

Review

Maintenance Budget Allocation Models of Existing Bridge Structures: Systematic Literature and Scientometric Reviews of the Last Three Decades

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Abstract

Bridges play an increasingly indispensable role in endorsing the economic and social development of societies by linking highways and facilitating the mobility of people and goods. Concurrently, they are susceptible to high traffic volumes and an intricate service environment over their lifespans, resulting in undergoing a progressive deterioration process. Hence, efficient measures of maintenance, repair, and rehabilitation planning are critical to boost the performance condition, safety, and structural integrity of bridges while evading less costly interventions. To this end, this research paper furnishes a mixed review method, comprising systematic literature and scientometric reviews, for the meticulous examination and analysis of the existing research work in relation with maintenance fund allocation models of bridges (BriMai_all). With that in mind, Scopus and Web of Science databases are harnessed collectively to retrieve peer-reviewed journal articles on the subject, culminating in 380 indexed journal articles over the study period (1990–2025). In this respect, VOSviewer and Bibliometrix R package are utilized to create a visualization network of the literature database, covering keyword co-occurrence analysis, country co-authorship analysis, institution co-authorship analysis, journal co-citation analysis, journal co-citation, core journal analysis, and temporal trends. Subsequently, a rigorous systematic literature review is rendered to synthesize the adopted tools and prominent trends of the relevant state of the art. Particularly, the conducted multi-dimensional review examines the six dominant methodical paradigms of bridge maintenance management: (1) multi-criteria decision making, (2) life cycle assessment, (3) digital twins, (4) inspection planning, (5) artificial intelligence, and (6) optimization. It can be argued that this research paper could assist asset managers with a practical guide and a protocol to plan maintenance expenditures and implement sustainable practices for bridges under deterioration.

Keywords: bridges; systematic review; scientometric review; maintenance fund allocation; VOSviewer; Bibliometrix R package



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1. Introduction

Transportation infrastructure assets form the backbone of modern society, enabling mobility, commerce, and access to essential services [1]. Robust transport networks are vital for human well-being and economic prosperity, as they facilitate daily activities and the efficient movement of goods and people [2]. Bridges are vital components of transportation infrastructure that connects these networks together [3]. However, aging bridge stock, increasing traffic demands, and the intensifying effects of climate change present significant challenges for bridge management and conservation globally [4]. Bridges are subject to various forms of deterioration and degradation factors related to material properties, including chemical, design and construction, physical, operational, environmental, and force majeure factors [5]. Inadequate maintenance or delayed repairs can further accelerate deterioration, as small defects (cracks, leaks, etc.) grow to larger problems. Over time, the compounding effects of weathering, material aging, and heavy use can compromise structural capacity and serviceability. Without timely intervention, these factors may render bridges as structurally deficient, posing restrictions or safety risks to users.

Recent assessments of bridge infrastructure underscore the urgency of the maintenance challenge [6]. In the United States, the Federal Highway Administration (FHWA) has reported that there are over 617,000 bridges, and as of the latest evaluations, about 7.4% of them are rated in “poor” condition [7]. The American Society of Civil Engineers (ASCE) has given U.S. bridges an overall grade of “C” in its infrastructure report card, reflecting a middling state of health, with many structures in need of rehabilitation [8]. Similarly, in Canada, national evaluations reveal significant maintenance needs. The 2019 Canadian Infrastructure Report Card found that nearly 40% of municipal roads and bridges were in fair, poor, or very poor condition, with about 80% of them being over 20 years old [9]. Such statistics highlight a substantial backlog of aging bridges that require maintenance or replacement in the coming years. While a bridge rated as poor is not necessarily unsafe for use, it does flag structural deficiencies that mandate repair or stricter inspection to ensure safety.

Effective maintenance strategies are essential to preserve bridge functionality, extend service life, and ensure public safety. Worldwide, transportation agencies employ formal Bridge Management Systems (BMSs) to guide the upkeep and preservation of bridge networks [10]. A BMS is a decision-support system designed for structuring optimal programs and strategies of maintenance, repair, and rehabilitation (MRR) while satisfying their structural and resource constraints [11]. Allocating MRR funds efficiently helps to avoid a growing backlog of bridge work. Such accumulated deferrals can increase repair expenses to the extent that restoring deteriorated bridges may cost more than building new ones [12,13]. However, the challenge lies in the optimal allocation of limited financial resources to a growing inventory of aging structures. In response, researchers have developed maintenance optimization models that analyze possible actions (such as routine maintenance, repair, rehabilitation, or replacement) and schedules under budget constraints to recommend the optimal maintenance program [12]. The goal is to achieve the best possible outcomes in terms of safety, serviceability, and cost effectiveness over the bridge’s lifecycle. Traditional maintenance approaches often rely on periodic inspections and reactive repairs, which may not be sufficient to address the complexities of bridge deterioration and budget constraints.

Recent advancements in technology and analytical methods have led to more sophisticated maintenance optimization models. These models incorporate various factors, such as bridge condition assessments, deterioration predictions, risk analyses, and budget limitations, to prioritize maintenance actions [14]. For instance, optimization techniques, including multi-objective optimization and decision-support systems, have been devel-

oped to balance tradeoffs between different maintenance objectives and constraints [15]. Moreover, the integration of emerging technologies, such as machine learning and artificial intelligence, has enhanced the predictive capabilities of maintenance models. These technologies enable the analysis of large datasets from structural health-monitoring systems to identify patterns and predict future deterioration, facilitating proactive maintenance planning [16]. In addition to technical considerations, effective bridge maintenance optimization also involves organizational and policy aspects. Implementing comprehensive BMSs that integrate data collection, analysis, and decision-making processes is crucial for systematic maintenance planning. Such systems support asset managers in making informed decisions regarding maintenance priorities and resource allocation.

In essence, bridge maintenance budget allocation models improve equity, transparency, and accountability by replacing subjective or intuition-driven decisions with a data-driven, systematic process. Basically, these models apply standardized criteria, such as structural condition, traffic volume, and age to all bridges, ensuring that funding is allocated based on objective needs rather than favoritism. In addition, these models foster transparent decision-making because their inputs, weighting factors, and final scoring are documented and visible, allowing bridge managers to see exactly how and why each funding decision is made. Finally, accountability is strengthened as decision-makers are thereby able to create a defensible and clear audit trail for public expenditure against biased maintenance interventions.

Despite significant scholarly contributions, there remains a lack of consolidated understanding regarding the evolution, impact, and research gaps in maintenance budget allocation modeling for bridge infrastructure. A scientometric review, combined with a systematic literature review, offers a rigorous approach to evaluating knowledge trends, identifying leading contributors, and mapping intellectual structures in this field. Scientometric methods allow for a data-driven analysis of publication patterns, citation networks, and thematic developments, providing a meta-perspective on how bridge maintenance budgeting models have matured and diversified since the early 1990s [17].

2. Research Methodology

The allocation of maintenance budgets for existing bridge structures has been a critical concern in infrastructure management over the past three decades. Aging bridge inventories, constrained financial resources, and increasing traffic demands necessitate efficient and effective budget allocation strategies to ensure structural safety and serviceability. This conducted review systematically examines the evolution of maintenance budget allocation models, highlighting key methodologies, advancements, and trends in the field. This study employs a systematic literature review methodology, adhering to the widely recognized standards outlined in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement. In this context, PRISMA offers a methodical framework for systemized identification, screening, and synthesis of pertinent research studies, bolstering scientific replicability and credibility of the review process [18–20]. Appendix A outlines PRISMA checklist 2020 and a PRISMA flow diagram of this research study. Figure 1 depicts a graphical representation of the data collection and processing of the literature review work on BriMai_all. It is a mixed-review methodology, comprising of both bibliometric analysis and systematic review of the current state of the art in the field of BriMai_all. The retrieval period spanned from 1990 to 20 April 2025, encompassing journal articles and book chapters in English language. In order to extract the most relevant documents, initial phrase searches and data extraction were carried out using Scopus and Web of Science databases. Several databases are available for performing bibliographic analysis, including Web of Science, Scopus, PubMed, Cochrane Library, Lens, Dimensions, and OpenAlex; each offer distinctive features and functions. Web of Science and Scopus are the most com-

prehensive and dominant literature databases across nearly all academic disciplines, which are often used for bibliometric analysis and systematic review [21–23]. With that in mind, the pertinent literature was gathered from the Scopus dataset using the TITLE-ABS-KEY search syntax, allowing for probing the title, abstract, and keywords of research records. In the Web of Science core collection, related indexed documents were garnered using the topic search function that looks into their title, abstract, keywords, and keywords plus fields. Thereafter, the designed search strategy yielded 1065 Scopus publications (1032 journal articles and 33 book chapters) and 1578 WOS publications (1547 journal articles and 31 book chapters). It is worth noting that thesaurus files were created in VOSviewer software to evade semantic errors, remove redundant and non-informative terms, and merge duplicates [24,25]. Thereafter, the resultant search strings are listed in Table 1.

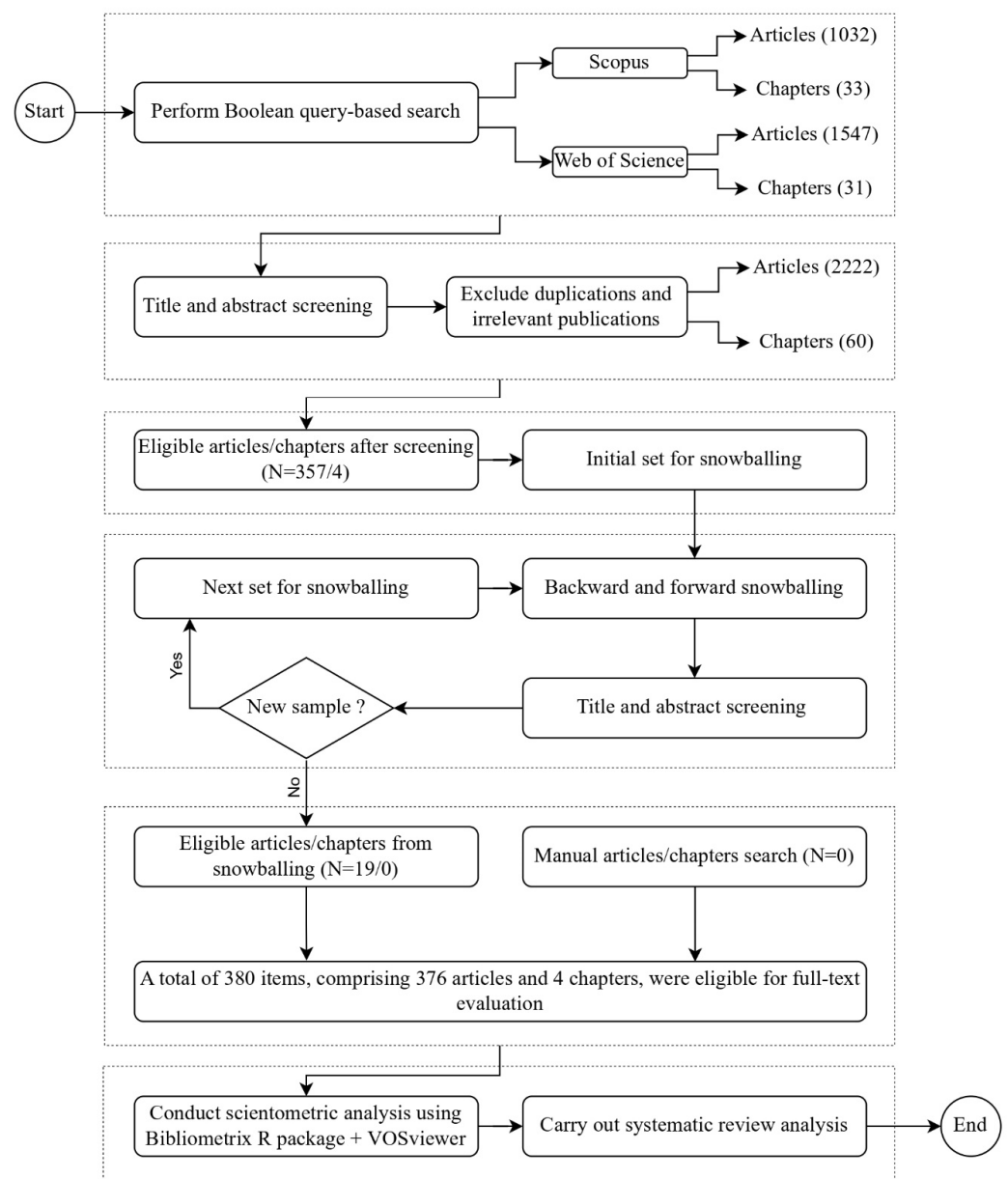


Figure 1. Methodological framework of the mixed review approach of BriMai_all literature.

Table 1. Descriptions of formulated query strings.

Database	Search String
Web of Science	((TS = ("bridge*")) AND ((TS = ("remedia*")) OR (TS = ("rehabilitation")) OR (TS = ("repair")) OR (TS = ("maintenance")) OR (TS = ("budget")) OR (TS = ("fund")) OR (TS = ("decision support system")) OR (TS = ("prioritiz*")) OR (TS = ("inspection")) AND ((TS = ("optimiz*")) OR (TS = ("Pareto")) OR (TS = ("multi criteria decision making")) OR (TS = ("mcdm")) OR (TS = ("madm"))))
Scopus	((TITLE-ABS-KEY ("bridge*")) AND ((TITLE-ABS-KEY ("remedia*")) OR (TITLE-ABS-KEY ("rehabilitation")) OR (TITLE-ABS-KEY ("repair")) OR (TITLE-ABS-KEY ("maintenance")) OR (TITLE-ABS-KEY ("budget")) OR (TITLE-ABS-KEY ("fund")) OR (TITLE-ABS-KEY ("decision support system")) OR (TITLE-ABS-KEY ("prioritiz*")) OR (TITLE-ABS-KEY ("inspection")) AND ((TITLE-ABS-KEY ("optimiz*")) OR (TITLE-ABS-KEY ("Pareto")) OR (TITLE-ABS-KEY ("multi criteria decision making")) OR (TITLE-ABS-KEY ("mcdm")) OR (TITLE-ABS-KEY ("madm"))))

Subsequently, the scientific articles from Web of Science and Scopus databases were merged into a consolidated dataset to undertake bibliometric analysis. The titles and abstracts of the blended database were meticulously examined to filter out non-pertinent and repeated publications. After completing the review process, relevant literature documents were narrowed down to 357 journal articles and 4 book chapters. Snowballing is a supplementary method in systematic literature reviews where researchers identify additional relevant studies by examining references (backward snowballing) and citations (forward snowballing) of selected articles [26,27]. It enhances the comprehensiveness of reviews by uncovering key works missed in database searches, especially in interdisciplinary fields. Additionally, it aids in enhancing the reliability and depth of literature synthesis as well as tracing the evolution of research themes through citation networks, providing historical context, and identifying seminal works [28,29]. Hitherto, the processes of forward and backward snowballing resulted in including an additional 19 journal articles, expanding the final dataset to a set of 380 scientific documents divided into 376 journal articles and 4 book chapters. Following that, this research study adopts VOSviewer software (version 1.6.20) [17] and Bibliometrix R package (version 4.3.3) [30] to visualize co-occurrence, co-authorship, co-citation, authors' productivity, temporal co-word, publication growth, and citation trend analyses.

3. Scientometric Review Analysis

This section covers the main aspects of scientometric analysis examining publication data, citations, and authorship networks, which aid in identifying emerging fields and influential research contributions.

3.1. Publication Trend

The conducted publication trend aims to provide a historical understanding of the bridge maintenance-related studies, testing maturity and established interest, and understanding whether the interest trend is growing for this topic or it is declining. Figure 2 provides a detailed graphical representation of yearly publications concerning maintenance budget allocation models for existing bridge structures from 1993 to 2025. The figure's blue columns indicate the number of articles published each year. In contrast, the dashed blue regression curve—derived from a fourth-order polynomial model using (Y–1993) as the independent variable—captures the overall upward trend in research output. The early exploration phase, spanning from 1993 to 2001, is characterized by modest publication activity, with annual counts rarely exceeding five, highlighting the nascent state of the field. From 2002 to 2014, during the steady development phase, publication numbers

consistently ranged from 5 to 12 articles per year, reflecting a growing interest in the topic. However, the trend experienced a dramatic shift from 2015 onward, entering a rapid development phase, illustrated by a surge in publications that peaked at 38 articles in 2022. This increase underscores the intensifying scholarly focus within this domain. The regression equation (Equation (1)), determined through least squares fitting, has an R^2 value of approximately 73%, indicating that the regression model accounts for over 73% of the variability in publication counts.

$$AP = -1.9e-4(Y-1993)^4 + 1.08e-2(Y-1993)^3 + 1.71e-1(Y-1993)^2 + 1.32(Y-1993) \quad (1)$$

where AP is the annual number of publications and Y is the publication year.

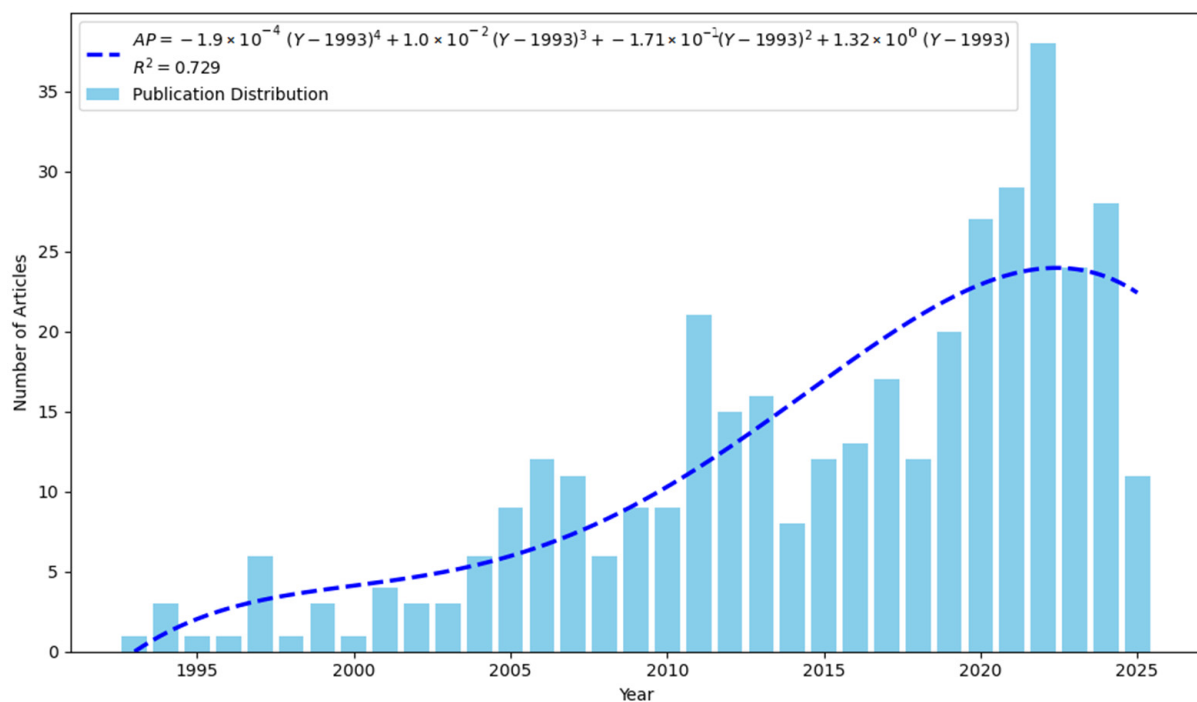


Figure 2. Yearly publication trends for maintenance budget allocation models of existing bridge structures (1990–2025).

Figure 3 illustrates the mean total citations per year from 1993 to 2025. The data reveal significant year-to-year variability: the earlier years show relatively low average citations, dipping to as low as 0.30 in 1996, alongside intermittent spikes such as 3.06 in 1997 and a peak of 4.65 in 2000. The subsequent years exhibit fluctuations, with notable increases during specific periods (for instance, 3.62 in 2003, 3.87 in 2014, and 4.06 in 2019) contrasted by lower averages in others. These variations indicate that the field experiences heightened impact and attention phases, likely reflecting bursts of influential research, while other years experience more moderate activity.

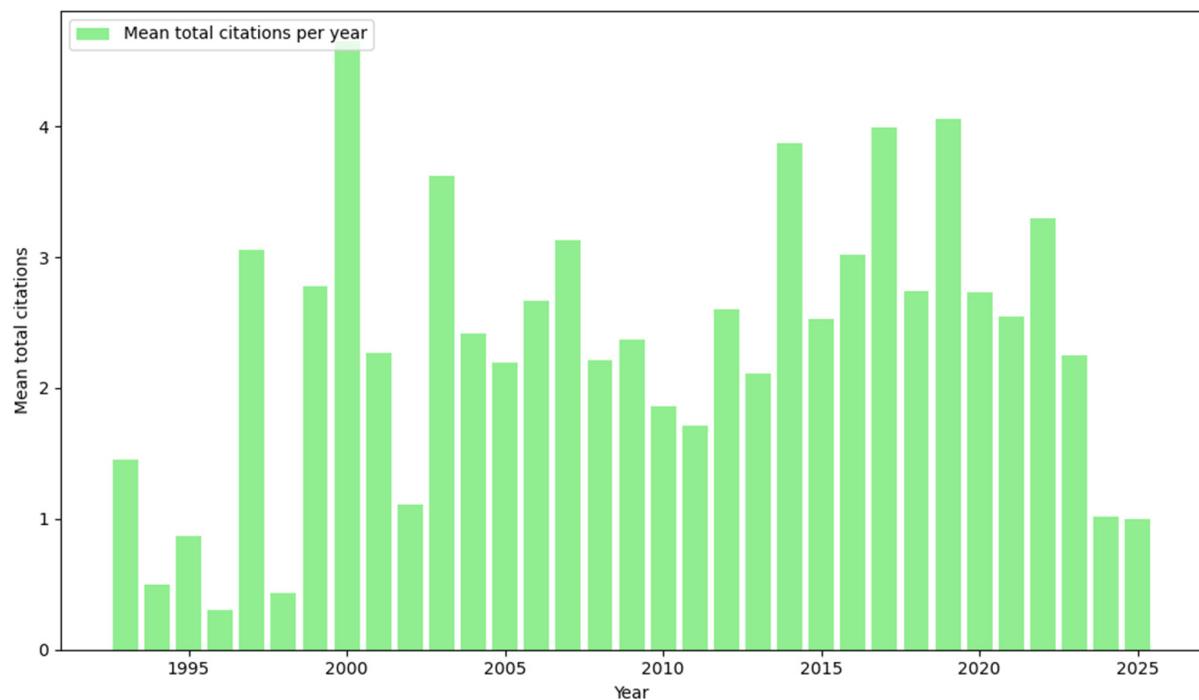


Figure 3. Yearly mean total citations for maintenance budget allocation studies of existing bridge structures (1990–2025).

3.2. Document Analysis

Tables 2 and 3 summarize the most highly cited articles on maintenance budget allocation models for existing bridge structures over the past three decades. Notably, the articles are ranked according to their total citations during the study period, emphasizing their significance within the field. The top-ranked article, “Maintenance and Management of Civil Infrastructure Based on Condition, Safety, Optimization, and Life-Cycle Cost” (2007), garnered 362 citations and achieved a normalized score of 6.08. This work illustrates how multi-objective optimization employing genetic algorithms can generate diverse maintenance strategies that balance structural performance, safety, and life-cycle costs, ultimately facilitating more informed decision-making. In second place, “Life-Cycle Cost Design of Deteriorating Structures” (1997) received 299 citations and a normalized score of 3.37. This article presents a reliability-based optimization approach that significantly reduces maintenance costs by utilizing non-uniform inspection intervals while preserving structural reliability. The other articles in the table further contribute by providing insights into system-level reliability approaches, advanced inspection scheduling through genetic algorithms, and innovative risk-based decision-making frameworks incorporating sustainability and resilience considerations. This table illustrates the evolution of maintenance optimization methodologies from early analytical models to sophisticated simulation and algorithm-based approaches. It highlights the increasing focus on balancing cost, safety, and performance in infrastructure management.

Table 2. Summary of influential articles on maintenance budget allocation models for existing bridge structures.

Rank	Reference	Title	Publication Year	Total Citations	Normalized Citations	Key Findings
1	[31]	Maintenance and management of civil infrastructure based on condition, safety, optimization, and life-cycle cost	2007	362	6.08	Multi-objective optimization using genetic algorithms produces a range of maintenance strategies that balance structure performance, safety, and life-cycle cost, thereby enabling more informed decision-making.
2	[32]	Life-Cycle Cost Design of Deteriorating Structures	1997	299	3.37	A reliability-based life-cycle cost optimization approach, especially via non-uniform inspection intervals, can substantially reduce maintenance costs while ensuring structural reliability, with the optimal strategy being susceptible to corrosion rates and failure costs.
3	[33]	Repair Optimization of Highway Bridges Using System Reliability Approach	1999	182	2.43	A system reliability approach to lifetime repair planning for highway bridges can minimize life-cycle costs while ensuring overall structural reliability; however, its effectiveness depends on regular updates through inspection and improved quantification of uncertainties.
4	[34]	Enhanced discrete particle swarm optimization path planning for UAV vision-based surface inspection	2017	174	4.84	A new method quickly computes efficient inspection routes that cover all areas and avoid obstacles, significantly reducing travel distance and processing time.
5	[35]	Life-Cycle Reliability-Based Maintenance Cost Optimization of Deteriorating Structures with Emphasis on Bridges	2003	168	2.02	A reliability-based methodology integrates random variable modeling, Monte Carlo simulation, and reliability index profile superposition to predict life-cycle performance and cost, enabling optimal maintenance strategies that balance long-term reliability with minimized cumulative costs under uncertainty.

Table 3. Summary of influential articles on maintenance budget allocation models for existing bridge structures (Cont’d).

Rank	Reference	Title	Publication Year	Total Citations	Normalized Citations	Key Findings
6	[36]	Optimal Resilience- and Cost-Based Postdisaster Intervention Prioritization for Bridges along a Highway Segment	2012	157	4.31	Integrating genetic algorithms with advanced traffic flow analysis, the framework automatically produces optimal bridge intervention schedules that balance resilience and cost after disruptive events.
7	[37]	Maintenance optimization of infrastructure networks using genetic algorithms	2004	148	3.22	By integrating genetic algorithms with Markov-chain models, the methodology was successfully applied to the maintenance programming of Quebec’s concrete bridge decks, resulting in an optimal mix of maintenance actions that minimize costs while keeping network conditions above acceptable thresholds.
8	[38]	Lifetime-oriented multi-objective optimization of structural maintenance considering system reliability, redundancy, and life-cycle cost using GA	2009	145	3.60	An automated genetic algorithm framework was developed to optimize maintenance strategies by balancing reliability, redundancy, and life-cycle cost. Its application to truss and bridge structures demonstrated that focusing on critical components yields more cost-effective and robust results.
9	[39]	Two probabilistic life-cycle maintenance models for deteriorating civil infrastructures	2004	143	2.68	A Monte Carlo-based reliability model was developed to optimize infrastructure maintenance by simulating multiple failure modes and uncertainties. Compared with an analytic model from the Netherlands, comprehensive reliability data yield more cost-effective, robust bridge maintenance.
10	[40]	Risk-Based Decision Making for Sustainable and Resilient Infrastructure Systems	2016	143	4.73	A risk-informed decision-making framework applied to highway bridge decks revealed that using high-performance concrete significantly reduces life-cycle costs and environmental impacts while minimizing damage and recovery times compared to conventional concrete designs.

3.3. Co-Authorship Analysis

The institutional co-authorship map streamlines a visual representation of the collaborative dynamics between the engaged organizations in the BriMai_all domain. In this network, 39 organizations are displayed, such that they are credited with at least 2 publications. Within this network, Lehigh University, The Hong Kong Polytechnic University, University of Colorado and Concordia University emerge as focal points underlining their pivotal contributions and expansive collaboration work in the research domain of BriMai_all. The created network is grouped into five clusters, such that the red cluster is the large one, including 11 institutions such as University of Waterloo, Wonkwang University, Southeast University, Beijing University of Technology, Beijing Jiaotong University, etc. The green cluster is the second-largest one, containing nine institutions and led by the Hong Kong Polytechnic University, Concordia University, Delft University of Technology, Valencia Polytechnic University, and Cairo University. The blue cluster is the third-largest one (7 institutions), and it encompasses the most prolific and cited institution, which is Lehigh University. The yellow cluster consists of six organizations with the University of Colorado being the most contributive institution in it. The purple cluster contains five institutions, all of which share approximately a comparable efficiency in relation to publication count and its significance. Furthermore, it is evident that notable collaboration ties exist between Lehigh University and the Hong Kong Polytechnic University (link strength = 4). In addition, an academic cooperation network is formed between the Hong Kong Polytechnic University, Concordia University, and Cairo University. Table 4 records a comprehensive overview of the most contributing institutions in the literature on BriMai_all. Normalized citations are computed by dividing the article's count of citations by the average number of citations for all publications from its same year of publication [17]. The total link strength denotes the total strength of the connections between a specific item in a network and all other items it is connected to. Hence, the total link strength attribute signifies the total strength of the co-authorship links of a given institution with other institutions [17].

It is observed that Lehigh University (52 documents), the Hong Kong Polytechnic University (18 documents), University of Colorado (18 documents), Concordia University (9 documents), and University of Waterloo (8 documents) stand as the most productive organizations in relation with the publication count on this topic. In terms of citation count, Lehigh University (2663), University of Colorado (1773), the Hong Kong Polytechnic University (274), Concordia University (202), and Valencia Polytechnic University (192) are positioned in the top five places. With respect to average citation frequency per year, it is elucidated that Delft University of Technology (3.31), Harbin Institute of Technology (2.54), University of Perugia (2.06), Paris-Saclay University (2.04), and Wuhan University of Technology (1.96) are featured in the top five rankings as shown in Figure 4.

Table 4. Quantitative summary of the forefront institutions in the BriMai_all field.

Rank	Country	Number of Documents	Total Citations	Normalized Citations	Average Publication Year	Average Citations	Average Normalized Citations	Total Link Strength
Publication count								
1	Lehigh University	52	2663	95.02	2015.19	51.21	1.83	28
2	The Hong Kong Polytechnic University	18	274	29.06	2020.89	15.22	1.61	20
3	University of Colorado	18	1773	32.12	2004.44	98.50	1.78	10
4	Concordia University	9	202	9.41	2015.44	22.44	1.05	6
5	University of Waterloo	8	185	6.4511	2012.75	23.13	0.81	5
Total citations								
1	Lehigh University	52	2663	95.02	2015.19	51.21	1.83	28
2	University of Colorado	18	1773	32.12	2004.44	98.50	1.78	10
3	The Hong Kong Polytechnic University	18	274	29.06	2020.89	15.22	1.61	20
4	Concordia University	9	202	9.41	2015.44	22.44	1.05	6
5	Valencia Polytechnic University	6	192	7.80	2019.17	32.00	1.30	2
Average normalized citations								
1	Delft University of Technology	2	151	6.61	2014	75.50	3.31	3
2	Harbin Institute of Technology	2	76	5.07	2022	38	2.54	0
3	University of Perugia	4	40	8.25	2023	10	2.06	2
4	Paris-Saclay University	2	106	4.07	2020	53	2.04	2
5	Wuhan University of Technology	2	8	3.93	2024.5	4	1.96	2

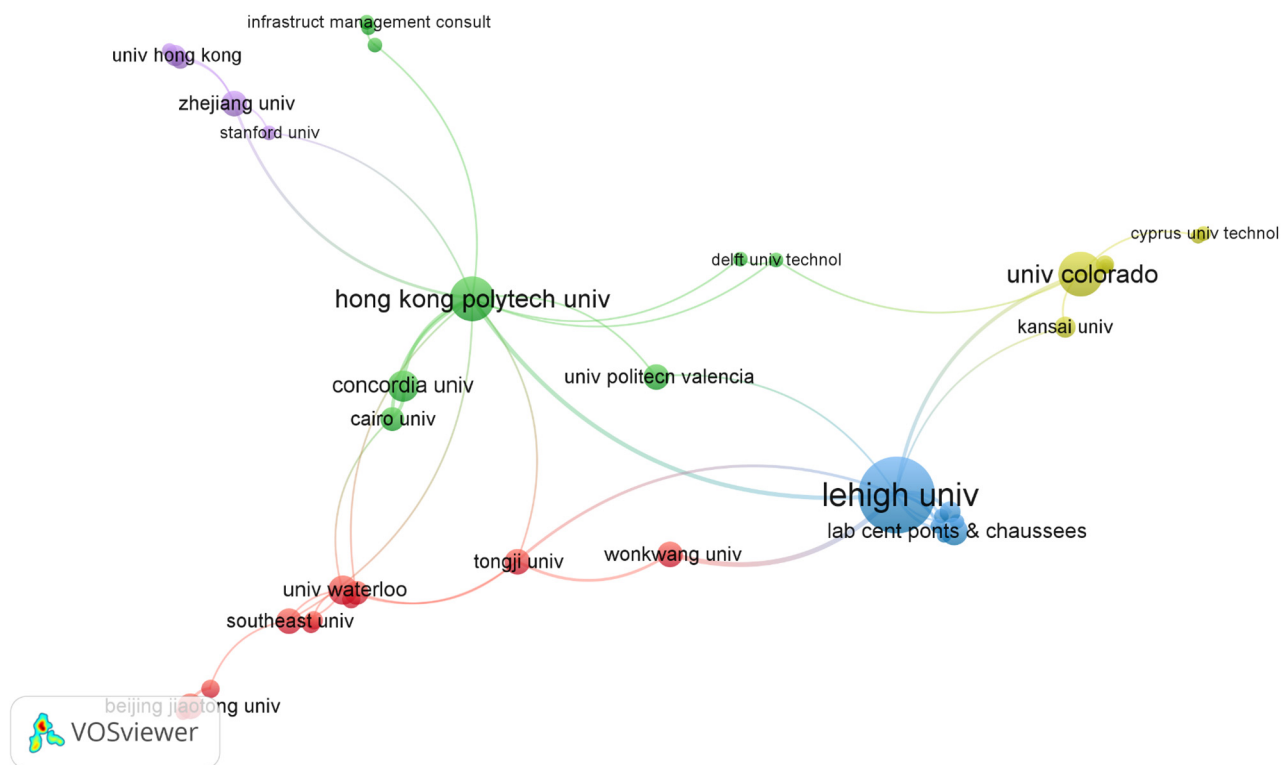


Figure 4. Co-authorship network of institutions in the research on BriMai_all.

Countries' co-authorship analysis is utilized to examine the collaboration intensity and dynamics between scholars from different countries and render a more concise understanding of the patterns of countries' contributions in the BriMai_all-related research. In this study, the minimum numbers of publications and citations of a country are set to two and zero, respectively. The size of the circle denotes the number of publications, and the thickness of lines between nodes indicates the extent of collaboration between partner countries. Figure 5 depicts a detailed picture of the countries' collaboration network in the BriMai_all domain. Generally speaking, current research efforts on BriMai_all appear to be concentrated in developed nations, likely due to greater funding resources and advanced infrastructure assets. It is manifested that there is a total of four clusters (encoded with varying colors), such that each cluster represents a distinctive group. The first cluster (yellow color) has 4 countries, namely United States of America, Japan, Turkey, South Korea and Taiwan. This cluster is the most prolific (200 documents) and received the largest number of citations (7033). The blue cluster is led by the People's Republic of China, Scotland, Switzerland, Germany, England, and Cyprus. This cluster is characterized by a substantial output of 102 publications, and it comes second in terms of citation count (1573). The green cluster is primarily formed based on the collaborations of Australia, Canada, Egypt, Hungary, Iran, and United Arab Emirates. The red cluster is composed of Belgium, Denmark, France, Ireland, Italy, Netherlands, Norway, Poland, Portugal, and Spain. Although publication output was identical between the green and red clusters (73 each), the research in the red cluster garnered a higher number of citations. The executed analysis expounds that a significant academic collaboration is present between the scholars of United States of America and the People's Republic of China (link strength = 12) as well as between United States of America and South Korea (link strength = 10). It is also corroborated that notable collaborative partnerships emerged, with the strongest links occurring between the United States and France (link strength = 7), and between China and Canada (link strength = 6). In

addition, it is noticed that the most cooperative countries are United States of America, the People's Republic of China, Canada, France, South Korea, and England.

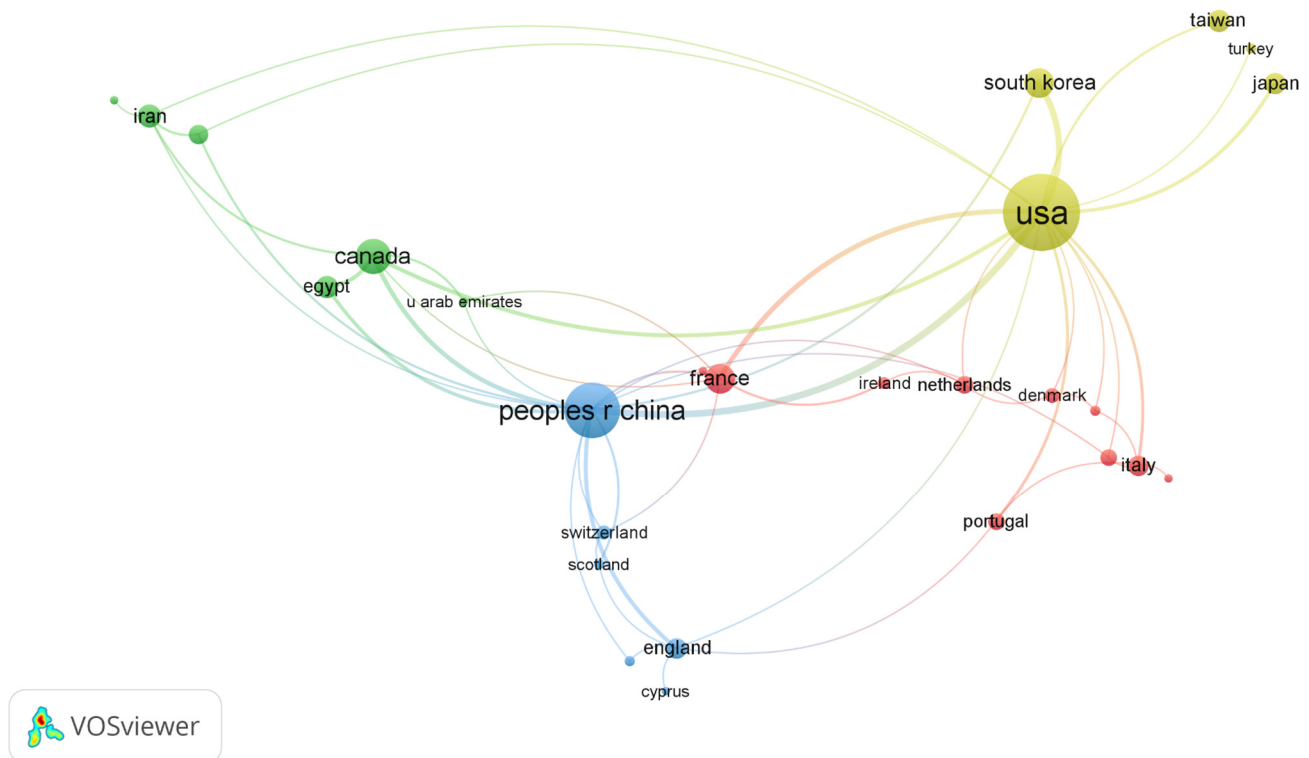


Figure 5. Collaboration network of countries in the research on BriMai_all.

Table 5 displays the top five rankings of countries from the perspectives of publication count, number of citations, and average normalized citations. It can be determined that significant contributions to the research of BriMai_all are coming from scholars of United States of America (150 documents), People's Republic of China (78 documents), Canada (32 documents), France (23 documents), and South Korea (22 documents). Overall, these countries account for more than 80% of the total worldwide publications in the BriMai_all field. In addition, it can be seen that the United States of America (5769), People's Republic of China (1112), Canada (706), France (631), and Taiwan (480) are ranked the highest in relation with the count of total citations. At the grand scheme of things, the highest counts of both publications and citations are originated from the United States of America, People's Republic of China, and Canada, pinpointing the high-quality research and outstanding academicians of scholars of these countries in this domain. Moreover, the rankings of countries by publication count align with their ranking by citation count. With regards to average normalized citations, it is noted that Norway (2.14) and Belgium (1.64) are accompanied by high average normalized citations despite contributing to three or fewer publications. Moreover, it is found that Spain (1.89), Australia (1.7), and Netherlands (1.65) come in the second, third and fourth places, respectively.

Table 5. Quantitative summary of the world’s leading countries in the BriMai_all domain.

Rank	Country	Number of Documents	Total Citations	Normalized Citations	Average Publication Year	Average Citations	Average Normalized Citations	Total Link Strength
Publication count								
1	United States of America	150	5769	191.29	2013.72	38.46	1.28	54
2	People’s Republic of China	78	1112	81.5	2020.54	14.256	1.04	41
3	Canada	32	706	28.61	2015.9	22.06	0.89	21
4	France	23	631	24.44	2012.13	27.43	1.06	15
5	South Korea	22	377	12.96	2016.5	17.14	0.59	12
Total citations								
1	United States of America	150	5769	191.29	2013.72	38.46	1.28	54
2	People’s Republic of China	78	1112	81.5	2020.54	14.26	1.04	41
3	Canada	32	706	28.61	2015.9	22.06	0.89	21
4	France	23	631	24.44	2012.13	27.43	1.06	15
5	Taiwan	13	480	9.74	2013.38	36.92	0.75	2
Average normalized citations								
1	Norway	2	23	4.28	2022.50	11.5	2.14	1
2	Spain	7	198	13.25	2020.00	28.29	1.89	3
3	Australia	10	357	17.01	2017.60	35.7	1.7	5
4	Netherlands	8	321	13.24	2017.13	40.13	1.65	4
5	Belgium	3	79	4.93	2019.33	26.33	1.64	3

3.4. Co-Citation Analysis

Journal co-citation analysis is leveraged to categorize and underscore the most relevant and impactful sources pertaining to the research area of BriMai_all. Figure 6 displays the co-citation diagram of journals, that is established based on a minimum publication count of three, inducing 24 inter-related journals. A significant co-citation relationship was traced between structure and infrastructure engineering, and journal of structural engineering (link strength = 851) as well as between structure and infrastructure engineering and automation in construction (link strength = 629). It is also observed that the created diagram is overwhelmed by the red cluster (20 sources) that consists of structure and infrastructure engineering, journal of structural engineering, automation in construction, engineering structures, structural safety, journal of infrastructure systems, sustainability, etc. It is noteworthy that buildings, journal of transportation engineering, and structural and multidisciplinary optimization were assigned to separate clusters since their scope is not directly to infrastructure asset management, and they accommodate fewer publications in the research field of BriMai_all. Table 6 delineates details of the top journals with high numbers of publications, citations, and average normalized citations. With regards to the number of publications, it is corroborated that structure and infrastructure engineering (37), journal of structural engineering (23), journal of bridge engineering (18), engineering structures (18), and automation in construction (17) are ranked in the top five places. In addition, it is revealed that journal of structural engineering (1712), structure and infrastructure engineering (1119), structural safety (845), engineering structures (782), and journal of bridge engineering (701) hold the highest citation count in the BriMai_all area. Further analysis exemplified that Automation in construction (2.15) sustains the highest average normalized citations followed by structural safety (2.08), reliability engineering and system safety (1.71), journal of structural engineering (1.61), and journal of cleaner production (1.51).

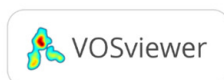
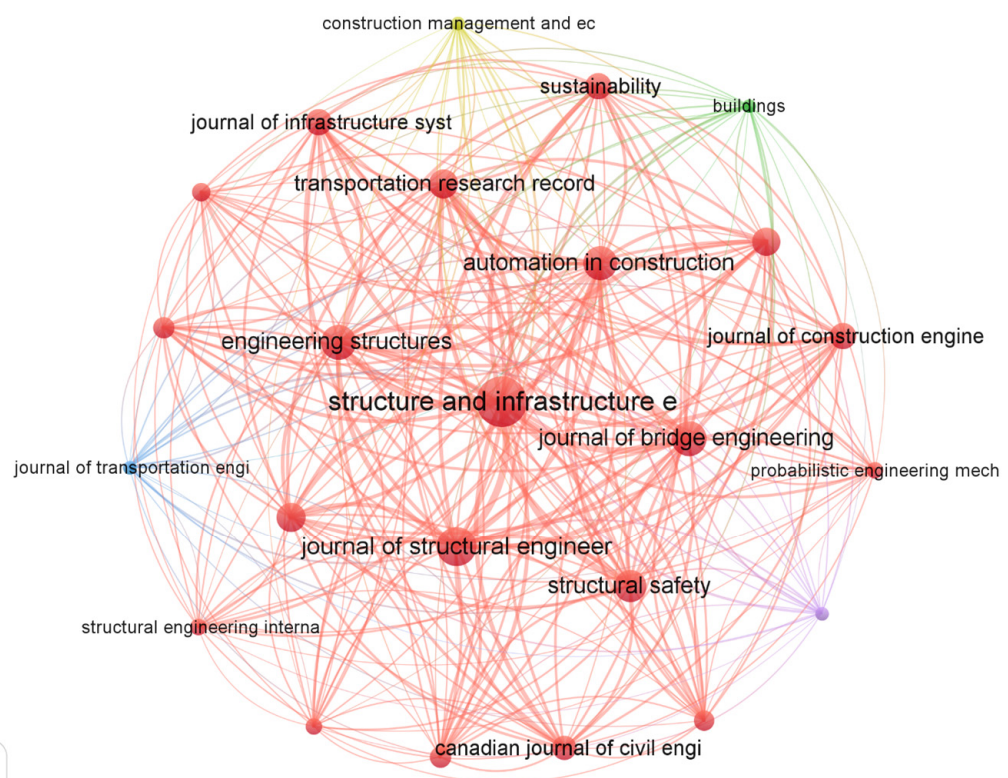


Figure 6. Journals' co-citation knowledge network of BriMai_all studies.

Table 6. Quantitative summary of the pre-eminent journals in the BriMai_all field.

Rank	Journal	Number of Documents	Total Citations	Normalized Citations	Average Publication Year	Average Citations	Average Normalized Citations	Total Link Strength
Publication count								
1	Structure and infrastructure engineering	37	1119	42.59	2015.95	30.24	1.15	8029
2	Journal of structural engineering	23	1712	36.97	2008	74.43	1.61	5313
3	Engineering structures	18	782	24.84	2013.06	43.44	1.38	4248
4	Journal of Bridge Engineering	18	701	25.62	2014.28	38.94	1.42	4248
5	Automation in Construction	17	616	36.62	2018.65	36.24	2.15	4029
Total citations								
1	Journal of structural engineering	23	1712	36.97	2008	74.43	1.61	5313
2	Structure and infrastructure engineering	37	1119	42.59	2015.95	30.24	1.15	8029
3	Structural safety	15	845	31.25	2013.33	56.33	2.08	3585
4	Engineering structures	18	782	24.84	2013.06	43.44	1.38	4248
5	Journal of Bridge Engineering	18	701	25.62	2014.28	38.94	1.42	4248
Average normalized citations								
1	Automation in Construction	17	616	36.62	2018.65	36.24	2.15	4029
2	Structural safety	15	845	31.25	2013.33	56.33	2.08	3585
3	Reliability engineering and system safety	12	621	20.47	2012.67	51.75	1.71	2904
4	Journal of structural engineering	23	1712	36.97	2008	74.43	1.61	5313
5	Journal of cleaner production	5	87	7.54	2021.40	17.40	1.51	1245

Figure 7 depicts a graphical representation of core journals according to Bradford's law. This law categorizes and sorts the sources (in a descending order) into several zones based on the number of published papers in a given research field [41]. As a result, it is revealed that zone 1 encompasses 7 journals (5.43%) totaling 132 papers (34.74%), middle zone 2 encompasses 18 journals (13.95%) totaling 123 papers (32.37%), and zone 3 encompasses 104 journals (80.62%) totaling 125 papers (32.89%). In this study, the core outlets include structure and infrastructure engineering (37 articles), automation in construction (18 articles), engineering structures (18 articles), journal of bridge engineering (18 articles), structural safety (15 articles), applied sciences (13 articles), and journal of structural engineering (13 articles).

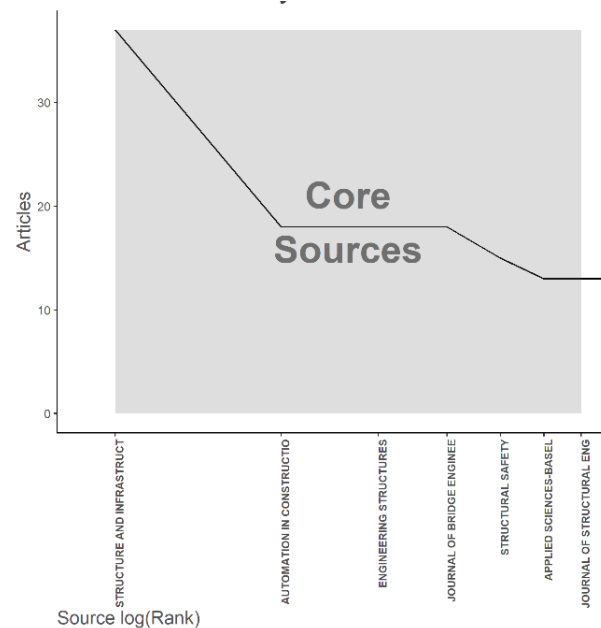


Figure 7. Bradford's law on core sources pertaining to BriMai_all.

3.5. Keyword Co-Occurrence Analysis

The co-occurrence analysis of keywords was carried out to construct and visualize the knowledge domain in the literature on BriMai_all. In addition, it aids in (1) identifying the core research themes by clustering strongly associated keywords, (2) streamlining temporal evolution by analyzing how these clusters and keywords vary across different time periods, and (3) pinpointing prevalent tools by identifying the most frequently occurring algorithms and techniques. This analysis adopted author keywords as the analysis unit, full counting as the counting method, and a threshold of minimum keyword co-occurrences of four, culminating in a total of 63 keywords. Figure 8 displays the results of the keyword co-occurrence analysis. As can be seen, there are four colored and distinctive clusters (red, blue, green, and yellow). The red cluster is the largest one, and it includes 18 keywords. It primarily focuses on themes pertinent to life cycle analysis and deterioration modeling of bridge components, and it is composed of some keywords such as "life-cycle", "life-cycle cost", "user costs", "Markov decision process", "machine learning", "dynamic programming", and "analytical hierarchy process". The green cluster is the second largest cluster (16 keywords), and it is broadly centered around asset management and bridge maintenance optimization, which is substantiated by the presence of "genetic algorithm" as a dominant keyword in this cluster. Further, this cluster covers some new aspects related to bridge intervention plans, such as bridge information modeling, deep reinforcement learning, sustainability, risk assessment, and resilience. Some frequent keywords are "bridge maintenance", "maintenance

optimization”, “multi-objective optimization”, “multi-criteria decision making”, genetic algorithm”, “deep reinforcement learning”, “bridge information modeling (brim)”, and “topsis”. The blue cluster comprises 15 keywords, and it concentrates on subjects pertaining to bridge inspection and condition assessment. Some of the most repeated keywords involve “maintenance”, “bridge inspection”, “corrosion”, “deterioration”, “deteriorating structures”, and “condition assessment”. The yellow cluster is principally dealing with stochastic driven analysis of bridge maintenance and structural deterioration, encompassing main keywords like “bayesian updating”, “reliability analysis”, “uncertainties”, and “structural health monitoring”. In addition, it is recognized that “maintenance” holds strong co-occurrence connections with the terms of “optimization” (link strength = 20), “bridges” (link strength = 12), and “bridge inspection” (link strength = 11), reflecting the growing interest in the topic of bridge maintenance optimization, and the pivotal necessity of inspection in ensuring the assignment of the required financial resources to maintain the safety and longevity of bridges.

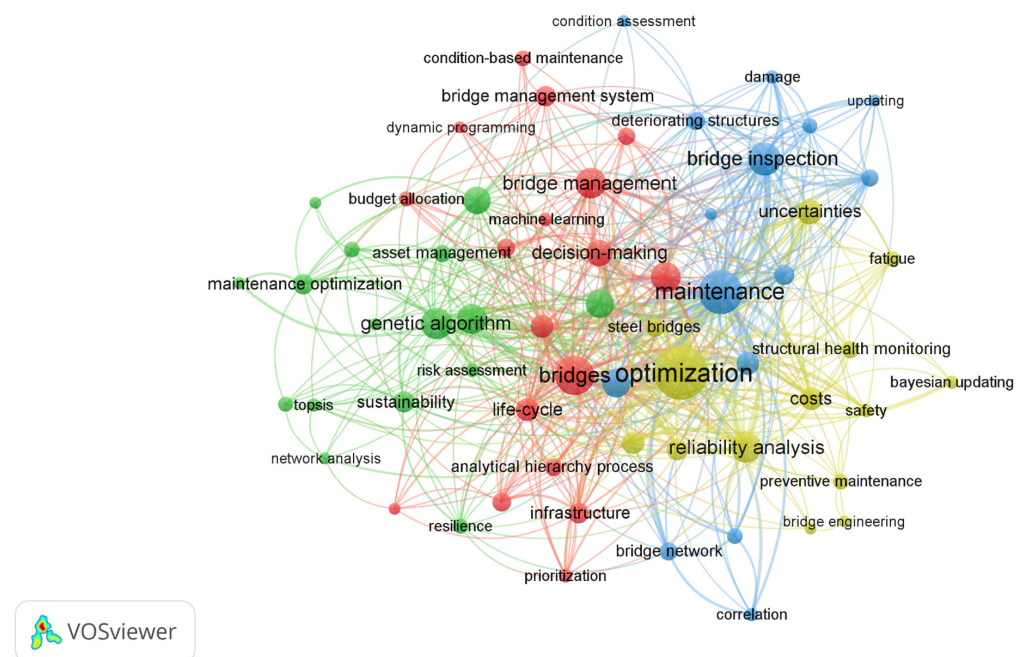


Figure 8. Analysis of keyword occurrence of BriMai_all.

Figure 9 upholds the temporal perspective of the co-occurrence network of author keywords. It is worth mentioning that circles with cold colors (blue and green) mark older publications, while circles with hot colors indicate more recent documents. It can be understood that most of the research work before 2014 was devoted towards the use of dynamic programming Markov decision process. Then, the direction shifted towards the use of reliability analysis, deterioration modeling, analytical hierarchy process, and genetic algorithm over the period 2014–2016. In the most recent years from 2016 onwards, research studies delved into the accommodation of multi-objective optimization, resilience assessment, risk modeling, resilience assessment, structural health monitoring, Topsis decision-making method, machine learning, and deep reinforcement learning. Table 7 lists a quantitative summary of the keyword co-occurrence analysis on BriMai_all. It records the frequency of occurrences, average publication year, average citations, average normalized citations, number of links, and total link strength. As can be seen, “optimization” (78 occurrences), “maintenance” (51 occurrences), “bridges” (41 occurrences), “bridge inspection” (29 occurrences), “genetic algorithm” (26 occurrences), “reliability analysis” (25 occurrences), “bridge management” (25 occurrences), “life-cycle cost” (24 occurrences), and “bridge main-

tenance” (24 occurrences) are the most widely used keywords. In relation with average normalized citations, it is concluded that “bridge information modeling (brim)” (2.77), “infrastructure management” (2.64), “safety” (2.13), “resilience” (2.12), and “maintenance optimization” (2.06) secured the highest five places. The keywords with the highest number of links (30 or more) are “optimization” (53), “bridges” (47), “maintenance” (45), “bridge maintenance” (34), “bridge management” (34), “life-cycle cost” (32), “reliability analysis” (31), “life-cycle” (30), and “bridge inspection” (30). In addition, it is noticeable that the largest total link strength is linked with the terms of “optimization” (216), “maintenance” (159), “bridges” (113), “bridge inspection,” (91), and “reliability analysis” (70). Accordingly, the conducted frequency analysis reveals that the analytical hierarchy process, genetic algorithm, and TOPSIS are the most used techniques in bridge maintenance optimization. In addition, emerging topics such as resilience, structural health monitoring (SHM), and deep reinforcement learning represent promising yet underdeveloped areas of research, and further investigation is crucial to effectively integrate them into the maintenance budgeting frameworks.

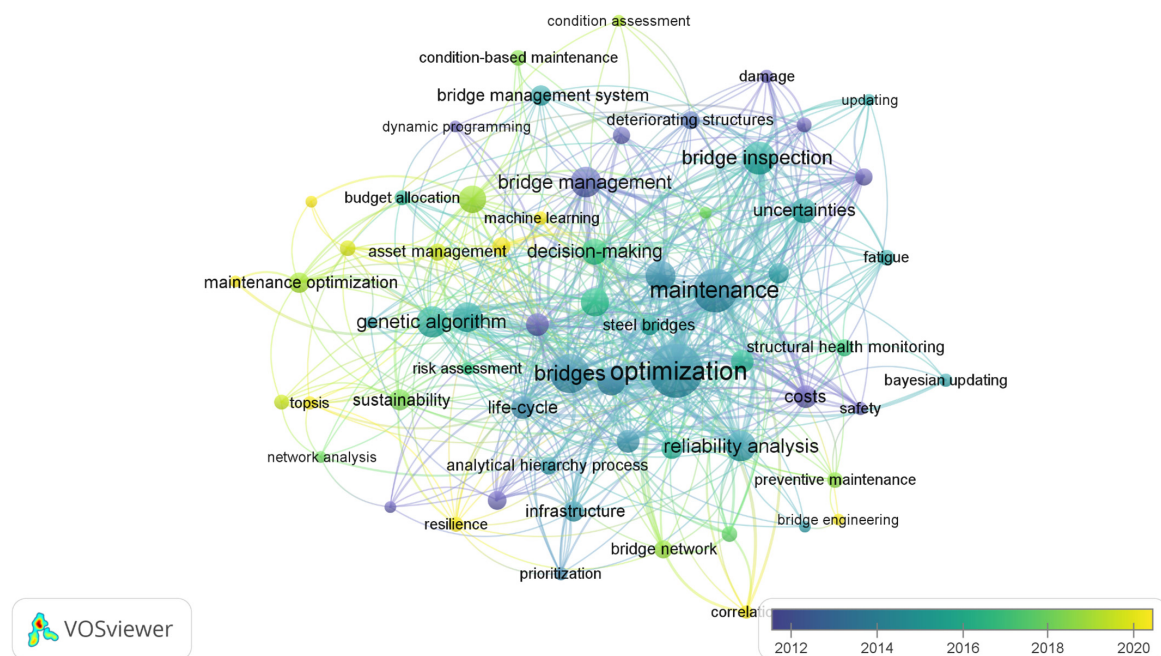


Figure 9. Temporal visualization of keyword co-occurrence of BriMai_all-related work.

Table 7. Details of the influential keywords in the BriMai_all-related literature.

Keyword	Occurrences	Average Publication Year	Average Citations	Average Normalized Citations	Links	Total Link Strength
Optimization	78	2014.21	31.51	1.09	53	216
Maintenance	51	2014.00	36.84	1.13	45	159
Bridges	41	2014.00	32.39	1.13	47	113
Bridge inspection	29	2015.31	29.55	1.03	30	91
Genetic algorithm	26	2015.50	29.15	0.97	29	60
Bridge management	25	2012.32	19.88	0.68	34	61
Reliability analysis	25	2014.48	31.96	1.12	31	70
Bridge maintenance	24	2015.17	24.75	0.89	34	53
Life-cycle cost	24	2014.04	40.92	0.98	32	63
Deterioration	21	2013.81	40.05	1.12	28	60
Multi-objective optimization	21	2016.33	39.57	1.20	29	53

Table 7. Cont.

Keyword	Occurrences	Average Publication Year	Average Citations	Average Normalized Citations	Links	Total Link Strength
Life-cycle analysis	20	2018.55	28.65	1.34	24	36
Decision-making	18	2016.83	24.06	0.90	25	48
Uncertainties	17	2015.00	51.53	1.52	29	58
Corrosion	14	2016.00	32.00	1.22	18	38
costs	14	2010.00	45.07	1.24	24	55
Highway bridges	14	2014.14	36.64	1.22	24	39
Life-cycle	14	2013.86	44.14	1.22	30	49
Markov decision process	14	2012.07	34.93	1.06	24	38
Maintenance management	12	2015.75	15.75	0.68	21	30
Sustainability	12	2018.00	43.92	1.57	18	23
Bridge management system	11	2014.82	16.27	0.51	14	14
Infrastructure	11	2014.27	38.82	0.85	15	26
Maintenance optimization	11	2018.64	41.18	2.06	15	21
Repair	11	2014.73	25.45	0.81	21	34
Rehabilitation	10	2011.60	20.90	0.47	15	24
Steel bridges	10	2015.30	23.60	0.97	18	24
Bridge network	9	2018.44	21.89	1.21	12	24
Decision support system	9	2020.44	10.11	0.59	12	13
Deteriorating structures	9	2012.78	41.22	1.17	18	25
Analytical hierarchy process	8	2014.50	23.25	0.95	9	16
Asset management	8	2019.25	15.50	0.56	16	18
Probability	8	2008.25	49.75	1.56	22	35
Structural health monitoring	8	2016.88	24.25	1.42	13	22
User costs	8	2012.13	24.25	0.67	8	14

4. Systematic Review Analysis

This section enumerates and expounds reported maintenance and inspection models that capitalized on multi-criteria decision making, life cycle assessment, digital twinning, optimization, and artificial intelligence.

4.1. Multi-Criteria Decision-Making (MCDM)-Based Models

Tables 8–10 record some of the reported MCDM-based maintenance models in the literature. These figures specify whether the reported studies rely on single or multi-criteria decision making. It also records the employed data analysis techniques, the main purpose of the study, and the data type of evaluation criteria (crisp or fuzzy). It is worth mentioning that single MCDM models rely on one MCDM technique in remediation planning of bridges while hybrid models use more than one MCDM technique in maintenance planning. In this regard, combined MCDM-based maintenance models encompass hybrid AHP models, hybrid TOPSIS, hybrid VIKOR, hybrid GRA, and assorted MCDM models. It is noticed that a considerable number of studies used AHP/ANP in maintenance management of bridges, whereas a portion of them capitalized solely on AHP/ANP while others blended it with another MCDM technique to rank repair priorities. In the context of AHP-based models, Yau et al. [42] implemented AHP in prioritizing post-disaster bridge maintenance efforts. Twelve decision criteria were identified and integrated into the assessment, encompassing both the susceptibility of bridges to damage and the potential consequences of such damage. These criteria involved disaster exposure history, landform characteristics, distance to disaster, intensity and classification of disaster, support system type, vertical clearance, restoration cost, traffic delay cost, age and location of bridge, average daily traffic, and accessibility to alternate traffic routes. It was shown that traffic delay cost (32.6%) and

restoration cost (22.4%) received the highest importance of the six criteria of the impact of damage category. In a second study, Rashidi et al. [43] deployed simplified analytical hierarchy process for the sake of repair management of bridges without exceeding available budget limits. In this respect, the eventual critical evaluation indicators encompassed structural safety, cost, serviceability, traffic flow disruption, environmental impact, and political/legal consideration. In addition, routine maintenance, minor rehabilitation, major rehabilitation, and reconstruction. It was corroborated that the highest priority was given to structural safety (45.81%), with legal/political issues (2.99%) contributing the least.

On the same note, Abu Dabous and Alkass [44] proposed a modified AHP-based approach for the purpose of comparing bridge rehabilitation strategies. The modified approach entailed coupling AHP with Monte Carlo simulation to account for the uncertainties caused by incomplete knowledge in the decision-making process. The selection criteria comprised environmental impact, useful life, structural safety, agency cost, and use cost, and four classes of MR&R actions were investigated, namely replacement, major rehabilitation, minor repair, and routine maintenance. It was explicated that structural safety dominated the importance priorities with 53% followed by environmental impact and agency cost with 13% each. As for using ANP techniques, a recent research endeavor was conducted by Navarro et al. [45] who compared the sustainability of five alternative concrete bridge designs in marine conditions. In this respect, ANP was undertaken to analyze the significance of the sustainability-related criteria, involving scarcity of resources, ecosystems, human health, public opinion, users, economic development of regions, employment generation, maintenance costs, and construction costs. Four design alternatives were proposed and evaluated besides the conventional design, which were as follows: (1) adding 10% silica fume, (2) adding 10% fly ash, (3) using surface treatment with a sealant, and (4) using high corrosion resistant galvanized steel reinforcement. Concrete incorporating silica fume demonstrated the optimal performance over its life cycle in chloride-exposed environments, and the design using conventional materials ranked as the least sustainable option.

Contreras-Nieto et al. [46] introduced a spatial-based MCDM framework for ranking and visualization of bridge maintenance priorities. The bridge condition was derived through a weighted average rating of substructure, superstructure, deck, and scour. In addition, the weights of assessment criteria (e.g., resilience, safety, serviceability, and riding comfort) were obtained using AHP. Afterwards, a user interface was designed in a geographical information system environment by compiling Google maps, fusion tables and AHP results in order to visually depict the bridge maintenance outcomes. Salem et al. [47] built a multi-objective decision making model that capitalized on AHP to scrutinize the importance priorities of the main criteria and sub-criteria of environmental impact, influence on adjacent communities, safety, cost, traffic, and economical impact. Cost (27%), local events (13.5%), traffic (13%), noise pollution (8.71%), and motorist safety (6.5%) were placed as the five most important bridged maintenance criteria. Sensitivity analysis was later applied to conceive how the bridge alternatives behaved according to the perturbations in the relative importance criteria.

Turning to the hybrid AHP-based models, Xu et al. [48] investigated three approaches for rigorous scrutiny of bridge components and their deficiencies, namely constant weight model (CWM), factor-based variable weight model (FVWM), and factor and age-based variable weight model (FAVWM). In CWM, the values of weights will remain constant regardless the values of factors while the weights are altered according to the values of the factors in the case of FVWM. As for the FAVWM, it follows the same logic as factor-based variable weighting, besides age-dependent weights are likewise subject to the constraints of normality, continuity, and penalization. It was concluded that the condition scores

of FAVWM are recommended over CWM and FVWM for setting bridge maintenance strategies. Additionally, Wakchaure and Jha [49] deployed AHP to derive the weights of bridge components and sub-components, and subsequently, these weights are merged with the severities of distresses to interpret the bridge health index, and condition states of bridge components and subcomponents. It was determined that foundations were ranked as the most critical component for bridge maintenance (33%), with superstructure second (22%), substructure third (18%), and bearings fourth (14%). On the other hand, the approaches (4%), appurtenances (4%), and waterway (5%) were assigned considerably lower priorities.

Alshibani et al. [50] introduced a decision-making framework for prioritizing bridge maintenance expenditures by blending AHP with MAUT. Several factors were identified to gauge bridge maintenance priority at the network level such as condition status, age, location, previous maintenance, traffic maintenance, and traffic volume. Additionally, several bridge components were assessed, including foundations, piers, abutment walls, expansion joints, bearing pads, and bridge decks. It was revealed that condition status (25.9%), bridge age (21.3%), and bridge location (17%) were the highest-weighted factors in determining bridge maintenance priorities. Beyond that, it was illustrated that bearing pads (20.7%), deck and parapet (17.3%), and expansion joint (16.9%) were identified as the most critical structural components of the bridge. Further research was conducted by Rashidi et al. [51], who proposed an integrated framework for maintaining steel bridges within acceptable safety, performance, and sustainability boundaries. In it, SMART and AHP were aggregated, resulting in simplified AHP that is capable of identifying and benchmarking the weights of the remediation criteria. Results elucidated that safety, cost, and service life emerged as the highest-weighted factors with 45.81%, 26.27%, and 13.76%, respectively.

Abu Dabous and Alkass [52] constructed a decision support system for ranking of rehabilitation programs predicated on AHP and MAUT. The optimal rehabilitation strategy was determined according to the factors of environmental consequences, useful life, safety, user costs and agency costs. It was revealed that safety (54.8%) constituted the most important selection factor while user costs factor (8.8%) was the least critical. Similarly, Abu Dabous and Alkass [53] built a fund allocation of bridges based on a MAUT model that aimed to maximize bridge safety and safety, maximize investment efficiency, and minimize deterioration. AHP was exploited to find the relative importance weights of attributes, which were integrated with a separate utility function to find an overall utility score of each bridge project.

Moving on to the hybrid TOPSIS models, Navarro et al. [54] conducted life-cycle sustainability analysis of coastal concrete bridge decks. The ecological and economic performance factors were measured using neutrosophic group AHP, and TOPSIS was undertaken to create a unified sustainability score of bridge deck designs. Among the sustainability evaluation criteria, there were construction costs, service life costs, damage to ecosystem, damage to human health, damage to resource availability, workers, users, public opinion, and regional economic development. In a second study, Gokasar et al. [55] formulated an integrated model for CO₂ Emission-Driven Optimization of Bridge Maintenance Scheduling. Type-2 neutrosophic number (T2NN) based fuzzy WASPAS was amalgamated with TOPSIS to rank bridge maintenance projects. The key examined criteria involved cost effectiveness, extra fuel consumption, physical condition, exposure to fatigue, importance factor, social impact for travelers, appropriateness for maintenance, and CO₂ emissions. Results underlined that cost effectiveness (13%) and CO₂ Emissions (13%) were ranked as the most crucial importance factors while the lowest weight was assigned to extra fuel consumption (11.9%). In a third study, Ors et al. [56] advanced a decision support system to identify the most suitable construction technique of bridge piers meanwhile, satisfy-

ing the critical factors of cost, time, lateral stiffness, ductility, risk, constructability, and maintainability. The examined construction techniques involved anchored post-tensioned, post-tensioned, and monolithic. AHP was utilized to define the significance of each criterion, and TOPSIS was then employed to facilitate the alternatives. The analysis concluded that post-tensioned construction was the preferred method in Egypt's current market. Moreover, risk, constructability, and cost sustained negligible impacts on recognizing optimal alternative. Another notable research attempt was presented by Das and Nakano [57] who deployed TOPSIS method to consolidate socio-technical dimensions into a framework for bridge maintenance ranking. The prioritization factors involved delay costs, truck influence, redundancy, accessibility, and bridge condition level. It was underscored that vector transformation was more efficient than linear transformation in TOPSIS method, and the bridges associated with higher delay costs were sorted as the highest priority for repair.

Shifting focus to the hybrid VIKOR models, Lad et al. [58] proposed a method to identify priority bridges for resilience upgrades. The CRITIC method was employed to determine the weighting of the specified criteria, namely age, area, design high flood level, and finish road level. Then, five MCDM techniques were applied to derive bridge priorities, which were TOPSIS, VIKOR, COPRAS, ARAS, and MOORA. Subsequently, WSM was adopted to generate a final ranking of bridges through merging the rankings of the aforementioned MCDM techniques. It was inferred that COPRAS and MOORA exhibited the highest Spearman rank correlation with 1 and 0.993, respectively. In the same vein, Gao et al. [59] evaluated bridge rehabilitation projects based on specific targets like cost, service years, average daily traffic, average daily truck traffic, among others. Afterwards, the objective weights of the priority assessment were determined predicating on the target-based standard deviation method and the entropy concept. This is followed by using VIKOR method to determine the priority for intervention among bridges requiring maintenance.

As for the hybrid GRA models, Tan et al. [60] employed a hybridization of FAHP and GRA to identify the optimal reinforcement scheme of a concrete-filled arch bridge deck. The decision factors comprised economic rationality, structural functionality, structural aesthetics, and technical feasibility. Besides, the investigated reinforcement schemes consisted of (1) replacing the overall bridge deck, (2) adding longitudinal concrete beams, (3) adding longitudinal steel beams, and (4) adding longitudinal steel box-concrete composite beams. Another research effort was delivered by Rogulj et al. [61] designed an integrated decision support system to assign priorities of historic bridges reconstruction. Several indicators were specified to determine the ranking index, including safety and stability, load, complexity of reconstruction, preservation of cultural heritage, reconstruction duration, functionality, cost, and environmental impact. Thereafter, EDAS was blended with GRD within an intuitionistic fuzzy environment to sort out pedestrian historical bridges for maintenance, and then the final ranking of each decision group was formed by combining ant colony optimization and integer linear programming.

Another branch of research efforts is WSM-based oriented. In this respect, Tabor et al. [62] solicited bridge experts through two-round Delphi process to allocate weighted factors to the structural safety and serviceability components. Then, a weighted sum equation was used to find the condition status of pedestrian bridges by merging the weighted factors of bridge components and their condition levels. In another attempt, Mohamadiazar et al. [63] addressed the societal and environmental aspects in their bridge rehabilitation framework besides the conventional structural and operational considerations. Among the studied social equity and environmental factors, there were population density, land use, average commuting time, crime rate, air quality index, etc. Thereafter, spatial-based MCDM was performed using simple additive weighting to create integrated vulnerability maps that can be used as an approach for bridge prioritization.

The last portion of research studies is the assorted MCDM models that investigate a diverse collection of MCDM techniques. For example, Seer and Saylan [64] scrutinized corrosion mitigation strategies in steel truss bridges meanwhile accommodating ultimate load capacity, and lifecycle direct costs. Also, study alternatives included full repainting time intervals for each type of steel bridge (pratt truss, parker truss and Baltimore truss). Eventually, MCDM scores were generated using TOPSIS, COPRAS, and SAW, which suggested undertaking a 25-year repainting interval for all three types of bridges. Another research endeavor was performed by Salmaninezhad and Jazayeri Moghaddas [65] to facilitate the comparative ranking of repair techniques of river bridge columns. They amalgamated EV and EW to quantify the importance criteria of cost, duration, durability, vulnerability to flood, geometry, and scouring depth. Then, the repair methods of high-performance concrete jacketing, steel jacketing, and fiber-reinforced polymer jacketing, were assessed using ELECTRE and SAW methods. It was inferred that both methods yielded high-performance concrete jacketing as the most feasible repair option. A third relevant work was developed by Karaaslan et al. [66], who devised a bridge value index that gathers the aspects of maintenance cost, bridge importance, serviceability, safety, and structure type. Moreover, they constructed a deep learning model that fuses CNN and LSTM for time-history forecasting of structural deterioration.

Table 11 elucidates some of the used MCDM techniques in bridge rehabilitation-related work. Several methods have been proposed to derive the criteria weights, and these weight determination methods can fall under one of three main categories, which are: subjective, objective, and combinative. Subjective weight determination methods rely on the preferences of decision makers to assign weights of importance criteria [67]. A key impediment of these methods is their decreasing efficiency as the number of criteria grows [68]. Analytical hierarchy process (AHP), analytical network process (ANP), fuzzy analytical hierarchy process (FAHP), fuzzy analytical network process (FANP), best-worst method (BWM), decision making trial and evaluation laboratory (DEMATEL), full consistency method (FUCOM), and stepwise weight assessment analysis (SWARA) are traditional examples of subjective weight methods [69,70]. In contrast, objective weighting methods adopt specific mathematical algorithms to analyze the initial decision matrix itself without taking into consideration human judgments [71]. The objective weights of criteria are usually obtained using criteria importance through intercriteria correlation (CRITIC), Shannon entropy, Standard deviation (SDV), method based on the removal effects of criteria (MEREC), criterion impact loss (CILOS), and logarithmic percentage change-driven objective weighting (LOPCOW) [67,72]. Combinative methods merge both decision-makers' preferences and data-driven insights from the decision matrix, rendering more accurate and practical weight assignments [73].

MCDM techniques can be clustered into distance-based, pairwise comparison, utility-based, and outranking methods [74]. Distance-based approach is predicated on ranking alternatives according to their proximity to the ideal and anti-ideal solutions. Key methods of this group include: VIKOR, TOPSIS, GRA, EDAS, combinative distance-based assessment (CODAS), while pairwise comparison approaches involve comparing all possible pairs of criteria and alternatives through pairwise evaluations, and it encompasses AHP and ANP [75,76]. Utility-based methods evaluate and rank alternatives by aggregating their performance across multiple criteria through a mathematical utility function into a single composite utility score. Its most used methods are CORAS, SAW, WASPAS, and MAUT. Outranking approaches are another class of MCDM techniques that compare pairs of alternatives to determine the degree to which one alternative dominates other alternatives across multiple criteria, whereas Popular outranking methods incorporate ELECTRE and PROMETHEE [74,77].

Table 8. Summary of some MCDM-based maintenance prioritization models.

Reference	Year	MCDM Approach	Data Analysis Techniques	Application	Data Type	
					Crisp	Fuzzy
[78]	2025	Hybrid	FBWM + FCE	Condition evaluation of bridges		✓
[64]	2025	Single	TOPSIS/COPRAS/SAW	Assessment of corrosion control methods	✓	
[63]	2024	Hybrid	GIS + SAW	Prioritization of bridge rehabilitation projects	✓	
[62]	2024	Hybrid	Delphi + WSM	Maintenance ranking of pedestrian bridges	✓	
[50]	2025	Hybrid	AHP + MAUT	Allocation of bridge maintenance funds	✓	
[58]	2024	Hybrid	CRITIC + VIKOR/TOPSIS/COPRAS/ARAS/MOORA	Sequencing bridges for resilience improvement	✓	
[65]	2023	Hybrid	EV + EW + ELECTRE I + SAW	Determining the best repair method of river bridge columns	✓	
[57]	2023	Single	TOPSIS	Socio-technical-based maintenance ranking	✓	
[42]	2023	Single	AHP	Bridge repair following natural disasters	✓	
[79]	2023	Hybrid	SMART + AHP + TLS + BrIM	Prioritizing bridge elements and remediation alternatives	✓	
[56]	2023	Hybrid	AHP + TOPSIS + Sensitivity analysis	Defining the optimum construction techniques of piers	✓	
[55]	2022	Hybrid	T2NN + fuzzy WASPAS + TOPSIS	Carbon footprint-driven planning of bridge repair		✓
[45]	2022	Single	ANP	Life cycle sustainability analysis of concrete bridges in coastal environments	✓	
[61]	2022	Hybrid	IFT + GRD + EDAS + ILP-ACO	Sorting of bridge reconstruction priorities		✓
[80]	2021	Hybrid	Rough neutrosophic symmetric cross entropy + Tangent function	Remediation planning of historic pedestrian bridges		✓

Table 9. Summary of some MCDM-based maintenance prioritization models (Cont'd).

Reference	Year	MCDM Approach	Data Analysis Techniques	Application	Data Type	
					Crisp	Fuzzy
[81]	2021	Hybrid	AHP + WSM	Determination of bridge condition index	✓	
[82]	2021	Single	Optimization index	Formulation of highway bridge maintenance	✓	
[60]	2021	Hybrid	FAHP + GRA	Optimal identification of reinforcement schemes		✓
[66]	2021	Single	CNN-LSTM + WSM	Selecting optimal intervention action	✓	
[83]	2020	Hybrid	FANP + IWO + GPR + TOPSIS + GRA	Maintenance ranking of bridge decks		✓
[54]	2020	Hybrid	Neutrosophic AHP + TOPSIS	Sustainability-based evaluation of designs of prestressed bridges		✓
[59]	2019	Hybrid	Target-based standard deviation + VIKOR	Sorting of concrete bridge rehabilitation projects	✓	
[46]	2019	Single	AHP + GIS + Fusion tables	Ranking of bridge maintenance systems	✓	
[48]	2019	Hybrid	AHP + WSM	Condition assessment of suspension bridges	✓	
[84]	2019	Single	MAUT	Maintenance Planning for Network-Level Bridges	✓	
[85]	2018	Single	MAUT + Sensitivity analysis	Maintenance management of bridge inventory	✓	
[86]	2018	Hybrid	FL + SE + TOPSIS	Planning MR&R actions of bridge components		✓
[51]	2017	Hybrid	SMART + S-AHP + WSM	Modeling of remediation actions of steel bridges	✓	
[43]	2016	Single	S-AHP	Assessing key factors of bridge repair	✓	

Table 10. Summary of another set of MCDM-based maintenance prioritization models.

Reference	Year	MCDM Approach	Data Analysis Techniques	Application	Data Type	
					Crisp	Fuzzy
[87]	2015	Hybrid	GA + MAUT	Sustainability-based planning of highway bridge maintenance	✓	
[88]	2014	Single	Dominance-based rough set	Network-scale bridge maintenance management	✓	
[89]	2013	Hybrid	ϵ —Constraint Method + WSM	Strategic management of bridge inventory	✓	
[47]	2013	Single	AHP + Sensitivity analysis	Optimizing factors of bridge rehabilitation/reconstruction	✓	
[90]	2011	Single	DEA	Prioritization of bridge maintenance needs”	✓	
[52]	2011	Hybrid	AHP + MAUT	Optimizing bridge infrastructure management with limited budgets	✓	
[53]	2010	Hybrid	AHP + MAUT	Allocation of bridge maintenance funds	✓	
[49]	2012	Hybrid	AHP + WSM	Analysis of bridge health index	✓	
[91]	2008	Single	AHP + Fuzzy synthetic evaluation	Condition assessment of reinforced concrete bridges		✓
[44]	2008	Single	AHP	Ranking of bridge rehabilitation plans	✓	

Table 11. Description of MCDM techniques.

MCDM Technique	Acronym	Description	Reference
Analytical Hierarchy process	AHP	A structured tool for deriving priority scales from experts’ judgments	[44]
Analytical Network Process	ANP	It is a network-structured MCDM method that generalizes AHP by emulating the interdependencies among criteria and alternatives, using pairwise comparisons	[92]
Criteria Importance Through Intercriteria Correlation	CRITIC	A weight interpretation method through quantifying statistical contrast and intercriteria correlation	[93]
Shannon Entropy	SE	An information-theoretic MCDM technique that calculates objective criteria weights by measuring data dispersion	[94]
Best-worst Method	BWM	A pairwise comparison-based MCDM technique for deriving criteria weights systematically by comparing the best and worst indicators	[95]
Technique for Order Preference by Similarity to Ideal Solution	TOPSIS	A selection method for the best alternative by identifying the ideal and negative ideal solutions	[96]
Complex Proportional Assessment	COPRAS	A ranking method of alternatives based on their utility degrees in relation to the ideal best and worst solutions	[97]
Grey Relational Analysis	GRA	A ranking method by measuring the similarities between data sequences using the grey relational grade	[98]
Weighted Aggregated Sum Product Assessment	WASPAS	A unified ranking method stepping on balancing additive and multiplicative aggregation approaches	[99]
Élimination Et Choix Traduisant la Réalité	ELECTRE	An outranking method that is based on determining the concordance and discordance sets through pairwise comparisons	[100]

Table 11. *Cont.*

MCDM Technique	Acronym	Description	Reference
Preference Ranking Organization Method for Enrichment Evaluation	PROMETHEE	A family of outranking methods based on positive and negative preference flows for each alternative	[101]
Evaluation based on Distance from Average Solution	EDAS	A distance-based MCDM technique of alternatives through quantifying their negative and positive deviations from the average solution	[102]
Multi-attribute Utility Theory	MAUT	A utility-based MCDM technique that assesses alternatives by aggregating single-attribute utility functions	[103]
Vlsekriterijumska Optimizacija I Kompromisno Resenje	VIKOR	A compromise ranking method that accommodates group utility and individual target values	[104]
Data Envelopment Analysis	DEA	A non-parametric linear programming technique that develops the efficiency frontier through optimizing weighted outputs to weighted inputs	[105]
Dominance-based Rough Set Approach	DRSA	A rough set-based MCDM method that uses dominance relations and collective decision rules for analyzing preference-ordered data	[106]

Table 12 outlines the considered criteria by some of the available MCDM-based maintenance models in the literature. Given the wide range of maintenance criteria, the authors reported a set that covers structural, physical, operational, financial, social, and environmental considerations. In this regard, MCDM-based maintenance prioritization models can be either factor-based or defect-based. As for the factor-based models, they focus on aggregating weighted performance scores across the different criteria (factors). Usually, these factors cover technical, physical, operational, economic, and environmental features of the bridge. Unlike factor-based approaches, defect-based models rank maintenance actions by compiling the severities of anomalies (e.g., corrosion, spalling, cracking) and relative importance priorities. It is viewed that maintenance agency costs, safety, condition/reliability, environmental impact, serviceability/useful life, and user costs are amongst the most utilized factors by the developed MCDM maintenance prioritization models. For example, Allah Bukhsh et al. [84] evaluated the user delay costs by determining the extra travel time (ETT) caused by the reduced speeds in the work zone (see Equations (2) and (3)).

$$UDC = \frac{ETT \times ADT_t \times VM_t \times N_t}{A} \quad (2)$$

$$ETT = \frac{L}{V_r} - \frac{L}{V_n} \quad (3)$$

where:

L is the work zone length in Km, and ADT_t is the average hourly traffic volume. VM_t is the monetary value per person per hour, and N_t denotes the duration of maintenance (hours). A is the bridge's deck area in m^2 while V_r and V_n stand for the reduced speed during maintenance work zone and normal speed, respectively.

Environmental-related factors incorporate climate event vulnerability, climate load vulnerability, embodied carbon/environmental impact, hydrology and climate, and geotechnics and seismicity. For instance, Salem et al. [47] accommodated air pollution and noise pollution associated with bridge rehabilitation. In another study, Bukhsh et al. [84] accounted for abiotic depletion potential, global warming potential, ozone depletion, acidification potential, eutrofication potential, human toxicity potential, freshwater toxicity potential, marine ecotoxicity potential, and terrestrial ecotoxicity potential. Likewise, Sabatino et al. [87] evaluated the environmental impact of detour management and bridge maintenance using the measures of CO_2 emissions and energy consumption. In their work, the annual expected carbon emissions as a result of bridge detour and bridge repair can be obtained using Equations (4) and (5), respectively. The annual expected energy consumption due to bridge repairs is expressed using Equation (6).

$$AEC(t) = p_{f,sys}(t) \times ADT(t) \times L_d \times D_d \left[CPD_C \left(1 - \frac{TT_p}{100} \right) + CPD_T \left(1 - \frac{TT_p}{100} \right) \right] \quad (4)$$

$$AER(t) = p_{f,sys}(t) \times CD_{REB} \times W \times L \quad (5)$$

$$AEE(t) = p_{f,sys}(t) \times EC_{REB} \times W \times L \quad (6)$$

where:

L_d is the detour length, and TT_p is the percentage of trucks in the average daily traffic. CPD_C and CPD_T are carbon dioxide emissions per unit distance (kg/km) for cars and trucks, respectively. $ADT(t)$ signify the average daily traffic at year t and D_d is duration of bridge detour (days). $p_{f,sys}(t)$ denotes the probability of system failure. CD_{REB} is the CO_2 footprint of rebuilding (Kg/m^2). W and L are width and length of bridge (m). EC_{REB} is the total amount of energy consumption accompanied with rebuilding (GJ/m^2).

Condition assessment is another important parameter in composing the priority maintenance score. Allah Bukhsh et al. [84] developed a weighted function that gauges the system-level performance of bridges (see Equation (7)). In this regard, the bridge structure is decomposed into several components, and a condition score is linked with each respective component, and eventually a holistic condition score is computed for the entire bridge. Defect-based models are another type of condition assessment models that evaluate bridge health through identifying the observed defects alongside their extent of severities. One of the early attempts in this regard was performed by Alsharqawi et al. [107] who analyzed the performance condition of bridge deck according to cracking, disintegration, corrosion, delamination, spalling, deposits, joint problems and pop-outs. In addition, they proposed an integrated condition function of bridge deck as presented in Equation (8). By the same token, Abdelkader et al. [83] prioritized their bridge maintenance strategy capitalizing in assessing the severity levels of corrosion, delamination, cracking, spalling, and scaling. Another research effort was carried out by Xu et al. [48] who appraised the condition of suspension bridges capitalizing on evaluating the defects present in the structural components of tower, auxiliary facility, substructure, anchorage, stiffening girder, suspender system, and main cable system. Among the studied bridge deficiencies, there were wire corrosion, ponding, oil leaks, crack, coating deterioration, deformation, connection looseness, and scour, among others. In addition, Tabor et al. [62] investigated the condition of pedestrian bridge by triggering the degree of deterioration in each component such as piers, railings, deck, stairs, drainage, main cables, trusses, etc. The condition of the bridge component using Equation (9), and its value ranges from 0 to 100 according to the seriousness of deterioration. Furthermore, Wakchaure and Jha [90] analyzed the bridge health index alongside the condition states of components and subcomponents predicating on the weights and severities of distresses (see Equations (10)–(12)). With that said, a series of equations were formulated to achieve this requirement.

$$CI = \sum_{i=1}^n CI_i \times W_i. \quad (7)$$

$$ICI = \frac{(1 \times p.\text{good} + 3 \times p.\text{medium} + 6 \times p.\text{severe} + 9 \times p.v.\text{severe})}{9} \quad (8)$$

$$CI_c = 100 - 100 \left(\frac{D_c}{4} \right) \quad (9)$$

$$BHI = \frac{\sum_{i=1}^n CI_i \times W_i}{\sum_{i=1}^n W_i} \quad (10)$$

$$CI_i = \frac{\sum_{j=1}^m CS_j \times W_j}{\sum_{j=1}^m W_j} \quad (11)$$

$$CS_j = \frac{\sum_{k=1}^d (100 - 100 \times S_k)}{d} \quad (12)$$

where:

CI_i is the condition score of bridge element, e.g., guardrail, railing, pavement, joints, abutment, bearings, and superstructure. W_i is the relative importance weight of bridge element i . $p.\text{good}$, $p.\text{medium}$, $p.\text{severe}$, and $p.v.\text{severe}$ represent the percentages of bridge deck's good, medium, severe, and very severe condition categories, respectively. D_c is the degree of deterioration in bridge component, and its value spans from 0 to 4 according to a provided description for the bridge component deterioration. For instance, the D_c is 0 if the bridge component is in an excellent condition or new and does not suffer from evident deterioration, and D_c is 1 if the bridge component is in a good condition and sustains slight or marginal deterioration. The terms of BHI , CI_i and CS_j represent bridge health

4.2. Life Cycle Assessment (LCA)-Based Models

Tables 13–15 provide a comprehensive summary of key studies in the literature on bridge Life-Cycle Assessment (LCA), categorized into three distinct areas: Cost-based LCA, Environmental LCA, and Integrated LCA. Cost-based LCA primarily focuses on economic factors, while Environmental LCA emphasizes environmental impacts. In contrast, Integrated LCA combines economic, environmental, and social dimensions to facilitate comprehensive decision-making. Studies in Cost-Based Life Cycle Assessment (LCCA) primarily aim to minimize total ownership costs through systematic decision-making processes. Various approaches have been adopted, including both deterministic and probabilistic methods, to address the complexities and uncertainties inherent in bridge maintenance management. Deterministic methods employ fixed input parameters, offering simplicity in life cycle cost analysis, but potentially lacking realism in capturing uncertainties [109–111]. On the other hand, probabilistic methods explicitly account for uncertainty related to loads, deterioration rates, and intervention timings, providing robust and realistic outcomes. The Hasofer–Lind reliability method has been applied to assess fatigue monitoring via weigh-in-motion (WIM) sensors for steel bridge girders. This approach has notably reduced load uncertainties, enhanced safety, and yielded significant economic savings. Seismic resilience studies have developed a time-dependent LCCA-based Monte Carlo simulation to effectively determine financial break-even points for structural health monitoring (SHM) systems for bridges in earthquake-prone regions. Additionally, renewal theory-based methodologies have provided analytically rigorous yet computationally efficient probabilistic solutions, strategically balancing the frequency of minor maintenance activities with infrequent significant repairs [112]. Probabilistic event-based simulations that incorporate Weibull-modeled damage and repair cycles have offered valuable sensitivity analyses, guiding the selection of optimal repair methods for chloride-contaminated concrete columns [113]. Finally, Markov deterioration process-based probabilistic analytical methods have been applied to forecast bridge deterioration and support maintenance resource allocation [114].

Environmental LCA methods primarily address cradle-to-grave environmental impacts, with a particular emphasis on greenhouse gas emissions and energy consumption. Hybrid Bayesian-fuzzy models have been explicitly applied to manage uncertainties related to imprecise and ambiguous data, enhancing understanding of complex interactions among various life-cycle phases [115]. Additionally, probabilistic life-cycle sustainability analysis, which employs Monte Carlo propagation combined with surrogate modeling, has effectively addressed uncertainties and characterized interactions between different lifecycle phases. These analyses have highlighted material production and maintenance phases as significant sources of emissions [116]. Moreover, studies conducted following ISO 14040/44 standards revealed that despite higher initial environmental impacts, bridge designs oriented toward enhanced durability substantially reduce lifetime emissions, particularly when maintenance schedules are accounted for [117]. Furthermore, dynamic LCAs that incorporate future decarbonization scenarios have significantly influenced decisions regarding the optimal timing for bridge rehabilitation, particularly in long-span cable-stayed bridges [118]. Lastly, informed material selection studies have underscored significant reductions in energy consumption and greenhouse gas emissions through careful evaluation and comparison of bridge-deck surfacing materials, notably identifying epoxy-asphalt as an environmentally advantageous option [119].

Integrated LCA approaches holistically merge cost, environmental, and social dimensions, providing comprehensive decision-making frameworks. Several studies have integrated social-cost evaluations, which quantify impacts such as user delays, business losses, and safety implications, highlighting their substantial dominance over direct agency expenditures and emphasizing the need for proactive interventions and enhanced reliability targets [120–122]. Deterministic social-cost evaluations demonstrate that preventive measures, such as increased concrete cover, stainless steel reinforcement, and cathodic protection, can significantly reduce total lifecycle costs by up to approximately 58%, primarily driven by user-delay costs during major maintenance activities [121]. Moreover, multi-level stochastic cost-benefit LCCA approaches that incorporate user and societal costs strongly advocate for earlier interventions, as user-related costs often exceed agency costs by more than ten times, underscoring the critical importance of minimizing total societal costs [122]. Additionally, analytical cost-benefit optimization methods that integrate failure probabilities and user and social cost penalties have justified earlier optimal deck replacement timing and higher reliability targets, reinforcing the alignment between infrastructure safety, social welfare, and fiscal responsibility [123]. Studies utilizing probabilistic LCCA combined with environmental assessments have highlighted the economic and environmental advantages of corrosion-resistant steel, which substantially reduces lifecycle costs and CO₂ emissions in chloride-rich environments, effectively offsetting higher initial investments [124]. Furthermore, eco-efficiency assessments based on parameterized life-cycle inventory and cost models comparing conventional and ultra-high-performance concrete (UHPC) overlays have demonstrated that despite their higher initial cost, UHPC overlays significantly lower total lifecycle costs and reduce embodied carbon, particularly when service life is extended beyond twice that of conventional overlays [125].

Table 13. Summary of cost-based life cycle assessment (LCCA) studies on bridges.

Ref.	Application	Analytical Methods	Findings
[126]	Financial evaluation of Weigh-In-Motion (WIM) sensor installation for fatigue monitoring in steel bridge girders.	Probabilistic life-cycle cost analysis using the Hasofer–Lind reliability method.	Continuous WIM data reduces load uncertainty, enables optimal repair scheduling, enhances safety and yields net savings.
[127]	Long-term financial assessment of seismic structural health monitoring (SHM) installation on highway bridges.	Time-dependent LCCA via Monte Carlo simulation of seismic damage and repair scenarios.	Seismic SHM achieves cost break-even by lowering expected post-quake repair costs.
[110]	Comparative life-cycle cost analysis of fiber-reinforced polymer (FRP) vs. traditional steel stay cables on long spans.	Deterministic LCCA with scenario and sensitivity analysis on discount rate and service life.	A mixed FRP/steel arrangement is identified as the most cost-effective option among those analyzed.
[128]	Life-cycle cost comparison of corrosion mitigation: painted carbon steel, weathering steel, and stainless-steel girders.	Probabilistic LCCA via Monte Carlo corrosion-progression simulation.	Stainless steel can minimize total LCC in aggressive environments; the optimal choice depends on coating life, discount rate.
[112]	Optimal intervention timing for reinforced concrete bridges in seismic zones using renewal-theory LCCA.	Renewal-theory-based LCCA with analytical expressions for expected cost and downtime.	Accumulated seismic damage drives life-cycle cost; renewal theory provides closed-form insights into optimal schemes.
[113]	LCCA of selected concrete repair methods for chloride-contaminated columns.	Probabilistic event-based simulation of damage progression and Weibull-modeled service-life distributions.	Patch repair + hydrophobic impregnation and Ti-mesh cathodic protection deliver the lowest total LCC.
[129]	LCCA framework for maintenance strategies on concrete and steel railway bridges.	Probabilistic LCCA via Monte Carlo coupled with a maintenance-optimization algorithm.	Element-level cost modeling accelerates budgeting and improves repair prioritization
[130]	Deck replacement scheduling under strength and serviceability constraints	Probabilistic LCCA based on limit-state reliability indices.	Serviceability-based criteria lead to higher LCC than strength-only; reliability-constrained optimization yields realistic, safety-aware timing.
[131]	Expected LCC comparison of single vs. multiple maintenance interventions for aging RC bridges.	Probabilistic LCCA with time-dependent reliability modeling.	Multiple smaller interventions smooth cost and risk profiles and outperform single-action strategies.
[132]	LCCA of maintenance profiles for various superstructure types (steel vs. concrete).	Probabilistic LCCA via Monte Carlo and stochastic dominance.	Preventive-maintenance profiles consistently outperform rehabilitation-heavy profiles.
[109]	Long-term LCA of all-aluminum bridge vs. hypothetical aluminum-deck replacement (100-year span).	Deterministic cradle-to-grave LCA based on historical and projected cost data.	The aluminum deck option extends service life and minimizes disruptions despite a higher initial investment.

Table 13. *Cont.*

Ref.	Application	Analytical Methods	Findings
[133]	Preventive-maintenance scheduling for reinforced concrete bridges based on life-cycle cost minimization.	Monte Carlo simulation of random damage (Weibull) and repair events; expected-cost LCCA.	The optimal maintenance interval balances rising repair costs against escalating damage costs; Weibull-modeled damage/repair times drive the minimum expected LCC.
[111]	Life-cycle costing framework development for Myanmar highway bridges.	Deterministic component-based LCCA per ISO 15686-5; present-value analysis over a 40-year horizon.	Even a basic preventive maintenance plan can reduce 30-year LCC by ~20% versus reactive repairs; framework guides budgeting under limited funds.
[114]	Expected LCC evaluation for deteriorating reinforced concrete bridge elements.	Analytical probabilistic LCCA using a Markov /deterioration process and closed-form expected-cost equations.	Provides expected maintenance cost and intervention count over the service life; supports optimal allocation of resources under uncertainty.

Table 14. Summary of sustainability life cycle assessment (LCA) studies on bridges.

Ref.	Application	Analytical Methods	Findings
[115]	Environmental impact assessment of bridge life-cycle stages (design, construction, operation, end-of-life).	Probabilistic life-cycle LCA with Bayesian network for data gaps and fuzzy-mathematics aggregation.	>53% of impacts arise from material production and O&M; optimized traffic management reduces CO ₂ by ~330 t/year.
[116]	Integrated environmental and cost LCA across design, construction and O&M phases for bridges.	Probabilistic life-cycle sustainability analysis using Monte Carlo propagation and surrogate modeling.	Modeling phase interactions alters sustainability rankings; single-stage expected values can mislead decision-making.
[117]	Stage-by-stage environmental LCA (manufacturing, use, EoL) of two optimal concrete box-girder bridge designs.	ISO 14040 life-cycle inventory and impact assessment.	Manufacturing and maintenance stages dominate; the durability-oriented design yields lower total impacts despite higher initial footprint.
[118]	LCA and LCCA of rehab vs. rebuild options for long-span cable-stayed bridges (30-year horizon).	Cradle-to-grave LCA with dynamic energy-mix factors; deterministic LCCA.	Material production is the largest emitter; construction is smallest; dynamic energy modeling shifts the optimal renewal schedule.
[119]	LCA of epoxy-asphalt vs. GA + SMA pavement systems on steel bridge decks.	Cradle-to-grave LCA with Monte Carlo-based uncertainty assessment of inventory and impact factors.	Epoxy-asphalt systems consume ~2.5× less energy and emit ~3.4× fewer GHGs than GA + SMA mixtures; raw-material production dominates impacts.

Table 15. Summary of integrated LCA Studies (cost, environmental, and social dimensions).

Ref.	LCA Type	Application	Analytical Methods	Findings
[120]	Social and cost LCA	Combined financial and social-cost evaluation of design/maintenance strategies for reinforced-concrete bridges.	Stochastic social-cost LCCA: ranking by integrating quantified social factors into the life-cycle cost.	Social costs (e.g., user delays, business losses) dominate total LCC; including them shifts optimal maintenance timing.
[121]	Social and cost LCA	Financial and social-cost appraisal of preventive measures (increased concrete cover, SS rebar, cathodic protection) for prestressed concrete bridges in chloride environments.	Deterministic social-cost LCCA: ranking by discounted total cost.	A well-chosen preventive strategy can reduce total LCC by up to ~58%; user-delay costs dominate for frequent major works.
[124]	Cost and environmental LCA	Financial and environmental LCA of painted steel vs. corrosion-resistant steel for bridges.	Probabilistic LCCA combined with life cycle GHG LCA via Monte Carlo.	Corrosion-resistant steel reduces total LCC and CO ₂ emissions in chloride environments, offsetting its higher first cost.
[122]	Cost and social LCA	Bridge design/maintenance decisions incorporating user and social costs.	Multi-level stochastic cost-benefit LCCA with discounting and life-quality indices.	User-related costs (delays, closures) often exceed agency costs by a factor of 10 or more; therefore, total societal cost minimization is recommended.
[123]	Cost and social LCA	Optimal deck replacement timing for highway bridges, including user and social cost penalties.	Analytical cost-benefit optimization integrating failure probability and user/social costs.	The inclusion of user and societal costs raises optimal reliability targets and justifies earlier interventions.
[125]	Environmental and cost LCA	Comparative LCA and LCCA of conventional vs. UHPC overlays for bridge decks.	Parameterized life-cycle inventory and cost model; eco-efficiency scenario comparison.	Ultra-High Performance Concrete overlays—despite higher initial cost—yield lower total LCC and embodied carbon when service life $\geq \sim 2\times$ that of conventional overlays.

4.3. Digital Twin (DT)-Based Models

Digital Twin (DT) technology has emerged as a transformative solution for the management of bridge operation and maintenance (O&M), significantly enhancing safety, sustainability, and decision-making capabilities. By providing dynamic, real-time digital representations of physical structures, DTs facilitate proactive maintenance strategies, predictive analytics, and informed resource allocation. Central to the successful implementation of DT models are advanced data acquisition tools, which include terrestrial LiDAR geometry, UAV imagery, IoT strain gauges, Global Navigation Satellite System (GNSS), total-station controls, and structural health monitoring (SHM) systems. The integration of terrestrial LiDAR with periodic strain and vibration recordings has enabled the precise capture of geometric data and the effective monitoring of structural integrity, both essential for conducting detailed bridge assessments [134]. Additionally, UAV imagery, in conjunction with LiDAR scans and IoT sensors, has enhanced the collection of high-resolution spatial and condition data. This data serves as critical input for real-time bridge health monitoring and informed decision-making [135]. Moreover, the merging of LiDAR point clouds with GNSS and total-station data has supported accurate geometric reconstruction and comprehensive lifecycle scenario simulations, thereby enhancing long-term maintenance planning [136]. SHM systems, which utilize metrics such as stress, ambient conditions, and visual inspections, provide essential information for assessing the conditions related to corrosion and fatigue deterioration in bridge components [137]. This integration significantly improves safety assessments and operational reliability as shown in Table 16.

Table 16. Summary of digital twin applications in bridge operation and maintenance.

Ref.	Data Type	Core Techs and Tools	Data-Analysis Techniques	Function/Service
[134]	Terrestrial LiDAR geometry + periodic strain/vibration records.	Revit; Solibri; Navisworks.	Scan-to-BIM segmentation; FE import and “what-if” rehab simulation.	Predictive rehab planning; heritage asset archiving.
[135]	UAV imagery, LiDAR, IoT strain gauges, Met-Office weather; GIS layers.	Xeokit; CesiumJS.	Mask R-CNN defect vision; Graph-based traffic rerouting; GraphSAGE logistics; optional FEA.	Traffic diversion, O&M scheduling, logistics optimization.
[136]	LiDAR point cloud; GNSS and total-station control; inspection docs.	Rhino; SketchUp; SCIA Engineer.	Template-matching segmentation; mesh remeshing; differential-evolution FE calibration.	Scenario simulation and life-cycle sustainability planning.
[137]	SHM stress/ambient data; visual inspections.	Python Tensorflow library; OpenSees.	Multi-physics corrosion-fatigue model; RL-based maintenance optimizer.	Dynamic inspection and maintenance optimization; hanger replacement timing.

The role of analytical methods and techniques is paramount in processing collected data, which in turn enables informed decision-making and optimized maintenance strategies. Techniques such as template matching-based segmentation have demonstrated effectiveness in achieving accurate geometric modeling within Building Information Modeling (BIM) software, including Revit and Solibri. These models can subsequently be exported into simulation software, such as Navisworks, to conduct ‘what-if’ rehabilitation simulations, thus enhancing structural condition assessments for heritage asset management [134]. Furthermore, advanced finite element (FE) modeling tools, including SCIA Engineer and SketchUp, combined with differential evolution algorithms, facilitate detailed structural modeling and scenario-based analyses. This capability supports both scenario simulation and lifecycle sustainability planning [136]. Specialized web-based visualization platforms, such as Xeokit and CesiumJS, offer comprehensive functionalities that support real-time operational management, intelligent traffic rerouting, efficient maintenance scheduling, and optimized logistics operations [135]. These platforms enhance decision-making through detailed visualization and spatial analysis, thereby significantly improving the efficiency and safety of bridge operations. Finally, the integration of multi-physics corrosion-fatigue modeling with reinforcement learning approaches has advanced predictive maintenance optimization. Such methodologies enhance intelligent real-time inspections and enable optimized maintenance decision-making, allowing for precise predictions of maintenance needs and intervention timing [137].

4.4. Bridge Inspection Models

The studies summarized in Tables 17 and 18 reflect an evolving landscape in inspection planning models that integrate advanced nondestructive testing (NDT) methods, probabilistic analyses, and optimization techniques. For concrete bridges, multi-modal NDT approaches, infrared thermography (IRT), ultrasonic surface wave (USW), ground-penetrating radar (GPR), and electrical resistivity (ER), and others, combined with simulation-based strategies (e.g., Particle Swarm Optimization (PSO) and Discrete Event Simulation (DES) [138]) to improve scheduling accuracy and reduce costs, while probabilistic methods such as kernel density estimation (KDE) and fuzzy logic integrated with Bayesian networks refine failure probability predictions [139,140]. In reinforced concrete (RC) structures, spatial Bayesian updating and co-active prioritization models target critical elements to enhance the Bridge Health Index (BHI) and minimize scheduling uncertainty [141,142].

Adaptive, risk-based inspection (RBI) strategies using Monte Carlo simulation have shifted practices away from fixed intervals toward dynamic, cost-effective scheduling [143,144]. For steel bridges, the use of phase-type multi-state Markov models, Markov Decision Processes (MDPs), and digital twin frameworks extends fatigue life by optimizing inspection intervals and maintenance actions [145–147], building on earlier probabilistic and reliability-based approaches [148–152]. Moreover, emerging research incorporating unmanned aerial vehicles (UAVs), vision-based robotic systems, and metaheuristic algorithms such as Ant Colony Optimization (ACO) and PSO addresses resource optimization and real-time decision-making challenges [34,153–155].

Table 17. Summary of inspection planning models: applications, techniques, optimization approaches, and contributions.

	Study	Application	Inspection Technique	Approach	Optimization	Key Contribution
Concrete bridges	Abdelkhalek et al. [138]	Bridge deck inspections	Camera, IRT, IE, USW, UPE, GPR, HCP, ER, PR	Multi-NDT integration with simulation	Multi-objective PSO + DES	Combines multiple NDTs to optimize scheduling, reduce cost/time, and enhance accuracy
	Abdelkhalek & Zayed [3]	Bridge networks over large areas		Crew routing with distance/work constraints	DES + GA	Reduces travel, idle time, and crew cost
	Kwon et al. [140]	Deteriorating bridges	Simulation-based adaptation *	Failure probability extrapolation	KDE	Improves timing accuracy for inspections using KDE-based prediction
	Mohamad & Tran [139]	Highway construction QA		Fuzzy logic + expert risk input	Fuzzy sets + Bayesian networks	Prioritizes inspection using quantified uncertainty and expert judgment
	Sein et al. [156]	Bridge management in Estonia		Stochastic degradation model	MCMC stochastic simulation	Reduces uncertainty in scheduling by optimizing with degradation forecasts
	Su et al. [157]	Concrete beam bridge		Logic-based optimization with linkages	C5.0 Boosting Decision Tree	Enhances efficiency via asset screening and coordination
	Vereecken et al. [141]	RC structures under corrosion (bridge girders)		Spatial Bayesian decision updating	VoI + Bayesian	Minimizes cost/risk by incorporating outcome-based updates
	Oyegbile & Chorzepa [142]	Concrete bridge (Georgia)		Co-active prioritization model	Heuristic logic	Boosts BHI by targeting critical elements with inspection timing adjustments
	Huang et al. [158]	Bridge routing and lodging		Vehicle routing optimization	ACO + local search	Minimizes cost via optimized routes/accommodation for multi-teams
	Washer et al. [143]	General bridge structures		Risk matrix-based interval planning	Simple risk matrix	Converts fixed intervals to adaptive risk-based timing
	Kim & Frangopol [144]	RC highway bridge		Damage detectability-driven timing	Monte Carlo simulation	Minimizes delay in detection and lifecycle cost

* Studies that leverage computational simulations to adapt inspection, maintenance, or monitoring strategies.

Table 18. Summary of inspection planning models: applications, techniques, optimization approaches, and contributions (Cont’d).

	Study	Application	Inspection Technique	Approach	Optimization	Key Contribution
Steel bridge	Sun & Vatn [145]	Steel road bridge	Simulation-Based Adaptation *	Markov deterioration with inspection delay	Phase-type multi-state Markov	Optimizes cost with fewer inspections and postponed repairs
	Jiang et al. [146]	Fatigue in steel bridges		Digital Twin + probabilistic fatigue model	Bayesian inference + surrogate optimization	Enables real-time repair sizing and inspection updates to extend fatigue life
	Cheng & Frangopol [147]	Corroded steel girders		Load rating + inspection planning	MDP with state augmentation	Reduces lifecycle cost with adaptive inspection/replacement rules
	Crémona & Lukić [152]	Welded joints in steel bridges		Fracture mechanics + reliability	Probabilistic fatigue model	Updates reliability and costs to determine inspection interval
	Sommer et al. [148]	Highway steel-girder bridges	LPI, UI, ECI	Reliability index for time-based intervals	Probabilistic reliability analysis	Recommends constant 5–10 year intervals based on corrosion/load degradation
	Soliman et al. [151]	Fatigue-prone steel bridges		Multi-objective NDT selection	Probabilistic optimization	Chooses best NDT + schedule under uncertainty and cost limits
	Orcesi & Frangopol [149]	Steel bridges		Lifetime functions + event tree	Probabilistic + cost optimization	Balances NDT strategy, failure, and maintenance costs under uncertainty
Others	Wu et al. [153]	UAV inspection of infrastructure	UAV	Model-based prognostics	Physics-based probabilistic analysis	Optimizes UAV flight parameters and inspection update rules
	Phung et al. [34]	Surface inspection (e.g., buildings)	CCD camera attached to a controllable gimbal	Vision-based robotic inspection	PSO on GPU	Reduces path computation time and improves controllable gimbal inspection efficiency
	Yang & Frangopol [154]	Civil and marine structures	Simulation-Based Adaptation *	Static vs. adaptive RBI	Bayesian + Monte Carlo	Adaptive plans lower costs and preserve safety better than fixed methods
	Sheils et al. [155]	Infrastructure maintenance		Two-stage Markov inspection planning	Markov modeling	Optimizes cost-effective technique combinations and intervals

* Studies that leverage computational simulations to adapt inspection, maintenance, or monitoring strategies.

4.5. Artificial Intelligence-Based Models

Many machine learning (ML) and optimization techniques have been explored for infrastructure maintenance decision-making, each with distinct advantages and limitations. Traditional statistical approaches, such as linear regression and time-series analysis, have been extensively used for cost prediction and trend analysis in maintenance planning [159]. The linear regression model, for instance, predicts maintenance costs as a function of relevant variables (e.g., bridge age) (Equation (13)). For more complex, multi-parameter decision-making, ML models such as probabilistic neural networks (PNN) and radial basis function networks (RBFN) have been employed [160]. These models can capture nonlinear relationships and are often enhanced by dimensionality reduction techniques like principal component analysis (PCA) to improve predictive accuracy. Support vector machines (SVMs) are also utilized for risk estimation and classification tasks, with the decision function defined as in Equation (14) [161]. Advanced deep learning (DL) architectures have further improved modeling capabilities. These include the Deep Neural Networks (DNN) model [162] (see Figure 10a), Neural Networks with Entity Embeddings (NN-EE) [163], and Self-Organizing Map-based Cluster Merging (SOMCM) using a multi-dimensional matrix composite neural network for surface image identification [164].

These models are especially effective in handling high-dimensional input data, uncertainty, and complex feature interactions. Optimization algorithms are crucial in maintenance planning, particularly for multi-objective problems (Equation (15)). The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is widely used to balance objectives such as cost, reliability, and sustainability [165]. Dynamic programming (DP) and decision tree (DT) analysis have also been applied to determine optimal maintenance schedules over the life cycle of structures [166–168]. The DP approach recursively solves sub-problems using the Bellman equation (Equation (16)). While these traditional and optimization-based methods are effective for smaller or less complex systems, they often struggle to scale to the high-dimensional, uncertain environments encountered in large infrastructure networks.

Recent advancements in artificial intelligence have significantly transformed the field of infrastructure maintenance, particularly through the application of Deep Reinforcement Learning (DRL). DRL synergistically combines the sequential decision-making framework of reinforcement learning (RL) with the powerful function approximation capabilities of deep neural networks, enabling the management of large and complex state-action spaces typical in civil infrastructure systems [169–173], illustrated schematically in Figure 10b. In DRL-based maintenance planning, frameworks such as Deep Q-Networks (DQN) have been widely adopted as surrogate models for value functions. The DQN architecture takes the current state of the infrastructure as input and outputs Q-values for each possible action, facilitating the selection of optimal maintenance policies. The fundamental Q-learning update rule is given by Equation (17). Multi-agent DRL frameworks have been developed to address the challenges of large-scale and networked infrastructure systems [174–176]. In these settings, decentralized agents make maintenance decisions for individual components or structures, while a centralized critic evaluates the overall system performance [173,174]. Advanced DRL algorithms, such as Proximal Policy Optimization and its multi-agent variants (MAR-PPO), have demonstrated superior performance in complex environments by promoting efficient information flow and collaboration among agents [174] (Equation (18)). Furthermore, integrating DRL with surrogate modeling, such as convolutional neural networks (CNNs) for spatio-temporal feature extraction, enhances predicting deterioration processes and optimizing maintenance schedules under uncertainty [170,173]. This integration is valuable for generating multiple management plans under various constraints [171].

A concise comparison of these methods is presented in Table 19, highlighting their strengths, limitations, and scalability.

$$y = \beta_0 + \beta_1 x + \varepsilon \quad (13)$$

where y is the predicted maintenance cost, x is the independent variable, β_0 and β_1 are regression coefficients, and ε is the error term. Time-series models like Autoregressive Integrated Moving Average (ARIMA) further capture temporal dependencies in maintenance data, enabling more accurate forecasting.

$$f(x) = \text{sign}(W^T x + b) \quad (14)$$

where w and b are parameters learned from the data.

$$\min[f_1(x), f_2(x), \dots, f_k(x)] \quad (15)$$

where $f_k(x)$ is the objective function to be minimized.

$$V(s) = \min_a [c(s, a) + \gamma V(s')] \quad (16)$$

where $V(s)$ is the value function, $c(s, a)$ is the immediate cost, and s' is the next state.

$$Q_{t+1}(S_t, a_t) = Q_t(S_t, a_t) + \alpha[r_t + \gamma \max_{a'} Q_t(S_{t+1}, a') - Q_t(S_t, a_t)] \quad (17)$$

where $Q_t(S_t, a_t)$ is the estimated value of taking action in state S_t at time t , r_t is the immediate reward, γ is the discount factor, and α is the learning rate.

$$L^{CLIP}(\theta) = E_t \left[\min \left(r_t(\theta) A^t, \text{clip}(r_t(\theta), 1 - \varepsilon, 1 + \varepsilon) A^t \right) \right] \quad (18)$$

where $r_t(\theta)$ is the probability ratio, and A^t is the advantage estimate.

Table 19. Statistical, shallow ML, DL, optimizations, and DRL comparison highlighting their strengths, limitations, and scalability.

Category	Methods	Strengths	Limitations	Scalability
Statistical Models	Linear Regression, Time-Series	Simple, interpretable; captures trends	Limited to linear or stationary patterns	Moderate
Shallow ML	SVM, PNN, RBFN, PCA	Captures nonlinearity; good for classification	Requires tuning; sensitive to hyperparameters	Moderate
DL	DNN, NN-EE, SOMCM	Handles complex, high-dimensional data	Requires large data and computational resources	High
Optimization Techniques	NSGA-II, DP, DT	Solves multi-objective problems; interpretable	Computationally intensive; poor for large-scale problems	Moderate
DRL Techniques	DQN, PPO, MAR-PPO	Learns optimal policies; scalable to complex systems	Needs extensive training and tuning	High
Hybrid DRL + DL	DRL + CNN, DRL + surrogate models	Captures spatio-temporal dynamics; robust to uncertainty	High computational cost	High

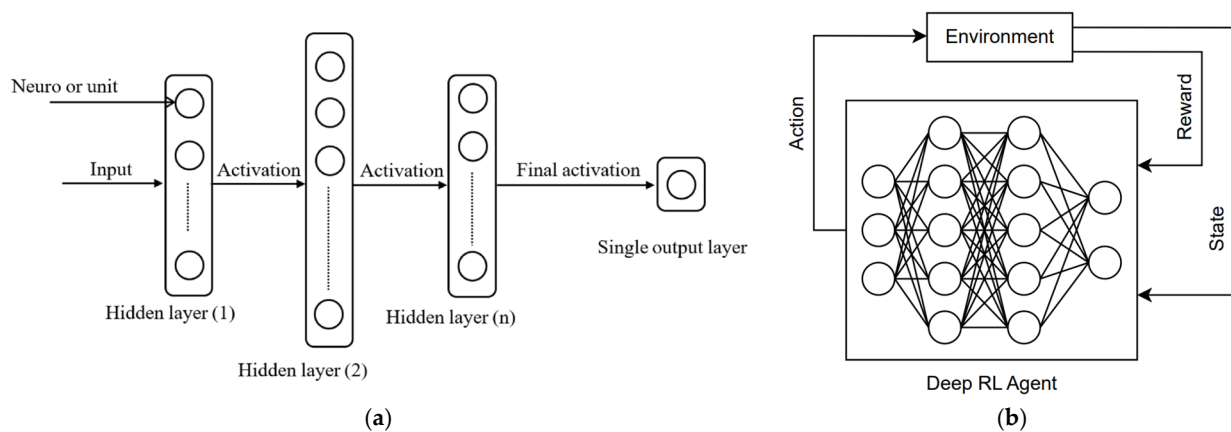


Figure 10. Schematic architectures of (a) a plain DNN for supervised prediction (from [177,178]) and (b) a DRL agent interacting with its environment.

Recent advancements have seen the integration of artificial intelligence (AI) and machine learning (ML) into maintenance budgeting. These technologies enhance predictive capabilities and optimize maintenance interventions. Tables 20 and 21 illustrate how artificial intelligence can enhance maintenance budget allocation models for existing bridge structures by providing a structured, rule-based framework that maps the Bridge Condition Index to specific maintenance treatments. By categorizing bridge conditions into defined ranges such as good, fair, or poor and linking each range to appropriate actions, AI algorithms can be trained to predict maintenance needs and prioritize interventions. This enables more data-driven and consistent decision-making, allowing maintenance budgets to be allocated efficiently based on the actual condition and projected deterioration of bridge assets. AI integration thus supports optimized resource use, timely interventions, and improved long-term infrastructure performance. In addition, 20 recent academic papers focus on optimizing bridge maintenance through life-cycle cost assessment, artificial intelligence, risk-based modeling, and sustainability-oriented strategies. These studies collectively reflect a growing emphasis on integrating advanced computational techniques, particularly reinforcement learning and neural networks, into bridge maintenance decision-making under uncertainty.

Table 20. AI-based approaches for bridge maintenance: methods, tools, and performance metrics.

Ref.	Application	Analytical Methods	AI Techniques and Tools	Performance Indicators
[165]	Optimize maintenance schedule of an RC girder bridge for safety, service life and cost	Multi-objective optimization; stochastic deterioration curves	Improved NSGA-II genetic algorithm	Condition index, reliability index, maintenance cost, service life
[171]	Plan 100-year life-cycle maintenance for a region of deteriorating bridges	Probabilistic deterioration modeling; life-cycle cost analysis	Deep Q-Network with encoder-decoder CNN	Life-cycle cost-effectiveness of maintenance actions.
[160]	Rank project-level bridge interventions under multiple criteria	Probabilistic modeling; multi-criteria decision analysis; degradation-rate factor; LCC estimate	Probabilistic Neural Network; Radial-Basis-Function NN	Accuracy of condition state, reliability index, degradation-rate prediction, LCC error, optimal timing
[174]	Derive cost-effective, risk-aware policies for a bridge network	Markov Decision Process; stochastic cost model	Multi-agent Ranking PPO (MAR-PPO)	Network maintenance cost-effectiveness; excessive-risk cost
[173]	Manage a steel-girder bridge under risk-based life-cycle criteria	Probabilistic LCC; reliability analysis	Double-Critic Multi-Agent A2C (DCMA2C) RL	Expected LCC; annual reliability index; annual failure risk
[175]	Formulate network-wide maintenance policies	Markov-chain deterioration; Bayesian updating; LCC analysis	Multi-agent Q-learning RL	Cost-effectiveness, condition distribution, mean annual maintenance cost
[167]	Allocate annual budget and schedule works across a bridge network	Dynamic programming optimizer	Hopfield neural-network search	Annual budget utilization rate
[162]	Speed up life-cycle cost analysis under multiple uncertainties	Monte-Carlo LCC; Markov deterioration; Poisson hazard and cost volatility	Deep fully-connected neural network as surrogate model	Agency cost; user cost; composite utility
[179]	Devise bridge maintenance strategy under climate-change scenarios	Hybrid LCA + LCC; reliability-index modeling; multi-objective optimization	Decision-tree classification framework	Environmental cost; economic cost; probability of CO ₂ -reduction failure
[163]	Predict condition state, risk level and maintenance advice for bridges from routine inspection records	Supervised multi-task classification; cost-sensitive learning to handle class imbalance	Entity-embedding multi-task neural network plus comparative logistic-regression and tree-based learners	Predicted condition state, risk level and maintenance advice classes for each bridge element

Table 21. AI-based approaches for bridge maintenance: methods, tools, and performance metrics (Cont’d).

Ref.	Application	Analytical Methods	AI Techniques and Tools	Performance Indicators
[166]	Minimize expected life-cycle cost by optimally timing inspections and repairs of corrosion-damaged steel bridges	Probabilistic optimization with Bayesian updating; event-tree life-cycle simulation	Event-tree search routine (model-based optimizer)	Minimum expected life-cycle cost, optimal inspection/repair schedule, network-level failure probability
[176]	Plan project-level maintenance interventions under multiple uncertainties to maximize stakeholder utility	Markov decision process; life-cycle cost and utility evaluation	Multi-agent DeepQ-Network with Advantage Actor–Critic (MARL)	Convergence of expected reward, agency-cost change, user-cost change, stakeholder-utility gain
[170]	Derive the optimal maintenance policy for a deck system and cable-stayed bridge across its life-cycle	Markov decision process with reward-based life-cycle-cost evaluation; Monte-Carlo state simulation	Deep Q-Network optimizer	Long-term life-cycle cost compared with benchmark time-based and condition-based policies
[159]	Forecast routine maintenance cost of reinforced-concrete beam bridges	Hierarchical multivariate regression; autoregressive time-series forecasting	Cost-age regression model combined with AR forecast module (statistical ML)	Annual routine-maintenance cost profile for budgeting
[161]	Select risk-based maintenance timing and budget for deteriorating bridges	Monte-Carlo life-cycle simulation; expectancy–value theory for risk attitude modeling	Evolutionary Support-Vector-Machine with Symbiotic-Organisms-Search meta-heuristic	Expected life-cycle cost, optimal intervention years and annual budget envelope
[164]	Prioritize bridge maintenance using unsupervised patterns in historic inspection data	Self-organizing-map clustering; association-rule mining for attribute correlation	SOM neural network with cluster-merging algorithm	Targeted maintenance strategy list ranked by cluster risk profiles
[169]	Minimize total annual carbon emissions for a highway bridge network under budget limits	Two-dimensional Markov-chain deterioration; integer-programming budget allocation	Q-learning reinforcement learning for single-bridge policies	Network-level annual CO ₂ emissions and budget utilization curve
[180]	Produce sustainable life-cycle maintenance policies balancing cost, emissions and safety for a bridge network	Probabilistic deterioration and life-cycle carbon/safety evaluation; multi-attribute utility theory	Convolutional Autoencoder–Structured Deep Q-Network (ConvAE-DQN)	Maintenance-policy utility scores for cost, environmental and safety metrics across budget scenarios
[172]	Balance agency cost, CO ₂ and traffic-mobility delay over 100 years for a road-bridge network	Partially observable MDP with traffic-flow redistribution; Monte-Carlo roll-outs and multi-attribute reward	Hierarchical Branching-Dueling Q-Network with multi-reward back-propagation	Long-run reductions in life-cycle cost, carbon emissions, and congestion versus engineer-designed plans

Several studies proposed reinforcement learning frameworks for maintenance optimization. Notable examples include [170,171,174–176], which leveraged deep reinforcement learning and multi-agent systems to automate policy formulation at both project and network levels. These methods enable adaptive decision-making that responds to evolving bridge conditions and inspection data, offering more dynamic and cost-effective maintenance scheduling. Gui et al. [160] and Yang [173] introduced comprehensive evaluation algorithms and adaptive risk-based models, prioritizing interventions based on structural reliability and deterioration rates. These models are especially relevant under climate-change scenarios, as addressed in [179], which integrates reliability-based approaches under future climatic uncertainty. Life-cycle cost analysis remains central in many contributions [162,166,170], providing economic justification for different maintenance scenarios. These models typically incorporate uncertainties related to corrosion, traffic loads, and material degradation. Razaqpur et al. [167] contributed a classic approach using dynamic programming, which remains foundational for modeling maintenance over long horizons. In terms of machine learning innovations, the authors in [163,164] presented neural network-based strategies, including self-organizing maps and entity embedding, for routine maintenance prediction and cluster-based decision support. These methods facilitate knowledge discovery in large-scale bridge datasets.

The shift toward sustainable and holistic management is emphasized elsewhere [169,172,180], which propose frameworks that balance economic, environmental, and social factors in policy-making. These studies use informed DRL and sustainability metrics to guide decision-makers in maintaining aging bridge networks in a resource-efficient manner. Collectively, these works underscore a paradigm shift from reactive to proactive and intelligent infrastructure management, supported by advanced analytics and AI. The integration of uncertainty modeling, climate adaptation, and multi-agent systems marks a promising future direction in sustainable bridge maintenance.

4.6. Optimization-Based Models

Optimization algorithms are broadly decomposed into two main categories: exact and approximate algorithms. In this context, exact algorithms are mathematically proven to find the globally optimal solution in finite time. Nonetheless, most of the real-world problems are of an NP-hard nature, and solving these problems using exact algorithms usually requires an exponential amount of time and memory [181,182]. In computational terms, these problems are difficult to solve using exact methods, which necessitates the adoption of metaheuristics that can deliver practical near-optimal solutions within reasonable time frames. Looking at the metaheuristics, they are defined as high-level procedures that accommodate basic rules and heuristics to discover efficient and mostly optimal approximate solutions to challenging large-scale combinatorial problems [183]. These algorithms can be segmented into distinct classes, involving biological-inspired algorithms, nature-inspired algorithms, physics-inspired algorithms, chemistry-inspired algorithms, mathematics-inspired algorithms, and music-inspired algorithms [184,185]. Table 22 records a summary of the applied metaheuristics in maintenance optimization works.

Table 22. Description of the used metaheuristics in maintenance optimization literature.

Metaheuristic	Acronym	Type	Description	Reference
GA	Genetic algorithm	Biological-inspired	It is inspired by Darwin’s theory of biological evolution, and mimics the principles of natural selection and survival of the fittest	[186]
NSGA-II	Non-dominated sorting genetic algorithm-II	Biological-inspired	It emulates natural selection by ranking solutions into Pareto fronts and preserving diversity using the crowding distance	[187]
DE	Differential evolution	Biological-inspired	It simulates Darwinian evolution through three key operations: mutation, crossover, and selection	[188]
EFO	Electric fish optimization	Nature-inspired	It is modeled after the electrolocation and electrocommunication behaviors of weakly electric fish	[189]
IWO	Invasive weed optimization	Nature-inspired	It draws inspiration from the colonization behavior of weeds, and combines the basics of reproduction, spatial distribution, and competitive selection	[190]
WOA	Whale optimization algorithm	Nature-inspired	It imitates the hunting behavior of humpback whales, particularly their bubble-net feeding strategy	[191]
PSO	Particle swarm optimization	Nature-inspired	It models the social behavior of birds or individual particles flocking and adjusting their positions based on their own experience and the best-known position of the group	[192]
SFLA	Shuffled frog leaping algorithm	Nature-inspired	It is influenced by the foraging behavior of frogs, combining local search with global exploration	[193]
HS	Harmony search	Music-inspired	It is sparked by the improvisation process of musicians who adjust their notes or melodies to achieve the best harmony	[194]
SA	Simulated annealing	Physics-based	It is motivated by the metallurgical process of annealing, where a material is heated and slowly cooled to remove defects	[195]

Bridge maintenance optimization is a critical aspect of infrastructure management, aiming to ensure structural safety, extend service life, and minimize lifecycle costs. Over recent decades, various methodologies have been developed to enhance decision-making processes in bridge maintenance. Tables 23–28 expound some of the several available metaheuristic-based maintenance optimization models. In this context, the designed models can be divided into two groups, single-objective and multi-objective, meanwhile satisfying a set of constraints that limit feasible solutions. Single-objective optimization involves one primary goal while multi-objective optimization encompasses two or more conflicting objectives; there is no single best solution, but instead, there is a set of tradeoff solutions, commonly known as “Pareto set” or “non-dominated solutions” [196,197]. One of the earliest works that harnessed single-objective optimization is the ref. of [198]. In it, the authors compared the performances of genetic algorithm and shuffled frog leaping in optimizing bridge deck repair programs. The optimization problem was formulated based on a single-objective function that minimizes the present worth of annual repair costs of all bridges. Four repair methods were considered, namely do nothing, light repair, medium repair, and extensive repair. It was illustrated that shuffled frog leaping was able to provide a significant better performance than genetic algorithm. Among the single-objective optimization studies, there is a study by Xu and Huang [199] who utilized AHP in conjunction with hybrid chaotic whale optimization algorithm to enhance

the replacement decision system of bridge expansion and contraction installation. In this respect, AHP was implemented to derive the hierarchical weights of the assessment criteria of design requirements, construction requirements, and management requirements. In addition, Hybrid Chaotic Whale Optimization Algorithm (HCWOA) was applied to minimize the inconsistent comparison matrix through a single objective optimization problem. Eventually, the obtained weights of evaluating criteria are blended with their performance coefficients to form a performance index of the replacement plan. Moreover, it was evinced that HCWOA was able to improve the consistency levels of the comparison matrix more than the classical WOA and particle swarm optimization.

In the same field of optimization, Wang et al. [10] developed an improved electric fish optimization (IEFO) model for the purpose of reliability-based maintenance planning of bridge infrastructures. In this regard, Lévy Flight chaotic mechanism was adopted to boost the search efficiency of classical electric fish optimization. They deployed a biquadratic deterioration function to estimate the future reliability of bridge components over time. In addition, the optimal MR&R strategies were determined capitalizing on minimizing the annualized maintenance expenditures of bridge superstructure. Another significant body of research was delivered by Li et al. [200] who created a risk-based optimization model of deteriorated steel bridges. Monte Carlo simulation was utilized to estimate the failure mode parameters of flexure failure, shear failure, deflection failure, fatigue failure, and chloride attack. This study also involved building a risk-cost optimization program that minimizes the total risk of steel bridges using genetic algorithm.

Moving on to the multi-objective optimization, one of the first known works in this field was conducted by Liu and Frangopol [201] who planned a multi-objective genetic algorithm (MOGA) model for annual maintenance prioritization of bridges. The optimal annual intervention actions were determined based on: (1) minimizing the present worth of life cycle maintenance costs, (2) maximizing the lowest lifetime performance condition, and (3) maximizing the lowest lifetime safety index. Moreover, the uncertainties linked with structural behavior and lifecycle costs were assessed using Monte Carlo simulation. Later, Park et al. [202] deployed genetic algorithm to optimize the maintenance strategies of deteriorated steel box girder bridges. Pertaining to this, the lifetime maintenance scenarios were evaluated according to the minimization of lifecycle maintenance costs, maximization of lifecycle condition of bridge members, and maximization of reliability. Further, Monte Carlo simulation was employed to model the uncertainties related to the application of maintenance intervention action.

A third notable study was conducted by Alsharqawi et al. [12], who constructed a quality function deployment for defect-based condition assessment of bridge decks. The assessment process accommodated the defects of pop-outs, deposits, joint problems, spalling, delamination, corrosion, erosion and cracks. Then, they devised a multi-objective optimization model that implemented genetic algorithm to simultaneously minimize the total rehabilitation cost of the bridge deck and maximize its performance condition status. Fourthly, Allah Bukhsh et al. [14] established a multiyear maintenance planning method of bridge networks through merging multi attribute utility theory with genetic algorithm. In it, MAUT was used to rank bridges through their social and economic aspects. Then, a multi-objective genetic algorithm model was introduced based on the competing objectives: (1) minimization of the overall maintenance costs, and (2) maximization of the condition status of bridges.

Fifthly, Jaafaru and Agbelie [203] presented a maintenance planning framework that integrated machine learning, multicriteria decision analysis, and multi-objective optimization. Xgboost model was utilized to combine the bridge condition predictions that are retrieved from random forest, support vector machines, and artificial neural network. Subsequently, MAUT was undertaken to compute an aggregated score from the utility functions of performance indicators. Eventually, NSGA-II was applied to find the optimal maintenance treatments through minimizing the total maintenance expenses and maximizing the performance scores of bridges. A sixth research work by [204] amalgamated disease transmission concept and NSGA-II for the optimal assignment of maintenance funds of bridge network. The authors scrutinized the transmission paths of the diseases present in deck pavement, bearings and expansion joints. This includes studying design defects, maintenance defects and construction defects in each bridge component besides investigating their impact on the damage process. In addition to that, NSGA-II was exploited to design optimal maintenance plans across varying budget-demand scenarios.

Apart from genetic algorithm and its variants, some research endeavors adopted particle swarm optimization in their models. For instance, Yang et al. [205] introduced a multi objective particle swarm optimization model for preventive maintenance planning of deteriorated bridges. Additionally, Monte Carlo simulation was implemented to tackle the ambiguities pertaining to maintenance costs and deterioration process. It was envisaged that multi-objective particle swarm optimization (MOPSO) was able to achieve higher hyper volume value than NSGA-II, and island paradigm was found to provide more efficient solutions than the parallel computing paradigms of diffusion and master-slave. On the same note, Yang et al. [206] created a probabilistic life cycle optimization model of maintenance schedules considering the competing objectives of (1) minimization of lifecycle maintenance expenses, and (2) maximization of lifecycle performance. It was illustrated that MOPSO managed to render notably more efficient and diverse solutions as opposed to NSGA-II.

Table 23. Summary of some of the metaheuristic-based maintenance optimization models.

Reference	Year	Employed Algorithms	Application	Optimization Type	Objective Functions	Design Constraints
[207]	2024	Modified NSGA-II (NDX crossover operator + adaptive hybrid mutation operator)	Resource-driven maintenance optimization of in-service bridges	Multi-objective	a. Minimize the cumulative structural safety loss b. Minimize the entire duration of planned maintenance	a. Structural reliability of bridge component b. Cumulative number of construction labors for bridge repairing
[208]	2022	NSGA-II	Maintenance programming at the bridge element level, bridge-level, and network-level	Multi-objective	a. Maximize the network health index b. Minimize the network LCC	a. Total budget b. Network health index
[199]	2021	AHP + HCWOA	Supporting bridge expansion and contraction installation	Single-objective	Minimize the inconsistent comparison matrix	N/A
[12]	2021	QFD + GA	Short-term and long-term MRR optimization for bridge decks under performance-based contracting	Multi-objective	a. Minimize the total rehabilitation actions cost b. Maximize the average condition	a. Total available budget b. Performance at each year c. Level of service threshold

Table 24. Summary of some of the metaheuristic-based maintenance optimization models (Cont'd).

Reference	Year	Employed Algorithms	Application	Optimization Type	Objective Functions	Design Constraints
[209]	2025	NSGA-II	Dynamic maintenance optimization of regional transportation network	Multi-objective	a. Maximize the condition benefits of the bridge network b. Minimize the maintenance expenses	a. Maintenance funding of bridge network
[203]	2022	Xgboost + MAUT + NSGA-II	Formulating bridge network maintenance plans that maximize performance within financial limitations	Multi-objective	a. Minimize the total maintenance cost b. Maximize the performance condition rating	a. Condition level of bridges b. Available estimated budget
[14]	2020	MAUT + NSGA-II	Multi-year maintenance planning optimization for road bridge networks	Multi-objective	a. Minimize the total maintenance expenditures b. Maximize the bridge performance level	a. Bridge network condition index b. Budget limit
[205]	2012	MOPSO + MCS + parrallel computing	Maintenance planning of deteriorated bridges	Multi-objective	a. Minimize the discounted present worth of maintenance costs b. Maximize the lowest condition index c. Maximize the lowest safety index	a. Condition index b. Safety index c. Budget limit

Table 25. Summary of another set of metaheuristic-based maintenance optimization models.

Reference	Year	Employed Algorithms	Application	Optimization Type	Objective Functions	Design Constraints
[210]	2024	FST + AHP + PSO	Optimizing MR&R strategies of bridges	Multi-objective	a. Minimize the user and maintenance costs b. Maximize the reliability of bridge maintenance	a. Allocated budget limit for each bridge
[10]	2024	IEFO	Reliability-driven maintenance optimization of bridges	Single-objective	a. Minimize the equivalent annual maintenance costs	N/A
[204]	2023	NSGA-II + Disease transmission concept	Maintenance fund assignment of bridge networks	Multi-objective	a. Maximize the total economic benefits of bridge repair b. Maximize the total technical benefits of bridge repair c. Minimize the total maintenance costs of bridge repair	a. Available maintenance budget a. Annual budget limits b. Condition level of bridges c. Entire condition rating of bridge network
[198]	2006	GA/SFL	Optimization of bridge deck rehabilitation	Single-objective	a. Minimize the total life cycle costs of bridge repairs	

Table 26. Summary of another set of metaheuristic-based maintenance optimization models (Cont'd).

Reference	Year	Employed Algorithms	Application	Optimization Type	Objective Functions	Design Constraints
[211]	2022	NSGA-II	Condition-driven maintenance of corroded RC columns in seismic zones	Multi-objective	a. Minimize the seismic risk of columns b. Minimize the life cycle cost of maintenance	a. Time interval between successive maintenance actions b. Maintenance period c. Maximum permissible risk threshold
[206]	2019	MOPSO-II + LHS	Stochastic optimization of life-cycle maintenance actions to enhance bridge superstructure durability	Multi-objective	a. Maximize the life cycle performance b. Minimize the life cycle maintenance costs	a. Available maintenance funding b. Time interval between subsequent maintenance actions
[212]	2013	GA + LHS	Optimized maintenance scheduling of bridge networks	Multi-objective	a. Maximize the bridge network connectivity b. Minimize the total maintenance costs	a. Available maintenance fund b. Number of travels originated and attracted by each node
[201]	2005	MOGA + MCS	Annual optimization of limited maintenance funding for deteriorating bridge elements	Multi-objective	a. Maximize the lowest lifetime condition b. Maximize the lowest safety index c. Minimize the lifecycle maintenance costs	a. Condition index of bridge element b. Safety index of bridge element c. Limit of life cycle cost

Table 27. Summary of a third set of metaheuristic-based maintenance optimization models.

Reference	Year	Employed Algorithms	Application	Optimization Type	Objective Functions	Design Constraints
[200]	2022	GA + MCS	Risk-cost optimization of maintenance programs of steel bridges	Single-objective	Minimize the total risk of steel bridge failure	a. Allowable probability of each failure mode b. Allowable failure probability of steel bridges
[11]	2022	ECDE + CRITIC + COPRAS + GRA	Optimizing bridge maintenance plans of bridge elements	Multi-objective	a. Maximize the performance status of bridge elements b. Minimize the total life cycle maintenance expenditures c. Minimize the traffic disruption duration d. Minimize the environmental footprint	a. Minimum condition of bridge elements b. Estimated total budget c. Available annual funding d. Maximum permissible standard deviation of repair actions e. Number of intervention actions of bridges
[213]	2021	GA + DES	Simulation-based bridge maintenance planning	Single-objective	Minimize the crew and user costs	Available annual budget of repair activities
[214]	2020	GA + MCS	Optimizing maintenance schedules for enhanced disaster resilience	Multi-objective	a. Minimize the total annual maintenance cost b. Maximize the safety performance of each bridge element c. Maximize the resilience against natural disasters	a. Safety performance threshold b. Maximum number of bridges to be repaired

Table 28. Summary of a third set of metaheuristic-based maintenance optimization models (Cont'd).

Reference	Year	Employed Algorithms	Application	Optimization Type	Objective Functions	Design Constraints
[215]	2020	DES + ENN + DE + PROMETHEE II	Simulation and planning of bridge deck replacement projects	Multi-objective	a. Minimize the duration of bridge deck replacement b. Minimize the cost of bridge deck replacement c. Minimize the greenhouse gases of bridge deck replacement	Thresholds for managing the utilization of resources
[216]	2018	GA + MCS	Time dependent reliability-based optimization of bridges	Multi-objective	a. Minimize the cumulative probability of failure of bridges b. Minimize the life cycle cost of repair actions c. Minimize the life cycle environmental footprint of repair actions	a. Target failure probability b. Preventive maintenance timeframe c. Timing of application of initial preventive maintenance
[217]	2018	GA	Maintenance cost optimization of reinforced concrete bridge superstructure	Single-objective	Minimize the uniform equivalent annual expenditures of maintenance	Allocated funding limits
[202]	2012	GA + MCS	Safety-focused maintenance optimization of steel box girder bridges	Multi-objective	a. Minimize the total life-cycle maintenance expenditures b. Maximize the life-cycle condition index c. Maximize the life-cycle reliability index	a. Given budget limit b. Performance condition threshold

Table 29 outlines the main contributions of the exact optimization-based maintenance models. Ghafoori et al. [218] built a two-fold model for effective proactive planning of bridge maintenance. The first fold explored the performances of four machine learning techniques, namely support vector machines, decision tree, gradient boosting, and random forest to forecast the condition of concrete bridge elements. The second fold incorporated applying binary linear programming to maximize the average performance index of bridge elements subject to technical and economic requirements. Results delineated that random forest succeeded in outclassing other models according to the performance indicators of mean absolute error, mean squared error, mean absolute percentage error, and determination coefficient. Secondly, Mao et al. [219] established a nonlinear programming-based model for strategizing optimal maintenance schedules of bridge networks. Their work was envisioned based on two levels, whereas the first upper level comprised of a multi-objective non-linear programming model that aimed to minimize the traffic delays during maintenance while maximizing the number of bridges to be repaired given budgetary and crew constraints. The second lower level involved the use of simulated annealing algorithm to minimize the travel time in the bridge network. Also, the conducted sensitivity analysis demonstrated that the available budget, number of crews, traffic demand, and policy maker's priorities critically influence the optimal bridge maintenance schedule.

Table 29. Summary of some of the exact optimization-based maintenance models.

Reference	Year	Employed Algorithms	Application	Optimization Type	Objective Functions	Design Constraints
[218]	2024	Binary linear programming + DT/RF/GB/SVM	Optimizing long-term maintenance plans of bridge components	Single-objective	Maximize the average bridge performance index	a. Annual maintenance budget b. Selection of maintenance strategy c. Minimum permissible condition of bridge components
[220]	2022	Constrained nonlinear minimization	Optimal rehabilitation management of bridge girders	Single-objective	Maximize the time until specified failure probability of bridge is reached	a. Initial maintenance should not be conducted until at least two years of service have passed b. Maintenance intervals must be between 2 and 20 years
[219]	2020	Nonlinear programming + sensitivity analysis	Optimal maintenance scheduling of bridges, including time and job sequences	Multi-objective	a. Minimize the total traffic delays in the network b. Maximize the number of bridges to be repaired	a. Budget limit b. Number of maintenance operations handled by a crew c. Amount of simultaneous maintenance activities
[221]	2009	Dynamic programming	Optimizing maintenance of deteriorated coatings in steel bridges	Single-objective	Minimize discounted maintenance expenditures over a defined planning period	N/A
[222]	2007	DP + MCS	Optimizing maintenance works of highway bridge networks	Single-objective	Minimize the life-cycle maintenance expenses	Yearly maintenance budget

4.7. Critical Discussion

This review examined six paradigms for bridge management systems: multi-criteria decision-making, life cycle assessment, digital twin, inspection planning, artificial intelligence, and optimization. While each has its own specific application, they all present a unique combination of strengths and challenges. Optimization and MCDM techniques are applied to maintenance planning across all three decision-making levels: (1) element, (2) bridge, and (3) network. MCDM models are comparatively more subjective because of their reliance on experts' judgements, weighting criteria, and subjective scores, which can introduce bias and reduce reproducibility. On the other hand, they are characterized by their abilities to integrate a wide and diverse range of criteria into a structured evaluation framework, and they can simultaneously both qualitative (e.g., strategic importance) and quantitative (e.g., cost, traffic volume, remaining service life) metrics. In addition, MCDM models require extensive data collection stemming from the large number of alternatives and the complexity of the decision criteria associated with the nature of bridge maintenance planning. In contrast, optimization models, particularly multi-objective optimization, are formulated to systematically and objectively balance conflicting objectives (e.g., minimizing cost while maximizing condition or safety), providing a Pareto-optimal frontier of solutions. This causes optimization models to be more scalable for managing regional or large-scale transportation networks, where the number of bridges and constraints would make expert-based scoring impractical. Despite these advantages, optimization-based models require more computational resources.

Artificial intelligence-driven models can analyze intricate data sets and formulate responsive policies that surpass traditional static models. Further, they excel with large bridge datasets, offering scalability. However, their black-box nature raises concerns about trustworthiness, particularly in policy-making contexts that require accountability. Inspection planning models leverage advanced techniques like Monte Carlo simulation, Bayesian updating, non-destructive inspection, and multi-objective optimization to create dynamic and risk-based plans. Nonetheless, these models are highly data-dependent and contingent on a wide spectrum of precise inputs such as accurate historical deterioration rates, precise material properties, probabilistic failure models, reliable cost estimates, inspection technologies, crew size, and overtime policies. LCA models have evolved into an integrated framework that considers environmental impacts, user delays, resilience, and regional economic effects. This progression effectively addresses criticisms regarding the practicality concerns and sustainability aspects of traditional LCA methods. However, the comprehensive nature of LCA also presents challenges due to its reliance on detailed and accurate data, which may hinder the application of LCA models. Digital twin technology represents a groundbreaking shift in bridge management, offering the potential for dynamic, real-time integration of structural, geometric, and environmental data. By combining various NDI data, DTs enable engineers to visualize deterioration, conduct "what-if" scenarios, and virtually test reinforcement strategies before implementation. This capability transitions maintenance planning from static scheduling to proactive and adaptive management. However, the widespread adoption of DT faces significant obstacles. Establishing and maintaining a digital twin requires a robust IT infrastructure, continuous high-quality data streams, and the organizational capacity to manage vast amounts of information effectively.

Maintenance budget allocation models are an integral pillar of bridge management systems because they equip asset managers with informed, sustainable, strategic, and cost-effective action plans that maximize long-term network performance while satisfying budget limits and sustainable infrastructure requirements. In practice, these models compile many types of information, like a bridge's age, type, traffic levels, inspection results, repair history, climate, natural hazards, costs of different maintenance options, sustainabil-

ity needs, and the budget available. Using this input, the models generate practical outputs so that bridge managers can sustain clear priorities for (1) which bridges or elements need attention, (2) what intervention action is required, and (3) when to apply the maintenance intervention. Digital Twin can act as a central platform for a BMS, integrating disparate data types such as geometric and spatial information, nondestructive inspection and structural health monitoring data, environmental and operational conditions, material and physical properties, as well as inspection and maintenance histories. In addition, the digital twin model should house an integrated LCA module that quantifies the lifetime environmental impact (e.g., carbon emissions, energy use) and life cycle costs of each maintenance strategy. Leveraging the digital twin platform, asset managers can thereby run sophisticated artificial intelligence, optimize inspection schedules, and generate proactive, cost-effective maintenance plans.

4.8. Summary of Case Studies

This section outlines some of the actual case studies utilized to test and validate the reported bridge maintenance models (see Table 30).

Table 30. Summary of practical case studies of bridge maintenance models.

Reference	Location	Description
[12]	Quebec, Canada	A real reinforced concrete bridge with its inspection reports available from the Ministère des Transports du Québec. The bridge deck was scanned using the ground-penetrating radar technology
[44]	Montreal, Canada	A 2.7-km Jacques Cartier bridge connecting Montreal and Longueuil over the St. Lawrence River. It underwent major rehabilitation in 2001–2002 to rebuild its aging deck
[48]	China	A suspension bridge with a 1385-m main span, which was opened to traffic in 1999
[58]	India	Twelve bridges across the river Tapi in Surat city
[65]	Iran	Zohreh river bridge in the southwestern region. The flowing water under the bridge causes erosion and scour to the columns
[62]	Taoyuan, Taiwan	Six types of pedestrian bridges: (1) suspension, (2) truss, (3) tied arch, (4) open spandrel arch, (5) cable-stayed, and (6) girder
[199]	China	In-service Guo bridge that has a total length of 20.6 m and a width of 8.6 m. It incorporates a modular expansion joint with a capacity of 60 mm
[200]	Australia	A railway bridge, which had recently undergone maintenance, with a remaining service life of 60 years. It is a single-span bridge of 12-m length that incorporates two supported girders. The girder flanges have a width of 229 mm and a thickness of 19.6 mm
[209]	China	A regional transportation network within the southern region that is characterized by a humid subtropical climate. The study area consists of 22 rivers and 144 girder and reinforced concrete slab bridges in total.
[217]	Canada	A 17 m bridge superstructure comprising four T-beams spaced 2.3 m and a 200-mm-thick deck slab. The total deck area is 514.5 m ² subjected to the application of deicing materials

5. Conclusions

This study offers a comprehensive and integrated review of bridge maintenance budget allocation models through a dual approach combining systematic literature analysis and scientometric mapping. By analyzing 380 peer-reviewed publications from 1990 to 2025 sourced from Scopus and Web of Science, it identifies key research trends, methodological advancements, and collaborative networks that have shaped the field. The use of tools like VOSviewer and Bibliometrix R provide valuable visualizations of the scientific landscape, while the in-depth examination of optimization models, decision-making variables, and

metaheuristic techniques adds critical technical insight. Ultimately, the findings of this review provide a robust foundation for infrastructure asset managers, offering practical guidance and strategic frameworks for allocating maintenance funds efficiently and sustainably to preserve bridge performance amidst ongoing deterioration challenges. This study provides a comprehensive and structured investigation into bridge maintenance fund allocation models through an integrated methodological framework combining scientometric and systematic literature reviews. By analyzing 380 peer-reviewed articles sourced from Scopus and Web of Science between 1990 and 2025, the paper identifies key trends, thematic evolutions, and research clusters shaping the field. The use of VOSviewer and Bibliometrix tools facilitated the visualization of co-authorship networks, keyword co-occurrences, and citation patterns, highlighting influential contributors and evolving priorities in bridge maintenance research.

The systematic literature review further dissects present research studies into six prominent themes: (1) multi-criteria decision making, (2) life cycle assessment, (3) digital twin, (4) inspection planning, (5) artificial intelligence, and (6) optimization. The findings reveal a notable shift towards the integration of intelligent decision-support systems, multi-objective optimization, and sustainability-oriented approaches to bridge asset management. Ultimately, this research contributes a practical reference for academics, policymakers, and infrastructure managers seeking to enhance the efficiency, cost-effectiveness, and resilience of bridge maintenance strategies. It underscores the importance of data-driven, adaptive methodologies in supporting long-term infrastructure sustainability amid growing challenges related to aging structures and constrained public budgets. Several avenues for future research and development have been identified as follows to enhance the robustness, adaptability, and sustainability of maintenance budget allocation models for existing bridge infrastructure. Future models should increasingly integrate real-time data from SHM systems (e.g., nanosensors) and IoT devices to allow for dynamic and data-driven budget allocation. SHM systems are characterized by their high sensitivity, rapid response, and simultaneous multi-parameter monitoring, and hence they can provide continuous and real-time data on a bridge's response (e.g., strain, vibration, displacement). These technologies can help in capturing structural performance, actual deterioration patterns, improving accuracy in intervention planning, and life-cycle cost analysis. By the same token, NDI needs to be systematically blended with maintenance planning models, allowing for more accurate and informed proactive repair decisions. While metaheuristics and classical machine learning have been widely applied, there is growing potential for deep learning, reinforcement learning, and hybrid AI models (e.g., combining neural networks with probabilistic reasoning) to deliver adaptive and intelligent decision-making in budget allocation under uncertain and dynamic conditions.

Maintenance planning must account for the increasing risks posed by climate change. Future models should integrate environmental resilience metrics, hazard vulnerability assessments, and scenario-based planning to guide budget prioritization in a changing climate. In addition to that, a pressing need exists to address uncertainties from deterioration modeling and funding fluctuations to policy shifts using stochastic simulation, Bayesian updating, and robust optimization approaches to inform resilient budget strategies. Prospective research should explore decentralized budget planning frameworks that support coordination across multiple agencies and jurisdictions. Blockchain or distributed ledger technologies may support transparent and accountable resource allocation across complex bridge networks. Furthermore, NDI performance curves can be integrated into a digital twin-driven framework that can dynamically adapt inspection schedules and resource allocation. As for the employed analytical tools, maintenance optimization models should leverage chaotic metaheuristics and hybrid metaheuristics to enhance con-

vergence efficiency and avoid local optima. With regards to MCDM-based model, it is anticipated that Adopting modern MCDM techniques—like MARCOS or LOPCOW—into bridge maintenance optimization will enable agencies to prioritize interventions more effectively meanwhile, balancing budget constraints. It is also observed that there is lack of integrated frameworks that explicitly incorporate resilience against natural disasters into bridge maintenance scheduling. Current maintenance models primarily focus on structural deterioration and cost-effectiveness, overlooking the occurrence of natural extreme events. Thus, this work bridges these domains by developing a methodology that optimizes maintenance plans not just for longevity, but for enhancing structural resilience and guaranteeing post-disaster preparedness of transportation networks. It is also advised to devote more research endeavors towards developing holistic decision-making frameworks that directly account for the sustainability dimensions of maintenance interventions. This includes quantifying the social disruption caused by long-term closures and evaluating the environmental footprint of different maintenance materials and methods (e.g., embodied carbon, and waste generation). Finally, the development of integrated decision support tools tailored for asset managers, with interactive dashboards and visualization interfaces, will be critical for translating complex models into actionable insights, whether for a short-term or long-term basis.

While this review aims to provide a comprehensive and objective analysis of the maintenance fund allocation of bridges, it still has certain shortcomings, which are discussed as follows. First, this review focused only on journal articles and book chapters, excluding conference proceedings and technical reports, which might contain insightful information. Journal articles and book chapters are widely accepted for their role in synthesizing established knowledge. However, the absence of conference proceedings and technical studies may have narrowed down the scope of our analysis. Secondly, this review is restricted to publications in the English language, which may underrepresent research and advancements published in other languages. Thirdly, this review's analysis was solely reliant on Web of Science and Scopus databases. Despite the extensive coverage of these databases and their strong representation, the main body of knowledge in bridge maintenance allocation, it is probable that some relevant documents indexed in other databases were omitted. Thus, future research should incorporate additional databases and sources to achieve a more consolidated analysis of the state of the art.

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Abbreviations

The following abbreviations are utilized throughout this manuscript:

Acronym	Description	Acronym	Description
ASCE	American Society of Civil Engineers	FHWA	Federal Highway Administration
BMS	Bridge Management System	MR & R	Maintenance, repair and rehabilitation
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses	TOPSIS	Technique for Order Preference by Similarity to an Ideal Solution
GRA	Grey Relational Analysis	CWM	Constant Weight Model
FVWM	Factor-based Variable Weight Model	FAVWM	Factor and Age-based Variable Weight Model
MAUT	Multi Attribute Utility Theory	WASPAS	Weighted Aggregated Sum Product Assessment
T2NN	Type-2 neutrosophic number	SMART	Specific, Measurable, Achievable, Relevant, and Time-bound
VIKOR	Vlsekriterijumska Optimizacija i Kompromisno Rešenje	WSM	Weighted Sum Model
ARAS	Additive Ratio Assessment	COPRAS	Complex Proportional Assessment
MOORA	Multi-Objective Optimization on the Ratio Analysis	EDAS	Evaluation Based on Distance from Average Solution
SAW	Simple Additive Weighting	ELECTRE	ELimination Et Choix Traduisant la REalité
DEMATEL	Decision Making Trial and Evaluation Laboratory	BWM	Best-Worst Method
CRITIC	Criteria Importance Through Intercriteria Correlation	SWARA	Step-wise Weight Assessment Ratio Analysis
FUCOM	Full Consistency Method	MEREC	Method based on the Removal Effects of Criteria
SDV	Standard Deviation	CILOS	Criterion Impact Loss
LOPCOW	Logarithmic Percentage Change-driven O Weighting	PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluations
TLS	Terrestrial Laser Scanning	EV	Eigenvector
BrIM	Bridge Information Modeling	ILP	Integer Linear Programming
EW	Entropy Weighting	GRD	Grey Relational Degree
CODAS	Combinative Distance-based Assessment	SE	Shannon Entropy
FL	Fuzzy Logic	DEA	Data Envelopment Analysis
IWO	Invasive Weed Optimization	SHM	Structural Health Monitoring
LCCA	Life Cycle Cost Analysis	UAV	Unmanned Aerial Vehicle
ACO	Ant Colony Optimization	MPI	Magnetic Particle Inspection
AI	Artificial Intelligence	NDI	Non-destructive Inspection
BHI	Bridge Health Index	NDT	Non-destructive Testing
C5.0	Boosting Decision Tree algorithm	PI	Penetrant Inspection
DES	Discrete Event Simulation	PoD	Probability of Detection
ECI	Eddy Current Inspection	PR	Polarization Resistance
ER	Electrical Resistivity	PSO	Particle Swarm Optimization
GA	Genetic Algorithm	RC	Reinforced Concrete
GPR	Ground-Penetrating Radar	RBI	Risk-Based Inspection
HCP	Half-Cell Potential	UI	Ultrasonic Inspection
IE	Impact Echo	BIM	Building Information Modeling
IRT	Infrared Thermography	USW	Ultrasonic Surface Wave
LPI	Liquid Penetrant Inspection	UPE	Ultrasonic Pulse Echo
MDP	Markov Decision Process	VI	Visual Inspection
MCMC	Markov Chain Monte Carlo	VoI	Value of Information
ML	Machine Learning	DL	Deep Learning

BriMai_all	Maintenance fund allocation models of bridges	AHP	Analytica Hierarchy Process
ANP	Analytical Network Process	LCA	Life Cycle Assessment
MCDM	Multi-criteria decision making	DRL	Deep Reinforcement Learning
PNN	Probabilistic Neural Network	PCA	Principal Component Analysis
RBFN	Radial Basis Function Network	SVM	Support Vector Machines
CNN	Convolutional Neural Network	LSTM	Long Short-Term Memory
DNN	Deep Neural Network	RL	Reinforcement Learning
SOMCM	and Self-Organizing Map-based Cluster Merging	DT	Decision Tree
NN-EE	Neural Networks with Entity Embeddings	DQN	Deep Q-Network
NSGA-II	Non-dominated Sorting Genetic Algorithm II	MAR-PPO	Proximal Policy Optimization and its multi-agent variants
DP	Dynamic programming	ARIMA	Autoregressive Integrated Moving Average
DCMA2C	Double-Critic Multi-Agent A2C	ConvAE-DQN	Convolutional Autoencoder-Structured Deep Q-Network
HCWOA	Hybrid Chaotic Whale Optimization Algorithm	MOPSO	Multi-objective Particle Swarm Optimization
QFD	Quality Function Deployment	FST	Fuzzy Set Theory
MCS	Monte Carlo Simulation	MOGA	Multi-objective Genetic Algorithm

Appendix A

Table A1. PRISMA checklist of this research study.

Selection and Topic	Item Number	Checklist Item	Location Where Item Is Reported
TITLE			
Title	1	Identify the report as a systematic review	Title
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist	Abstract
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	Introduction
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses	Introduction
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses	Research Methodology
Information sources	6	Specify all databases, registers, websites, organizations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted	Research Methodology
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used	Research Methodology
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process	Research Methodology

Table A1. *Cont.*

Selection and Topic	Item Number	Checklist Item	Location Where Item Is Reported
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process	Research Methodology
Data items	10.a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g., for all measures, time points, analyses), and if not, the methods used to decide which results to collect	Research Methodology
	10.b	List and define all other variables for which data were sought (e.g., participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information	Research Methodology
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process	Not Applicable
Effect measures	12	Specify for each outcome the effect measure(s) (e.g., risk ratio, mean difference) used in the synthesis or presentation of results	Not Applicable
Synthesis methods	13.a	Describe the processes used to decide which studies were eligible for each synthesis (e.g., tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5))	Research Methodology
	13.b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions	Research Methodology
	13.c	Describe any methods used to tabulate or visually display results of individual studies and syntheses	Research Methodology
	13.d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	Research Methodology
	13.e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g., subgroup analysis, meta-regression)	Not Applicable
	13.f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results	Not Applicable
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases)	Not Applicable
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome	Not Applicable
RESULTS			
Study selection	16.a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram	Scientometric Review Analysis and Systematic Review Analysis
	16.b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded	Scientometric Review Analysis and Systematic Review Analysis

Table A1. *Cont.*

Selection and Topic	Item Number	Checklist Item	Location Where Item Is Reported
Study characteristics	17	Cite each included study and present its characteristics.	Scientometric Review Analysis and Systematic Review Analysis
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	Not Applicable
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g., confidence/credible interval), ideally using structured tables or plots.	Scientometric Review Analysis and Systematic Review Analysis
Results of syntheses	20.a	For each synthesis, briefly summarize the characteristics and risk of bias among contributing studies.	Not Applicable
	20.b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g., confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	Scientometric Review Analysis and Systematic Review Analysis
	20.c	Present results of all investigations of possible causes of heterogeneity among study results.	Scientometric Review Analysis and Systematic Review Analysis
	20.d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results	Not Applicable
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed	Not Applicable
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed	Not Applicable
DISCUSSION			
Discussion	23.a	Provide a general interpretation of the results in the context of other evidence	Critical Discussion
	23.b	Discuss any limitations of the evidence included in the review	Conclusions
	23.c	Discuss any limitations of the review processes used	Conclusions
	23.d	Discuss implications of the results for practice, policy, and future research	Conclusions
OTHER INFORMATION			
Registration and protocol	24.a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	Not applicable
	24.b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	Not applicable
	24.c	Describe and explain any amendments to information provided at registration or in the protocol.	Not applicable
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	Funding statement (p. 69)
Competing interests	26	Declare any competing interests of review authors.	Conflict of Interest statement (p. 69)
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	Data Availability Statements (p. 69)

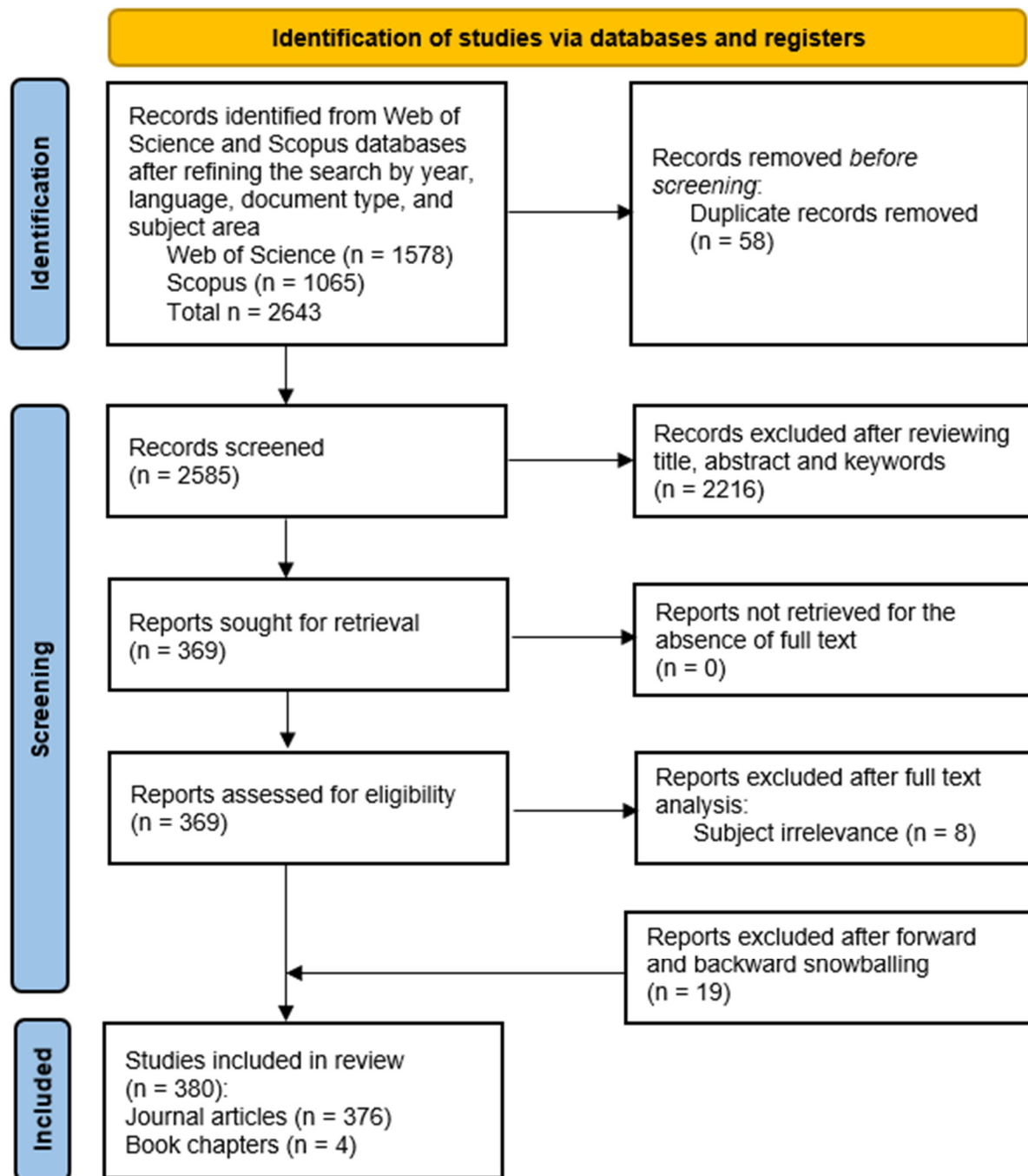


Figure A1. PRISMA flow diagram of this research study.

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