore, KUBA BMS, Pontis, and Slovenia BMS implement an incremental cost-benefit analysis aiming to determine the margin by which one option is more convenient than another [16], [167]. An incremental cost analysis considers increasing budgets from zero to the maximum constraint. For each budget, a different set of interventions and activities can be afforded, and the resulting benefits quantified. The lowest cost-benefit ratio indicates the most economically advantageous maintenance strategy. The restriction imposed by the limited budget influences the final choice of maintenance activities to be executed in a predefined time frame [16], [156]. The Slovenia BMS does not consider the entire service life of the structure in the incremental benefit analysis, but only the period for which the maintenance strategy is adopted and implemented [28].

One of the main issues in single-objective optimization procedures is that they disregard economic, societal, functional, and environmental aspects. These aspects could be taken into account using multi-criteria optimization methods [170]. Despite the extensive research on this matter, as far as the authors' knowledge, there is not yet literature relevance that BMSs incorporate multi-criteria optimization processes [171]. A discussion on multi-criteria optimization and other future directions is reported in the dedicated section of this paper.

Table 5
Budget optimization approaches in BMSs.

BMS name	Country	Budget optimization approach
Autonomous Province of Trento BMS (APTBMS)	Italy	Top-down[151]
Bridgit	United States of America	Bottom-up[11]
DANBRO	Denmark	Top-down[166]
KUBA	Switzerland	Bottom-up[167]
North Caroline Department of Transportation (NCDOT BMS)	United States of America	Bottom-up[11]
Ontario BMS	United States of America	Top-down[165]
Pontis	United States of America	Top-down[16]
Slovenia BMS	Slovenia	Top-down[28]
STRUMAN	South African	Top-down[157]

9. Illustrative case study: The APTBMS

In 2004, the Autonomous Province of Trento in Italy implemented a BMS called APTBMS, based on reliability concepts. This system aimed to evaluate the condition and safety of its extensive inventory of approximately 950 bridges. The development of APTBMS was a collaborative effort involving the Autonomous Province of Trento, the University of Trento, and specialists in database and web design. The system is fully web-based and interactive, and its development was carried out incrementally, with calibration and adjustments made as needed. It is continuously maintained and transparent to users [151].

The APTBMS is composed of various components tailored to specific functions, including data management, safety assessment, priority indexing, cost evaluation, and decision-making. Each component consists of a package of procedures and operational tools, which can be computer-based or paper-based. The BMS encompasses modules at the system level, focusing on individual bridges, and modules at the network level, which pertain to the entire bridge inventory. The system-level modules contain inventory data for each bridge, information on the condition of individual bridge components as well as the entire bridge, and safety and structural reliability evaluations for each bridge. On the other hand, the network-level module includes information relevant to the entire inventory, such as the intervention price list and cost model.

The subsequent sections analyze these components and organize them within the four modules of BMS presented in this paper.

9.1. Data management

Within the framework of the APTBMS, data acquisition relies on visual inspections. The inventory data encompasses details about bridge identification, location, construction, and retrofitting. The primary objective of the inspection system is to gather information regarding the inventory and condition of each bridge, which is achieved through five types of inspections: inventory, superficial, regular routine, in-depth routine, and special inspections. To facilitate data management, each bridge is divided into Structural Units, such as decks, piles, and abutments. These units represent conceptual entities defined by shared attributes like length, material, typology, and spatial location. The database is populated with information obtained from documentation and direct analysis of each bridge. Inspectors and evaluators carry out manual data entry, encompassing inspections and safety evaluations. During inventory inspections, the inspector verifies the conformity of the design documents with the actual constructed state. Superficial inspections are carried out annually. They consist of a brief visual examination aimed at detecting defects of a certain severity. Regular routine inspections are conducted every three years. Their objective is the periodic control of structures and the collection of data related to the degradation of individual components. In-depth routine inspections are carried out every six years. In-depth main inspection differs from the regular routine inspection only in terms of the inspection approach, as it requires close-range examination and the use of appropriate equipment such as mobile platforms or scaffolding. Special inspections, on the other hand, are triggered by specific events, such as the inability to evaluate an element during routine inspections or the detection of structural anomalies that pose safety risks.

9.2. Diagnosis

After storing the inspection information in the database, the bridge inventory is assessed at the component, system, and network levels. At the component level, inspectors assign Condition States (CSs) based on the results of visual inspections contained in evaluation sheets. The CS of a component is ranked using an indicator ranging from 1 (indicating good condition) to a variable maximum between 3 and 5 (indicating poor condition), depending on the type of component being assessed. The component level CSs are divided in 5 different groups depending on the type of structure they belong to: deck components (e.g. slab and joints), main superstructure components (i.e., beams, arches and vaults), main substructure components (i.e., piers, abutments), secondary components (i.e., secondary beams, bracings), and accessory components (e.g., parapets and guardrails) [151].

At the structure level, different indicators are defined in APTBMS. The most important indicator, resulting directly from the component level CSs assigned by means of visual inspections, is the bridge condition state CS_{bridge} which provides an overall assessment of the bridge, offering an immediate and comprehensive judgment on both its components and the bridge as a whole. It consists of a numerical value ranging from 1 (very good conditions) to 5 (very bad conditions). The procedure for the calculation of the CS_{bridge} consists of four steps, starting from the CSs collected at the component level [151].

First, a condition state CS_N is calculated for each component of the bridge. CS_N is normalized with respect to the maximum CS value for that component ($CS_{\max}$ ranges from 3 to 5 depending on the component) and to the maximum value of the bridge condition state CS_{bridge}, which is set equal to 5. See Eq. 1.

$$CS_N = \left[\frac{(CS-1)}{(CS_{\max}-1)} \bullet (CS_{bridge}-1)\right] + 1 \tag{1}$$

Second, each bridge component is categorized into five groups (deck components, main superstructure components, main substructure components, secondary components and accessory components) and a maximum normalized condition state $CS_{NMax}^{type,i}$ is calculated for each group type i as shown in Eq. 2.

$$CS_{NMax}^{type,i} = \max\left\{CS_{N_1}^{type,i}; \ldots; CS_{N_n}^{type,i}\right\} \quad i = 1, \quad \ldots, \quad 5 \tag{2}$$

Third, two weights are assigned to each group i: Table 6 reports the weight values $\%^i$ that describe the importance of the group type i in the evaluation of the overall substructure and superstructure condition states.

Thus, the coefficients $CS_{superstructure}$ and $CS_{substructure}$ are calculated as in Eqs. 3 and 4:

Table 6
Weight values for the estimation of the bridge condition index in APTBMS.

Type group i	Weight value for the Substructure CS	Weight value for the Superstructure CS
1 - deck	25 %	25 %
2 - main superstructure elements	0	70 %
3 - main substructure elements	70 %	0 %
4 - secondary elements	5 %	5 %
5 - accessory elements	0 %	0 %

$$CS_{superstructure} = \sum_{1}^{5} CS_{NMax}^{i} \bullet \%_{superstructure}^{i} \tag{3}$$

$$CS_{substructure} = \sum\nolimits_{1}^{5} CS_{NMax}^{i} \bullet \%_{substructure}^{i} \tag{4}$$

Finally, the condition state of the bridge CS_{bridge} is calculated as the maximum value between the conditions state coefficients of the superstructure and the substructure.

$$CS_{bridge} = \max\left\{CS_{superstructure}; CS_{substructure}\right\} \tag{5}$$

Other indicators defined in the APTBMS, such as the reliability index, the probability of failure, and the critical loads multiplier, are evaluated only in specific cases, e.g., when the condition state of a structure raises concern about structural safety [151].

At the network level, the priority index is calculated to rank the interventions on the bridge inventory. Its calculation requires the definition of deterioration models, maintenance models, and cost models. It serves as a decision support tool for the manager who employs the APTBMS. The subsequent sections focus on these aspects in more detail.

9.3. Prognosis

The evolution of the CS of bridge components is predicted through a Markov Chain algorithm. By incorporating factors such as loading time, environmental effects, and the quality of construction and maintenance, the algorithm provides a systematic approach to forecasting the condition of bridge components. The algorithm utilizes a transition matrix, which captures the probabilities of transitioning from one condition state to another. This matrix considers the various factors affecting the deterioration of bridge components and their impact on the condition state. By analyzing the transition matrix, it becomes possible to estimate the probability of a component belonging to a specific condition state at a given time.

Fig. 12 represents the estimation of the probability distribution of the condition states over time. It provides a graphical representation of how

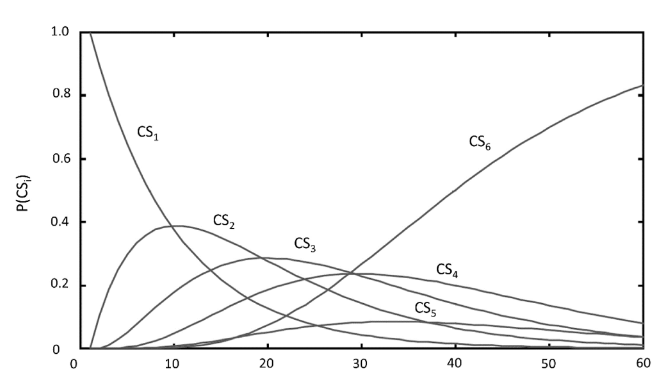

Fig. 12. Probability of being in a condition state vs time.
Adapted from [151].

the condition of bridge components is expected to change as time progresses.

Additionally, the impact of interventions on the CS is measured using a secondary transition matrix, which enables the estimation of the probability of a component improving its condition state when a maintenance action is implemented. The model encompasses various types of interventions, including preventive maintenance, retrofitting, and reconstruction actions.

9.4. Decision support tool

The APTBMS incorporates a decision support tool to prioritize interventions across the bridge network. In the prognosis phase, the tool estimates the probability of a specific bridge component being in a particular *CS*. To further evaluate the structural integrity, a capacity function is defined, allowing for the calculation of the cumulative probability of failure $P_X(t_L)$ at time t_L, based on the *CS* of its components.

The Decision support tool relies on the calculation of a priority index to determine the importance of interventions, which is defined as follows:

$$\alpha = \frac{P_X(t_L) - P_{X|a}(t_L)}{\Delta C} \tag{6}$$

where, $P_X(t_L)$ represents the probability of an unacceptable event X occurring during the period (0, t_L) if no action a (such as preventive maintenance, renovation, or reconstruction) is taken; $P_{X|a}(t_L)$ represents the probability of the same event X occurring if the action a is performed; ΔC denotes the cost difference between implementing action a and doing nothing. An example of the application of the APTBMS prioritization is reported in [172].

The assessment of unacceptability for a particular event depends on the stakeholders involved and could pertain to the collapse of the structure or the loss of functionality and traffic safety.

For each bridge and each potential action, a priority index is calculated. The highest index indicates the most favorable action to implement on the respective bridge. To prioritize interventions across the network, the priority indexes of each bridge in the portfolio are ordered, and a top-down approach is employed.

10. Future direction

Over the last decades, bridge management has experienced significant changes toward digitalization. The digital twin paradigm is becoming increasingly popular among researchers and bridge managers. A digital twin is the digital reconstruction of a real-life asset (the physical twin). It can include a numerical model of the bridge (e.g., finite element model), a building information model, and a deterioration model and can be updated whenever new information is acquired. A digital twin aims to provide feedback in "what-if" simulations to predict asset performance and evaluate risks [173], [174]. In this way, critical phases and potential risks connected to the operation of these assets can be assessed and avoided or tackled before the criticality occurs. Design and construction parameters, environmental conditions, and loading history can be attributed to the digital twin and contribute to the prediction of the future condition state of the structure. A key feature of digital twins is the continuous updating of the virtual model which progressively and automatically evolves with the physical asset.

Digital twins provide components assessment and deterioration prediction for specific disruptive scenarios. The simulation of a deterioration phenomenon and the subsequent insurgence of damages on the structure can provide a guide in inspection SHM data analysis, prognosis, and scheduling aiding emergency protocols. Nevertheless, their practical application for civil engineering systems is in its infancy and is limited mainly due to the computation and resource burden [175].

In order to counteract these limits, surrogate models are increasingly utilized. Surrogate models aim to simplify the description of complex structures and deterioration phenomena thereby enabling fast analyses and simulations. Surrogate models can be based on several approaches, such as response surface models [176], Kriging models [177], high polynomial functions [176], and Artificial Neural Networks [178–180]. Surrogate models can be continuously updated by collected SHM data allowing for real-time condition assessment [176].

In the data collection context, bridge management will be increasingly based on integrated results of both SHM and visual inspections. Bridge inspection is already progressively relying on cutting-edge technologies [60]. Smartphones and tablets are being complemented with Augmented Reality (AR) to control drones equipped with advanced sensors, which can access hard-to-reach areas, capturing detailed visual and thermal images for centralized analysis [181]. These techniques can enhance visual inspections by overlaying digital information onto physical structures, and by allowing for the detection and localization of early-stage defects [182]. Artificial Intelligence (AI) is increasingly expected to play a crucial role in detecting, recognizing, and quantifying surface damage on bridge components. Specifically, Convolutional Neural Networks (CNNs) are typically utilized [185]. Qualitative damage classes can be defined [186] and crack width and length can be measured [187]. A digital shadow of the bridge is created by the collected digital clouds and detailed surface damage information can be integrated [188]. Lately, Recurrent Neural Networks (RNN), such as Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU), and Generative Adversarial Networks (GAN) are finding great interest in the research community [189]. Further, Unmanned Air Vehicle (UAV), photogrammetry and LiDAR (Light Detection and Ranging) can be used for Virtual Reality (VR) applications. The integration of advanced technologies (such as VR, AR, AI, and IoT) to create an immersive and interactive virtual environment for bridge management is referred to as "Metaverse" [183]. For example, in some applications, interactive digital representations of physical bridges are created and associated with SHM data. The combination of visual data with SHM data can potentially enhance the understanding of the dynamic behavior of the bridge and allow experts from different locations to virtually inspect the bridge for final assessment [184].

Network-scale SHM approaches are gaining popularity to address scalability issues characterizing classic contact-based SHM approaches including indirect SHM, satellite-based InSAR monitoring, and Transfer learning.

Indirect or "drive-by" SHM (ISHM) gathers data from sensors in moving vehicles, significantly cutting instrumentation costs for bridge managers. Issues in ISHM relate to modeling vehicle-bridge interaction, road roughness, and complex time-varying loading patterns [198]. Crowdsourced strategies have been developed involving drivers using their smartphones to collect data while crossing bridges [59].

Satellite-based Monitoring uses Interferometric Synthetic Aperture Radar (InSAR) data for bridge monitoring, eliminating the need for on-site sensors. InSAR focuses on static monitoring, providing velocity maps and millimeter-level time series of displacements. It allows for continuous, non-intrusive monitoring, even in difficult environments, and offers historical data for trend analysis and proactive maintenance [190]. Additionally, remote monitoring has proven to be effective in studying large-scale or local geotechnical and hydraulic phenomena, such as scour, subsidence, and landslides [191–193].

Transfer-Learning Strategies, also known as "population-based" SHM, enhance knowledge about structures with limited or unavailable data by leveraging information from similar structures. This method involves assessing similarities between bridges and transferring knowledge about structural anomalies observed in some bridges to others within the monitored population [194].

These advancements streamline the documentation process, by enabling real-time cloud communication and high-quality data capture, which enhances immediacy and accuracy during inspections [195]. To this end, efficient data storage solutions are crucial, given the large file sizes and diverse formats involved. Enhanced cloud-based systems are now at the forefront of innovation, offering scalability, remote access, and robust data management, including version control, metadata tagging, blockchains, and secure protocols to maintain data integrity [61–63].

To foster the development of SHM systems, an important research effort has been mounted over the past decade toward the quantification of the return on investment in an SHM system, for instance through the VoI from Bayesian decision theory. The VoI can be compared with the cost of the SHM system to establish if the SHM should be adopted: if the VoI is higher than the corresponding cost, the SHM should be installed [196–199].

In the prognosis context, to overcome the shortcomings of Markov Chain and regression deterioration models, reliability-based mechanistic deterioration models were proposed to be applied in the next generation of BMSs. Corrosion and fatigue represent the two main degradation phenomena affecting the durability of steel and concrete bridges. The fatigue life of steel, reinforced concrete, and prestressed concrete components is significantly affected by corrosion as it reduces the available cross-section and fosters the creation of pits acting as stress concentrators and crack initiators. Thus, deterioration models consider both phenomena [200], [201], also considering changing traffic loads [202], [203]. Further, the use of DTs and surrogate models to predict components' fatigue life facilitates inspecting/monitoring planning and maintenance optimization [204].

Although substantial research has been dedicated to in-plane stress-induced fatigue in welded details, distortion-induced fatigue—caused by out-of-plane deformation—has not been adequately addressed in current codes and regulations, despite its significant impact on structural integrity [205]. Addressing this gap is crucial for enhancing fatigue design and life evaluation for steel girder bridges. Distortion-induced fatigue typically manifests in the web gaps of steel girders, where differential deflections between adjacent girders or components result in out-of-plane bending stresses [206]. Stress concentrations can lead to the initiation and propagation of fatigue cracks, particularly in the web gap areas of skewed or curved bridges [205]. To address the gaps in understanding and predicting distortion-induced fatigue, numerical simulation techniques have emerged as powerful tools [205], [207–210]. The digital simulations offer high efficiency and broad applicability, making it a promising direction for the future development of fatigue research in steel bridges.

As for the decision-making module, the set of intervention options should integrate the latest developments in reinforcement and maintenance technologies. Forefront advancements for the reinforcement and maintenance technologies include Fiber Reinforced Composites (FRC), such as Ultra-high Performance Fiber Reinforced Concrete (UHPFRC), Fiber Reinforced Cementitious Mortar (FRCM), Externally Bonded (EB) techniques, Near Surface Mounted (NSM) techniques, and anchorage systems [211] [212].

Fatigue cracking represents a critical challenge for the safety and longevity of steel bridges. To address these issues, effective reinforcement methods are essential to ensure structural integrity and extend the service life of these structures. These methods can be broadly categorized into hot reinforcement and cold reinforcement techniques [210]. Hot reinforcement methods involve techniques that typically introduce significant tensile residual stresses or create new fatigue-prone details. For example, welding is a common hot reinforcement approach where new steel plates are welded directly to cracked areas or existing welded connections are reworked [213]. In contrast, cold reinforcement methods aim to avoid introducing additional tensile residual stresses or creating new fatigue-prone details. Techniques such as drilling stop-holes at crack tips [214] [215], bolting steel angles to cracked regions [216], and bonding steel plates using adhesives fall into this category [217], [218]. Research has demonstrated that cold reinforcement methods can significantly enhance fatigue performance.

Although only a few examples of optimization methods in BMSs are documented in the literature, bridge management optimization constitutes an active research field. BMS decision support systems take into consideration different parameters when determining optimal management strategies. Current research focuses on the identification of the most significative parameters and on the definition of a Multi-Objective Optimization Problem (MOOP), which could be integrated into the next BMS generation. The MOOP can be solved by considering the weighted sum of single objective optimization problems [219] or adopting some advanced resolution methods, such as Multi-Criteria Decision-Making (MCDM), grid searching, and genetic algorithms [220], [221]. MCDM includes a wide number of analytical frameworks to perform such optimizations accounting for multiple and often contrasting objectives, such as maximum reliability, minimum cost, minimum environmental impact, minimum impact on users, and maximum network functionality, by proposing a trade-off among them. Further, several European Projects, such as IM-SAFE and BRIDGITISE, aim to investigate a common decision-making flow for optimized and digitalized bridge management [222], [223].

The topic of transportation network resilience has been recently discussed by several authors aiming to describe the ability of transportation systems to respond, react, and recover from adverse events such as earthquakes, floods, climate change, and cyber-attacks [174], [224]. Further, national guidelines, such as the Italian Guidelines for bridges [44], report the necessity to identify bridges of significant importance within a road network and perform resilience analyses to evaluate the consequences of a possible interruption of the bridge operation on the socio-economic context.

11. Conclusions

The need for efficient management of existing bridges has become increasingly pressing in recent years. BMSs have emerged as a powerful tool for managing infrastructure assets, with significant advancements in associated technologies in recent years. This paper provides a comprehensive overview of the current state of the art of BMSs, including a historical perspective on the development of BMS software and the definition of the four main modules of a complete BMS: data collection, diagnosis, prognosis, and decision making.

While BMSs have shown great potential in managing infrastructure assets, there are still several limitations that need to be addressed. The current practices in bridge diagnosis and prognosis are closely related to the methods adopted for data collection. Visual inspections remain the most common method for data collection; however, they come with notable drawbacks, including the subjectivity of results and challenges in accessing hidden structural components. New technologies, such as SHM and drone inspections, have emerged as promising additions to overcome these limitations.

In terms of bridge diagnosis, condition ratings based on data collected through visual inspections is the main tool for assessing structural conditions. Although damage indicators extracted from SHM data have been extensively investigated by the research community, their systematic integration into BMS frameworks requires further research and standardization efforts.

In the prognosis phase, most of the analyzed BMSs utilize Markov chains and deterministic methods to forecast the future state of a structure. While these traditional methods have been widely implemented, they have several limitations, including their reliance on simplifying assumptions and potential inaccuracies in predicting complex deterioration processes. As a result, there is increasing interest in novel approaches that combine artificial intelligence techniques with physical modeling. These hybrid methods, which are actively being explored in the literature, promise to address the shortcomings of traditional methods by offering better predictions of structural conditions.

Finally, even though several decision-making tools have been reported in the literature, most BMSs hardly implement them yet. Current approaches rely on prioritization of interventions based on priority indices that take into account both the structural conditions and the costs associated with different remedial actions. There is a need for further research to improve decision-making processes, and BMSs will likely become more sophisticated in this aspect in the future.

In summary, the four modules of BMSs have undergone significant changes toward digitalization and automation, and innovative technologies, such as digital twins, are expected to enhance innovation in bridge management and lead to more sustainable, safer, and cheaper transportation infrastructure. The overview provided in this paper has demonstrated the significant progress in BMSs in recent years, but there is still a long way to go to achieve optimal, all-around management of infrastructure assets.

CRediT authorship contribution statement

Daniele Zonta: Writing – review & editing, Supervision. **Valeria Francesca Caspani:** Writing – original draft, Conceptualization. **Francesca Brighenti:** Writing – original draft, Conceptualization. **Maria Pina Limongelli:** Writing – review & editing, Supervision. **Pier Francesco Giordano:** Writing – review & editing, Supervision, Conceptualization. **Giancarlo Costa:** Writing – original draft, Conceptualization.

Data availability

Bibliographical data can be provided upon request to the corresponding author.

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