Knowledge Driven Approach for Smart Bridge Maintenance Using Big Data Mining

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Abstract: Life cycle bridge maintenance is highly complex and multi-disciplinary oriented, different ICT technologies have been widely adopted, but the generated data and information are often intensive, specific and isolated, it is very difficult to contribute effectively for holistic bridge maintenance decisions. This paper investigates state-of-the-art methods used in bridge maintenance, a total of 2732 papers were selected for visualization analysis and 323 papers were pinpointed for further critical review. The review informs that mindset shifting from traditional and pre-digital, through data driven to knowledge-based approach is required for bridge engineers to holistically understand multi-sources of data and information to enable systematic thinking. The review further reveals the need for a knowledge-driven approach that can leverage bridge maintenance big data to provide smart holistic decisions, a novel knowledge-oriented framework and methodology were proposed in the end with an aim to unify and streamline different sources of data and information to facilitate new developments towards smart bridge maintenance.

Keywords: Bridge maintenance; Multi-disciplinary; IoTs; Visualization analysis; Holistic decision making; Knowledge-driven approach; Big Data ; BIM

1 Introduction

Bridges are essential for highway networks and play an important role in human society [1,2]; they are facing ageing challenges involving factors, such as environmental corrosion, vehicle overload and human-made hazards [3,4]. According to the 2016 Canadian Infrastructure Report, 25% of the existing bridges are in poor or very poor condition [5]. According to the 2017 American Society of Civil Engineering report, approximately 240,000 bridges have exceeded their 50-year service life, and over 56,000 bridges have been classified as structurally deficient [6]. In China, the total number of dangerous bridges posing serious safety risks to human society was approximately 70000 by the end of 2017 [2]. To restore the sub-standard bridges back to perfect condition, ¥69.7 billion was invested in the renovation of 34,000 dangerous bridges in China between 2016 and 2020 [7]. According to the UK government, the number of substandard bridges has risen to more than 3,100 by January 2021 [8], and the cost for proper maintenance for those sub-standard bridges was estimated to be £1.16 billion by March 2022 [9]. Therefore, an effective maintenance procedure can considerably reduce the cost [5], and this becomes increasingly pivotal [10].

Bridge maintenance tasks are complex and multi-disciplinary oriented, e.g., structure, cost, health and safety, sustainability and environmental issues. resulting in an extremely complex process. Hence, proactive, holistic and smart lifecycle approaches are required to comprehend the complexity of bridge structural conditions. Embracing advanced technologies has continuously improved the intelligence level of bridge maintenance. The wide application of IoTs along with traditional bridge surveys, e.g., non-destructive technologies [11] and sensors [12], make it possible to obtain more comprehensive detection and monitoring data. Unstructured and structured datasets are quickly accumulated to form multisource, heterogeneous and autonomous maintenance ‘Big Data’, but only a small part of those are utilised successfully for bridge maintenance decision-making. Cloud computing [13], building information modelling (BIM) [14], artificial intelligence [15,16], etc., have greatly improved the data processing power. Virtual reality (VR) [17], digital twins (DT) [5], semantic web technology (SWT) [18], etc., provide a more intelligent data visualisation and reasoning approach for superlarge-scale bridge maintenance. All of these innovations are leading the industry towards a more productive, more effectively managed digital age, where real-time data and project reporting will be available for maintenance projects. Recent developments are showing a gradual shift from data to knowledge-driven decision-making for bridge maintenance, and those accumulated large amounts of data can be turned into a vast base for knowledge mining for knowledge-driven approaches.

Regarding smart bridge maintenance, some studies focus on specific technical applications, e.g., Abu Dabous et al. [19] comprehensively reviewed the commonly used noncontact testing technology for condition monitoring of concrete bridges. Agnisarman et al. [20] reviewed the application of automated visual inspection technology to inspect infrastructure, such as bridges. Fujino et al. [21] and Sun et al. [22] discussed the prospects and driving forces of big data technology in bridge monitoring. Zhou et al. [2] compiled the development of China's bridge maintenance information system. These articles indicated that using information technologies to improve the quality and efficiency of management is the unanimous choice of bridge engineers. Other studies review details of analytical methods, e.g., Banerjee et al. [23] conducted a systematic and comprehensive review of the literature on the resilience assessment of bridges and bridge networks under single and multiple hazardous conditions. Kabir et al. [24] reviewed the application of multicriteria decision-making technology in the field of infrastructure management. Frangopol et al. [25] briefly reviewed the research results related to the design, maintenance, and lifecycle management of infrastructure (involving bridges). Although these reviews cover the application of advanced technologies or analytical methods in bridge maintenance, thus showing benefits from data-driven approaches, they have not been pushed further to examine the potential of knowledge-based approaches. The relevant understandings about knowledge-driven approaches are still missing.

To address these gaps, this paper provides a critical review of smart bridge maintenance by collecting and analysing a large number of papers from the Web of

Science (WoS) core collection database, using literature visualisation analysis and critical review to study and conclude key areas for knowledge-driven smart bridge maintenance. The wider review visually analyses bridge maintenance using the CiteSpace software (6.1.R2), which covers four perspectives: literature quantity analysis, journal co-citation analysis, document co-citation analysis, keywords clustering and burst analysis; the later focused review summarises knowledge-driven smart bridge maintenance aiming at three areas: bridge maintenance tasks and issues, advanced technologies supporting smart maintenance, and holistic decision-making approaches. Based on the above review and analysis, a novel knowledge-oriented framework is finally proposed, with the aim of facilitating new developments towards smart bridge maintenance.

2 Review and Analysis Methodology

To explore the state-of-the-art development of intelligent technologies in bridge maintenance, a literature analysis is performed on the WoS core collection database. WoS is an important database resource for obtaining global academic knowledge supported by powerful combined retrieval functions [26,27]. The search is based on using the ‘AND’ and ‘OR’ operators search benchmark, and the search code in the database is as follows:

TS = (xxx* AND/OR xxx*)

Knowing that ‘TS’ represents the topic of the articles, ‘xxx’ and ‘*’ are standard for the search term and the fuzzy search, respectively. Further details of the operators’ search benchmark are as follows:

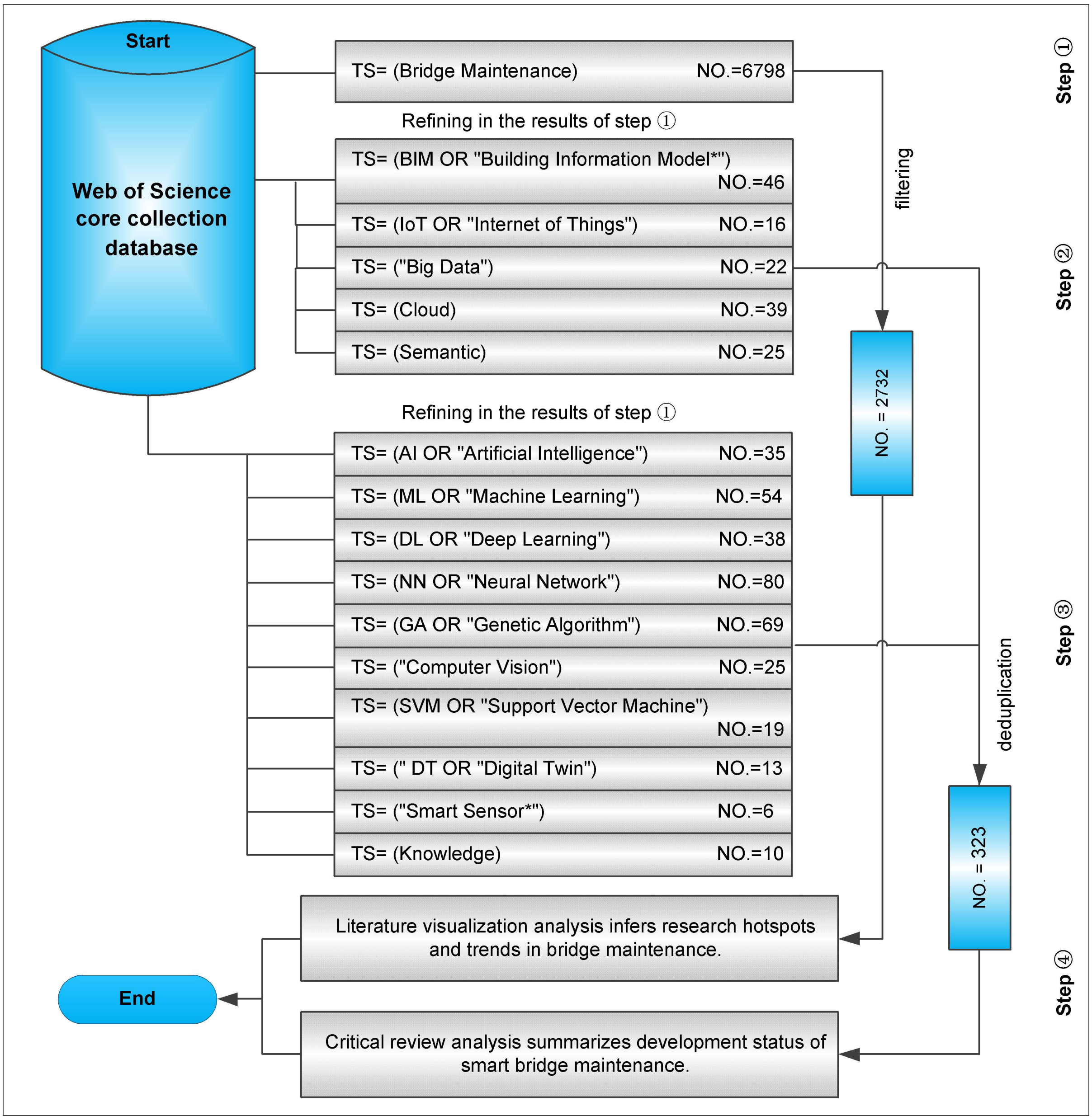


Fig. 1. Steps to search for papers in the WoS core collection database.

This search in this paper is composed of four steps (concluded in **Fig. 1**): in **step 1**, papers published between January 1, 2000, and December 31, 2021, are retrieved from the database on the topic of bridge maintenance. Papers that are not related to bridging engineering are excluded, such as the cytology, immunology and oncology categories, which include the term “intercellular bridge”. In addition, only articles and review articles written in English were selected for the document types because of their high quality and cutting-edge research [28]. After preliminary filtering, 2732 papers are selected, and their contents reveal that BIM, IoT, cloud technology and other technologies are often mentioned in smart bridge maintenance driven by data or knowledge approaches. Consequently, in **step 2**, the following search benchmarks are jointly used in the WoS core collection database to refine the search results: 'BIM OR "Building Information Model*"', 'IoT OR "Internet of Things"', '"Big Data"', 'cloud', and 'Semantic'.

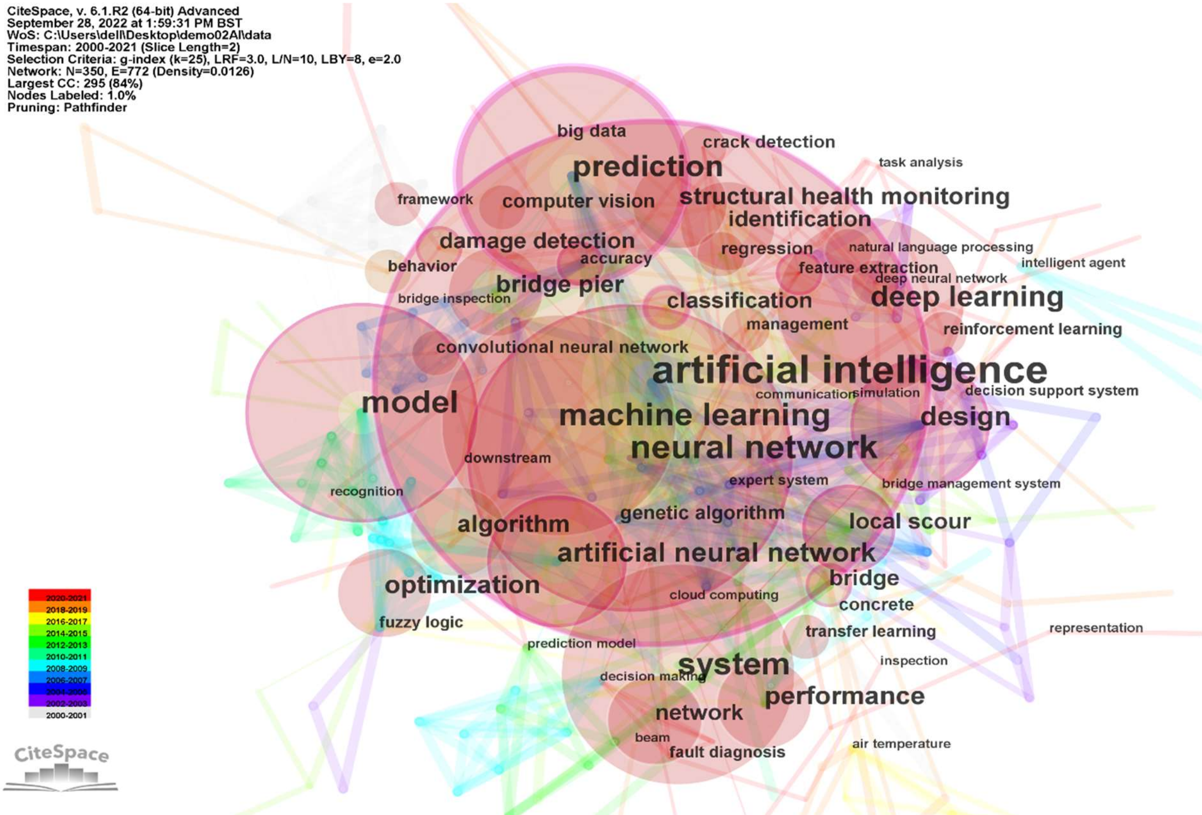


Fig. 2. Network of co-occurring keywords for AI.

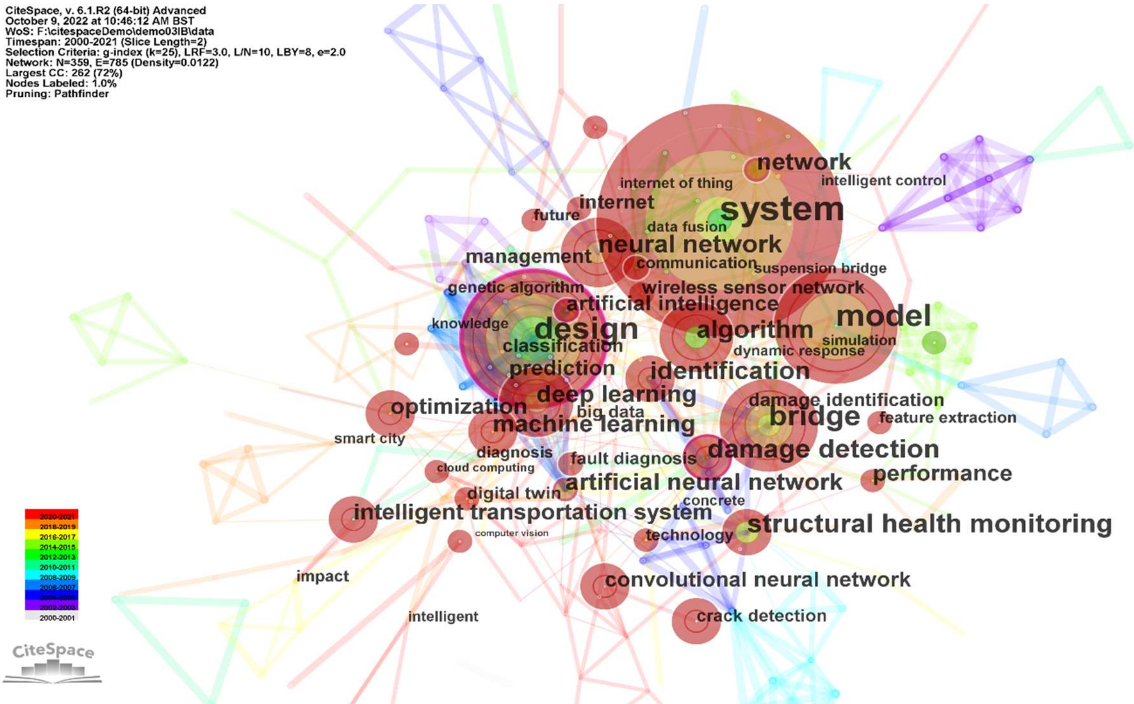


Fig. 3. Network of co-occurring keywords for the intelligent bridge.

Furthermore, to avoid missing important papers, **step 3** searches for intelligent technology-related keywords in the bridge engineering field by using 'AI OR "Artificial Intelligence"' and '"Intelligent Bridge"' as topics. As shown in **Figs. 2 and 3**, the CiteSpace software is used to rank and visualise the occurrence frequency of all the keywords. In the CiteSpace network, each node shown with a coloured circle (or cross, triangle, square) represents an object. Some objects are linked by lines. The thickness of the link is used to indicate the partnership strength. The colour is used to correspond to different years. In the keyword co-occurrence network, each node represents a keyword, and the node's size (or font size) reflects the frequency of the keyword occurring in the dataset. The higher the frequency is, the larger the node size. According to the results in **Figs. 2 and 3**, 10 keywords with high frequency and related to data- or knowledge-driven approaches are selected for research. A total of 323 papers were obtained. In **step 4**, 2732 papers are visually analysed to infer the research hotspots and trends of intelligent technology application in bridge maintenance, and a critical review analysis of 323 papers summarise the development status of smart bridge maintenance.

3 Literature Visualisation Analysis

The visualisation analysis relies on four types of bibliometric techniques [29,30] applied using CiteSpace, including literature quantity analysis, journal co-citation analysis, document co-citation analysis, keywords clustering and burst analysis. CiteSpace maps the knowledge domain by systematically creating various accessible graphics, which can discover the semantic knowledge hidden in a large amount of information and track the development frontier of technology [31,32]. CiteSpace software provides multiple options for input thresholds, e.g., time slicing, data selection criteria, and pruning strategies. Sensible input thresholds can make the generated network layout clearer and more reasonable.

3.1 Literature quantity analysis

As shown in **Fig. 4**, the paper publication times are identified according to the information in the bibliographic records. The number of papers published has grown steadily with slight fluctuations. In 2000, the number was only 27. In 2021, the number reached 414. In 2008 and 2014, there were slight fluctuations. The decrease is probably due to the limited budgets and lack of data for decision-making, which are long-existing challenges for bridge maintenance.

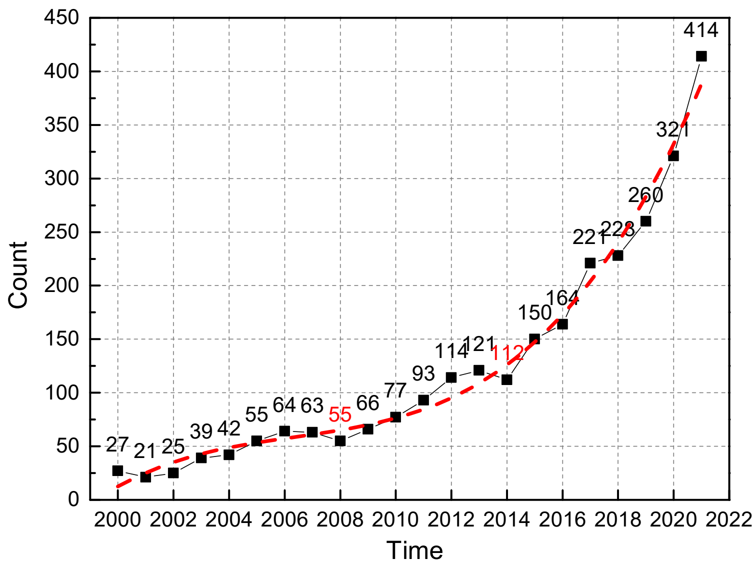
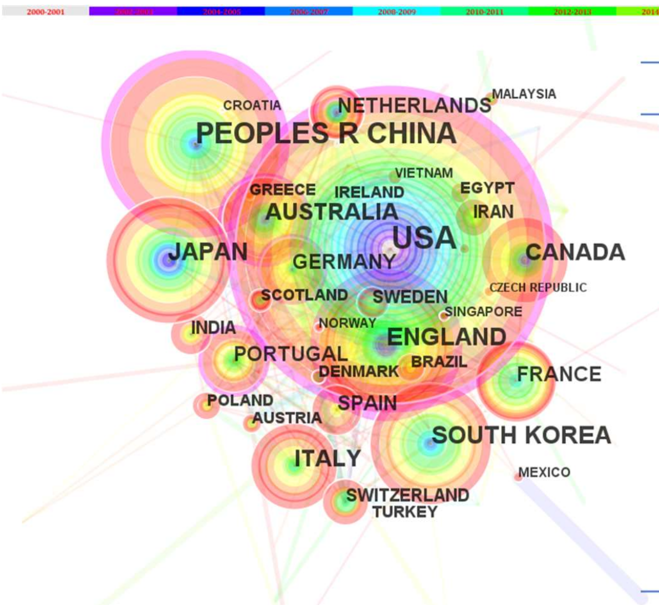


Fig. 4. Statistical graph of the number of papers over time.

Fig. 5 shows the co-occurring network of countries. In this network, the time slice length is 2. The criteria of data selection are g-index (k=25), LRF=3.0, L/N=10, LBY=8, and e=2.0. There are 92 nodes and 398 links. Each node represents a country, and the node's size reflects the number of published articles in that country. The more papers a country publishes, the larger the node size. The United States has issued the most papers, followed by China. This is not surprising because the peak period of bridge construction in developed countries, such as the U.S. and countries in Europe, was concentrated in the 1950s and 1970s. The large-scale 'ageing' of bridge structures appeared earlier than in China. Therefore, European countries and the U.S. have conducted relatively more research on bridge maintenance technology. There are many problems during bridge operation due to insufficient maintenance in China. Many bridges even collapsed due to improper management, e.g., Qijiang District Rainbow Bridge (1999.1), Liaoning Panjin Tianzhuangtai Bridge (2004.6), Sichuan Panzhihua Jinsha River Bridge (2012.12), Guangdong Heyuan Chengnan Ramp Bridge (2015.6) and Yilan Bridge (2019.10). Therefore, domestic scholars continue research to solve problems in the field of bridge maintenance in China.



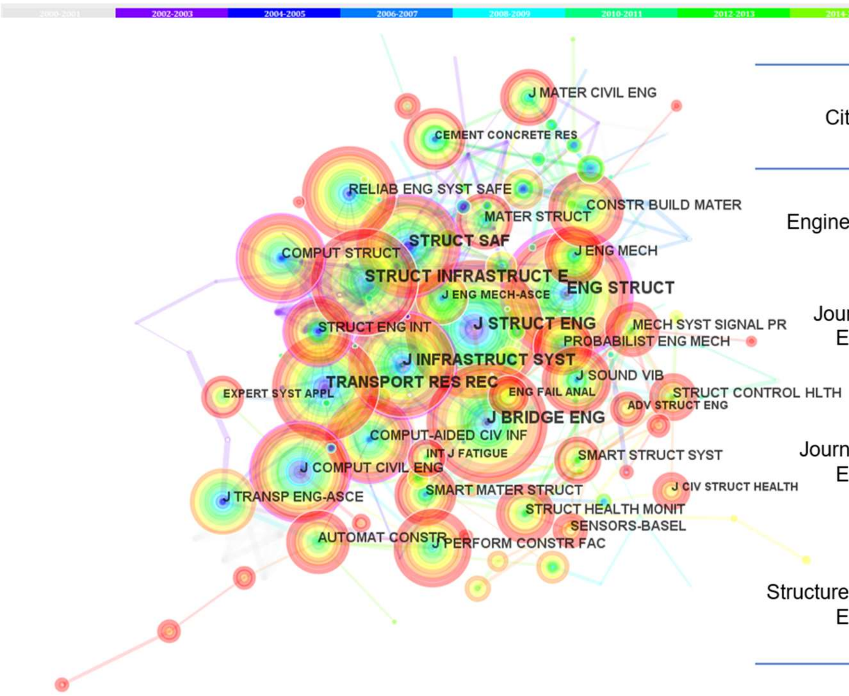
Countries	Count
USA	886
CHINA	558
ENGLAND	205
SOUTH KOREA	162
JAPAN	154
ITALY	131
CANADA	128
AUSTRALIA	106

Fig. 5. Countries' co-occurring network.

3.2 Journal co-citation analysis

Journal co-citation analysis reflects the correlation between various journals.

Through this type of analysis, the intellectual root sources for published works in a field are obtained. The number of co-citations of various journals is shown in **Fig. 6**, where the time slice length is 2. The selection criteria are Top 50, LRF=3.0, L/N=10, LBY=8, and e=2.0. To remove excessive links, network pruning is used through the Pathfinder strategy, which was recommended by Chen and Morris [33]. In this network, there are 201 nodes and 604 links. Each node represents a journal, and the node's size represents the number of times the journal has been co-cited. The more times the journal is co-cited, the larger the node size. Among them, "Engineering Structures", "Journal of Bridge Engineering", "Journal of Structural Engineering", and "Structure and Infrastructure Engineering" have the most co-citations.



Cited Journals	Count	Centrality
Engineering Structures	910	0.27
Journal of Bridge Engineering	867	0.05
Journal of Structural Engineering	824	0.05
Structure and Infrastructure Engineering	700	0.05

Fig. 6. Journal co-citation network.

Moreover, if a node connects two or more large groups of nodes with the node itself in between, it has high betweenness centrality represented by a purple ring in CiteSpace. **Table 1** lists journals with betweenness centrality values greater than or equal to 1.0. The journal "Engineering Structures" has the highest centrality, with a value of 0.27. The high centrality represents a large amount of importance for these journals. These analysis results provide a basis for follow-up in-depth research, and follow-up researchers can examine the direction of smart bridge maintenance in depth by collecting papers from these top journals.

Table 1. Cited journals sorted by centrality.

Cited Journals	Centrality	Count
Engineering Structures	0.27	910
Structural Engineering International	0.20	224
Journal of Infrastructure Systems	0.17	433
Computer-Aided Civil and Infrastructure Engineering	0.17	364
Structural Safety	0.12	409
Computers & Structures	0.12	307
Journal of Computing in Civil Engineering	0.12	304
Reliability Engineering & System Safety	0.10	379
Automation in Construction	0.10	283

3.3 Document co-citation analysis

Document co-citation analysis demonstrates the quantity and authority of references and their authors cited by publications [34]. Leading researchers for a knowledge domain can be identified. **Fig. 7** shows the co-citations network of various documents, where the time slice length is 2. The selection criteria are Top 50, LRF=3.0, L/N=10, LBY=8, and e=2.0. Network pruning is a Pathfinder strategy. In this network, there are 511 nodes and 744 links. Each node represents a document with the first author's name and the publication year, and the node's size represents the number of times the document has been co-cited.

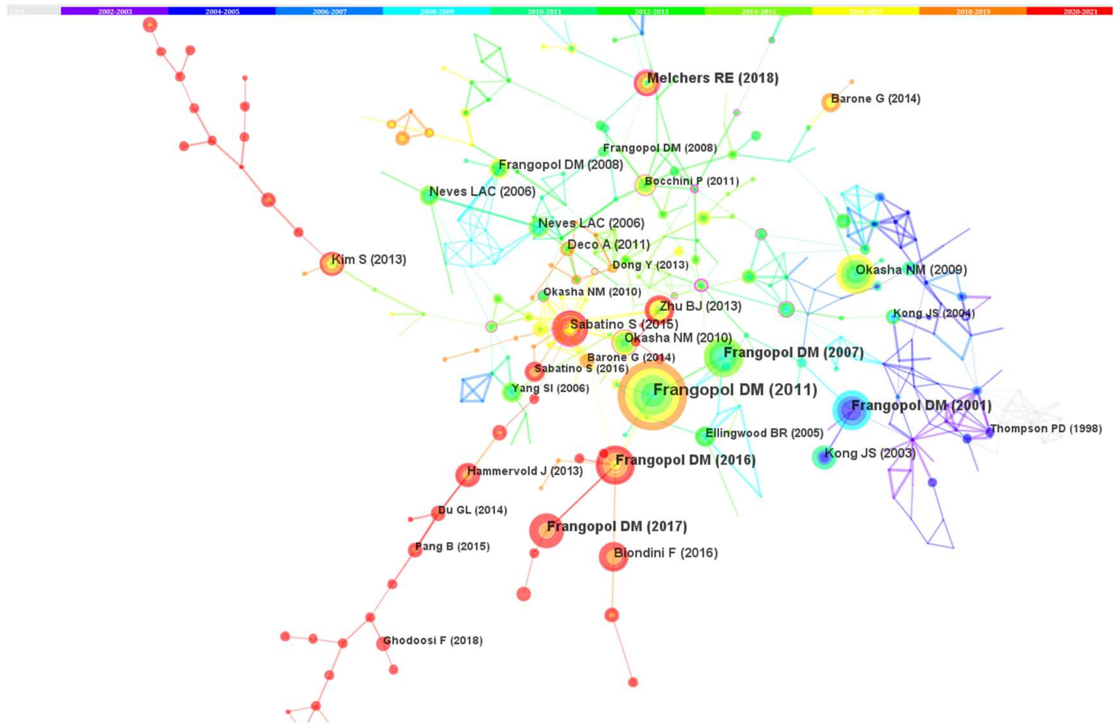


Fig. 7. Document co-citation network.

The top 10 documents are summarised in **Table 2**. Frangopol [35-39] received the most attention, with 238 citations in total. This was followed by Melchers [40], Okasha [41], Biondini [42], Sabatino [43] and Kim [44], with approximately 30 citations each. According to the WOS citation metrics, Frangopol has 650 publications in the WOS database, with a total of 15,543 citations and 7,030 citing articles. Melchers has 307 publications with a total of 7,548 citations and 4,729 citing articles. In addition, documents with high betweenness centralities are also worth attention. These documents with betweenness centrality values greater than or equal to 0.15 are listed in **Table 3**, including authors, Bocchini [45,46], Furuta [47], Van Noortwijk [48], and Liu [49]. According to the WOS citation metrics, the number and citations of published articles are high. Therefore, all documents listed in tables can be regarded as the major intellectual turning points, and their authors are leading researchers in the field of bridge maintenance.

Table 2. Cited documents sorted by count.

Cited References	CiteSpace Metrics		WOS Citation Metrics		
	count	centrality	publications	times cited	citing articles

Frangopol DM, 2011, Structure and Infrastructure Engineering [35]	75	0.05	650	15543	7030
Frangopol DM, 2017, Structure and Infrastructure Engineering [36]	44	0.01	\	\	\
Frangopol DM, 2007, Structure and Infrastructure Engineering [37]	43	0.02	\	\	\
Frangopol DM, 2001, Journal of Computing in Civil Engineering [38]	38	0.08	\	\	\
Frangopol DM, 2016, Structure and Infrastructure Engineering [39]	38	0.06	\	\	\
Melchers RE, 2018, Structure and Infrastructure Engineering [40]	34	0.14	307	7548	4729
Okasha NM, 2009, Structural Safety [41]	33	0.02	26	601	433
Biondini F, 2016, Journal of Structural Engineering [42]	31	0.01	112	1596	1054
Sabatino S, 2015, Engineering Structures [43]	30	0.11	16	316	256
Kim S, 2013, Journal of Structural Engineering [44]	28	0.08	38	1123	684

Table 3. Cited documents sorted by centrality.

Cited References	CiteSpace Metrics		WOS Citation Metrics		
	centrality	count	publications	times cited	citing articles
Bocchini P, 2011, Structural Safety [45]	0.26	5	51	1284	1134
Furuta H, 2006, Structure and Infrastructure Engineering [47]	0.21	11	75	966	739
Van Noortwijk JM, 2004, Probabilistic Engineering Mechanics 48]	0.17	11	44	2029	1506
Bocchini P, 2011, Reliability Engineering & System Safety [46]	0.15	16	\	\	\
Liu M, 2006, Journal of Bridge Engineering [49]	0.15	9	42	548	492

3.4 Keywords clustering and burst analysis

The current research trend of intelligent technology is explored through keywords clustering maps and burst word analysis. Cluster analysis is used to detect and analyse the emergence of research trends over time and identify the focus of research trends at a specific time in its knowledge base [31,32]. Clustering can reveal the interconnection between different research trends. Burst words represent a substantial increase in the number of occurrences of the keyword in a short period of time, which indicates that such articles have attracted substantial attention in the corresponding year [31,32]. First, a keyword cooccurring network is generated. As shown **Fig. 8**, keywords co-occurring network has 516 nodes and 1,442 links. The time slice length is 2. The selection criteria are g-index (k=25), LRF=3.0, L/N=10, LBY=8, and e=2.0. Network pruning is a Pathfinder strategy. There are 10 keywords with frequencies over 100, including bridge maintenance (frequency = 277), model (frequency = 208), system (frequency = 203), structural health monitoring (frequency = 165), bridge management (frequency = 163), optimisation (frequency = 154), etc.

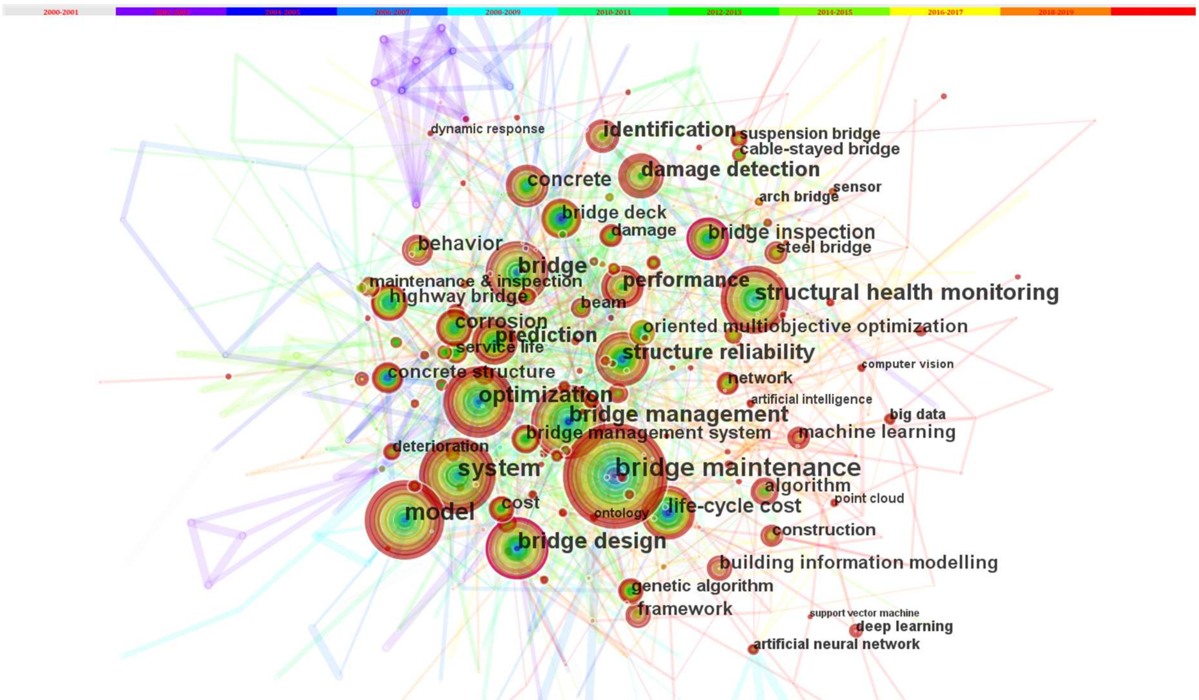


Fig. 8. Keywords co-occurring network.

Second, a total of 11 important clusters are identified and shown in **Fig. 9** based on the keywords by the log likelihood ratio (LLR) algorithm. The LLR algorithm can select the best cluster labels in terms of uniqueness and coverage [34]. Clusters are sorted by size, i.e., the number of members the cluster contains. The cluster #0 “optimisation” is the largest, with 71 members, while the cluster #11 “seismic effects” is the smallest, with only 6 members. **Table 4** lists all of the clusters and their information, including “cluster size”, “silhouette value”, “mean year”, and “LLR label”. The silhouette metric measures the average homogeneity of a cluster [50]. The greater the silhouette score represents, the more consistency of the cluster members. The silhouette values of clusters range from 0.667 to 0.946, which indicates that the members of each cluster are sufficiently consistent. The mean year of publication of a cluster refers to whether it consists of recent papers or older papers. Except for clusters #0 and #7, all other clusters are formed by recent papers. Based on the cluster map, clusters #0-11 form the application framework of the new-generation information technology with intelligent algorithms and BIM as the core to support bridge maintenance and management.

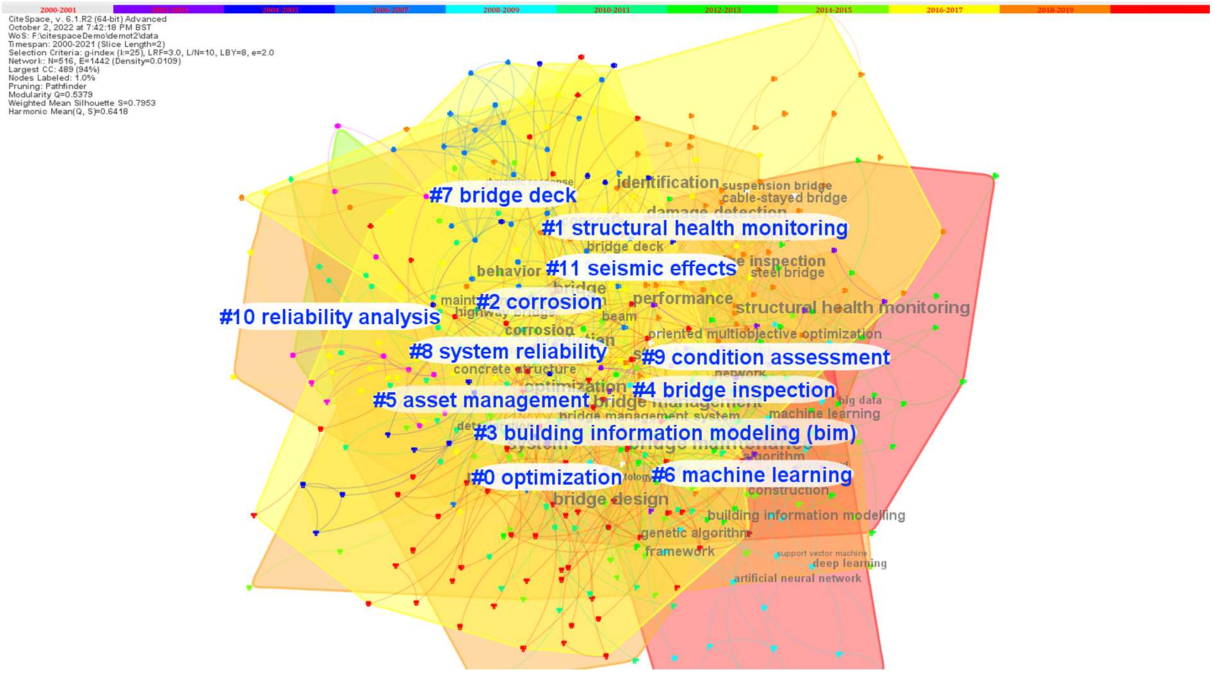


Fig. 9. Cluster map of keywords.

Table 4. Clusters sorted by size.

Cluster ID	Size	Silhouette	Mean (Year)	Label (LLR)
#0	71	0.898	2007	optimization; maintenance; uncertainty; life-cycle cost; genetic algorithm

#1	69	0.816	2013	structural health monitoring; damage detection; cable-stayed bridge; operational modal analysis; system identification
#2	69	0.724	2010	corrosion; concrete structures; reinforced concrete; service life; finite element analysis
#3	55	0.694	2014	building information modeling (bim); life cycles; risk management; bridge management system; structural health monitoring
#4	46	0.751	2016	bridge inspection; bridge health monitoring; digital twin; big data; optimization
#5	45	0.667	2013	asset management; bridge management system; railway bridge; bridge management; transition probability
#6	34	0.825	2015	machine learning; deep learning; artificial intelligence; computer vision; machine vision
#7	33	0.847	2008	bridge deck; bridge tests; fiber reinforced polymers; composite materials; signal processing
#8	22	0.853	2010	system reliability; semi-integral bridges; integral bridges; performance prediction; finite element
#9	21	0.881	2017	condition assessment; masonry arch bridges; long-span bridges; point cloud; terrestrial laser scanning
#10	13	0.941	2013	reliability analysis; concrete cracking; bond strength; reinforcement corrosion; maintenance planning
#11	6	0.946	2015	seismic effects; probabilistic modelling; hysteresis; generalised extreme value distribution; existing concrete bridges

Finally, burst detection is carried out based on the algorithm developed by Kleinberg [51]. The top 41 keywords with the strongest citation burst are sorted by strength in **Fig. 10**. Lifecycle cost (2004-2013) received the strongest attention, with a burst strength of 11.6, followed by bridge maintenance (burst strength = 11.13, 2004–2009) and machine learning (burst strength = 9.76, 2018–2021). Some keywords have always been the focus of attention in the field of bridge maintenance, such as bridge deck (burst strength = 9.68, 2002-2013), concrete structure (burst strength = 9.14, 2000–2013), oriented multiobjective optimisation (burst strength = 8.01, 2006–2017) and lifecycle (burst strength = 5.92, 2002–2015) with long duration and high strength.

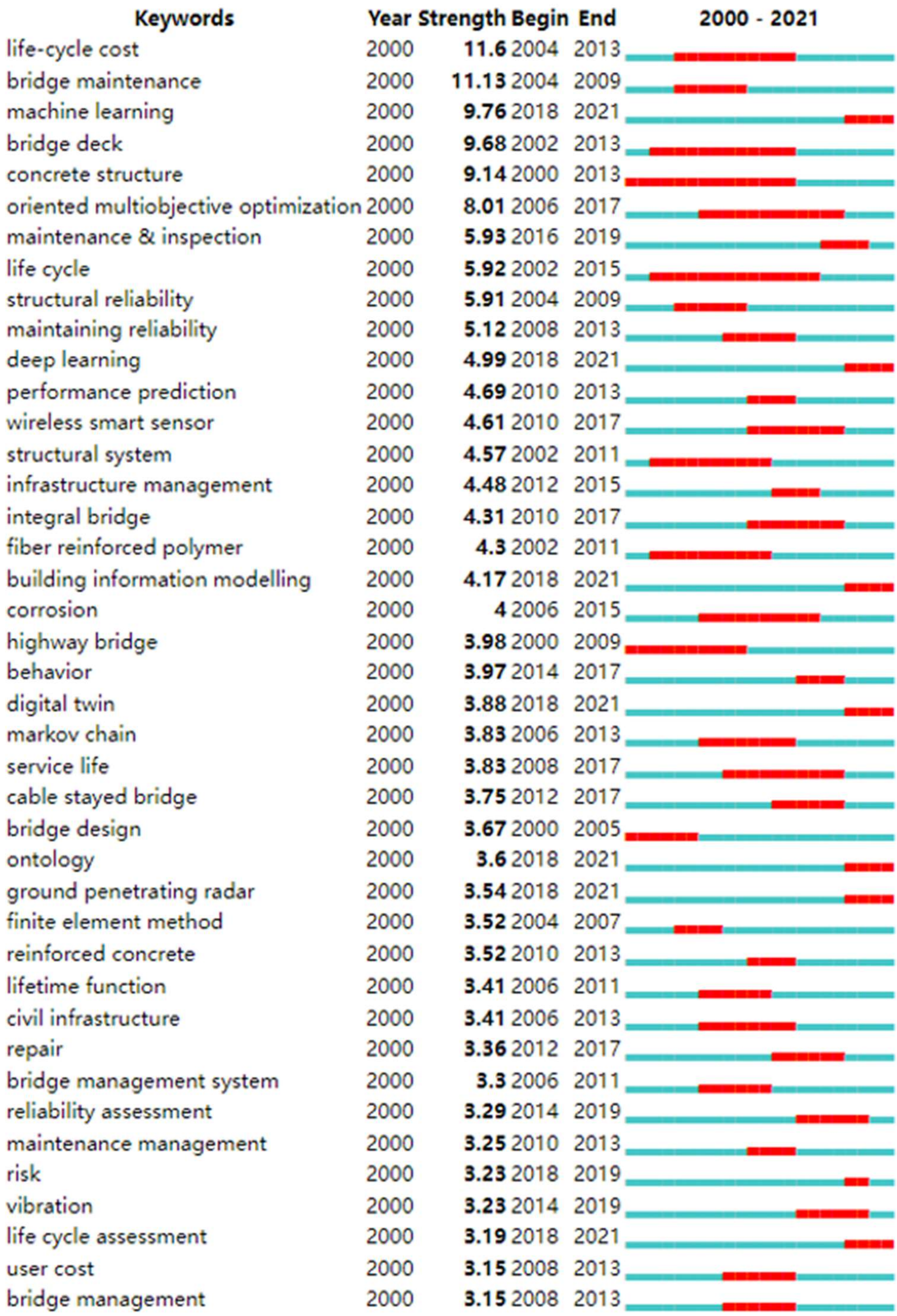


Fig. 10. Top 41 keywords with the strongest citation burst.

Fig. 11 shows the classification of some burst keywords extracted from **Fig. 10** that are extremely relevant to bridge maintenance. These burst keywords are sorted by the beginning time. From the perspective of maintenance projects, management has drawn attention earlier via bridge management system (burst strength = 3.3, 2006-2011), bridge management (burst strength = 3.15, 2008-2013), and maintenance management (burst strength = 3.25, 2010-2013). Inspection has recently started to gain attention via maintenance & inspection (burst strength = 5.93, 2016-2019). From the perspective of methods or technologies, the application of new-generation information technology, e.g., machine learning (burst strength = 9.76), deep learning (burst strength = 4.99), building information modelling (burst strength = 4.17), and digital twin (burst strength = 3.88), in the bridge maintenance phase has exploded recently. Moreover, in general, keywords cluster analysis can help map documents and classify them. However, when the topic is relatively new or the number of certain keywords is not enough to form a category, it is easy to ignore. Therefore, a critical review analysis is adopted in the following section to further analyse the collected literature.

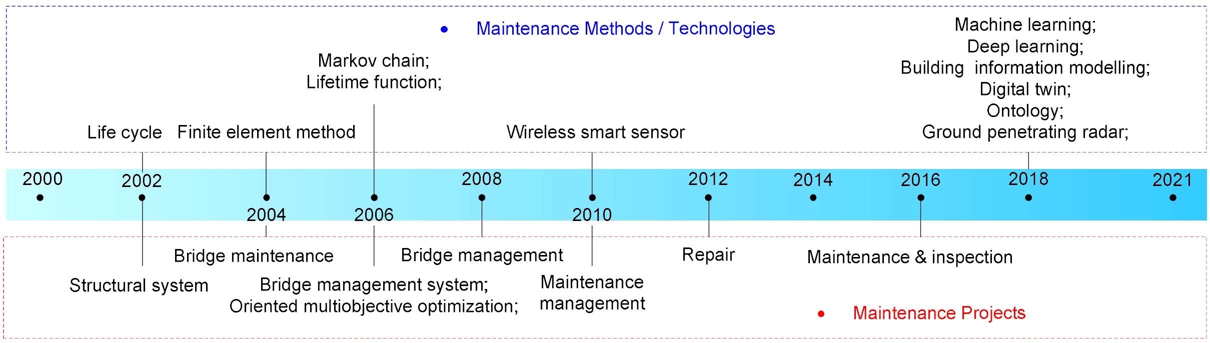


Fig. 11. Burst keywords classification.

4 Smart bridge maintenance – from data to knowledge-driven

After visually analysing the collected papers, those papers are further reviewed to identify the gaps and shape the vision development for smart bridge maintenance. Critical review analysis process is shown in **Fig. 12**. First, the tasks of bridge maintenance are summarised. Then, the current issues that limit development are identified. Finally, aiming at these issues, advanced technologies or approaches and their development trends are analysed.

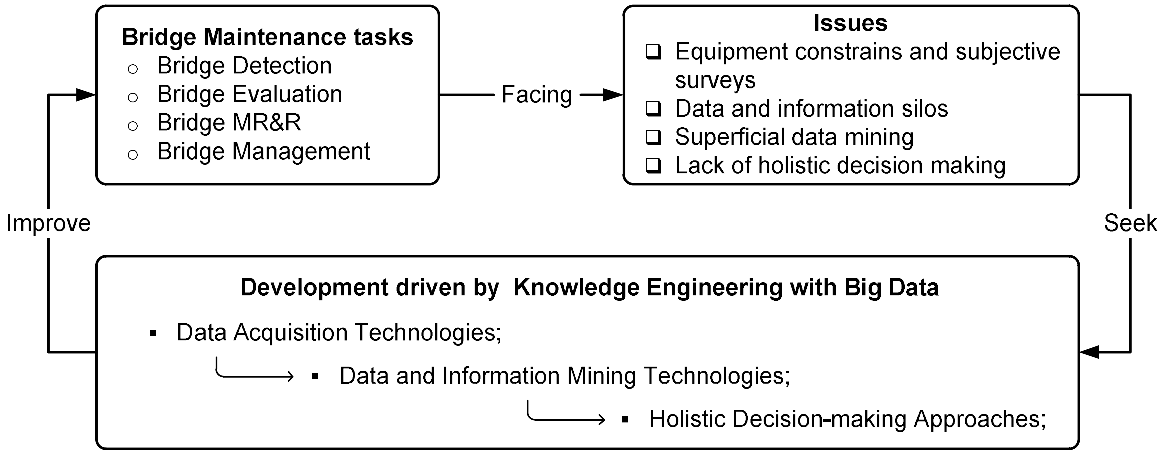


Fig. 12. Critical review analysis process.

4.1 Bridge maintenance tasks and issues

Bridge maintenance is very complex. According to all of these collected articles, bridge maintenance systems normally include four parts: detection, evaluation, MR&R (maintenance, repair, and rehabilitation), and management (**Fig. 13**). Bridge detection is the cornerstone of checking the hazards of bridges [52]. It is basic to evaluate the safety and maintenance of bridges. The development of detection technology has shifted from visual inspection in the early stage to full-coverage detection, which combines visual inspection, equipment inspection and monitoring technology [53]. Research shows that non-destructive technologies (NDTs) [54-57] are popular development directions. In the next stage, further exploration is carried out by combining new-generation information technologies, such as unmanned aerial vehicle systems [58-60] and robots [61-63].

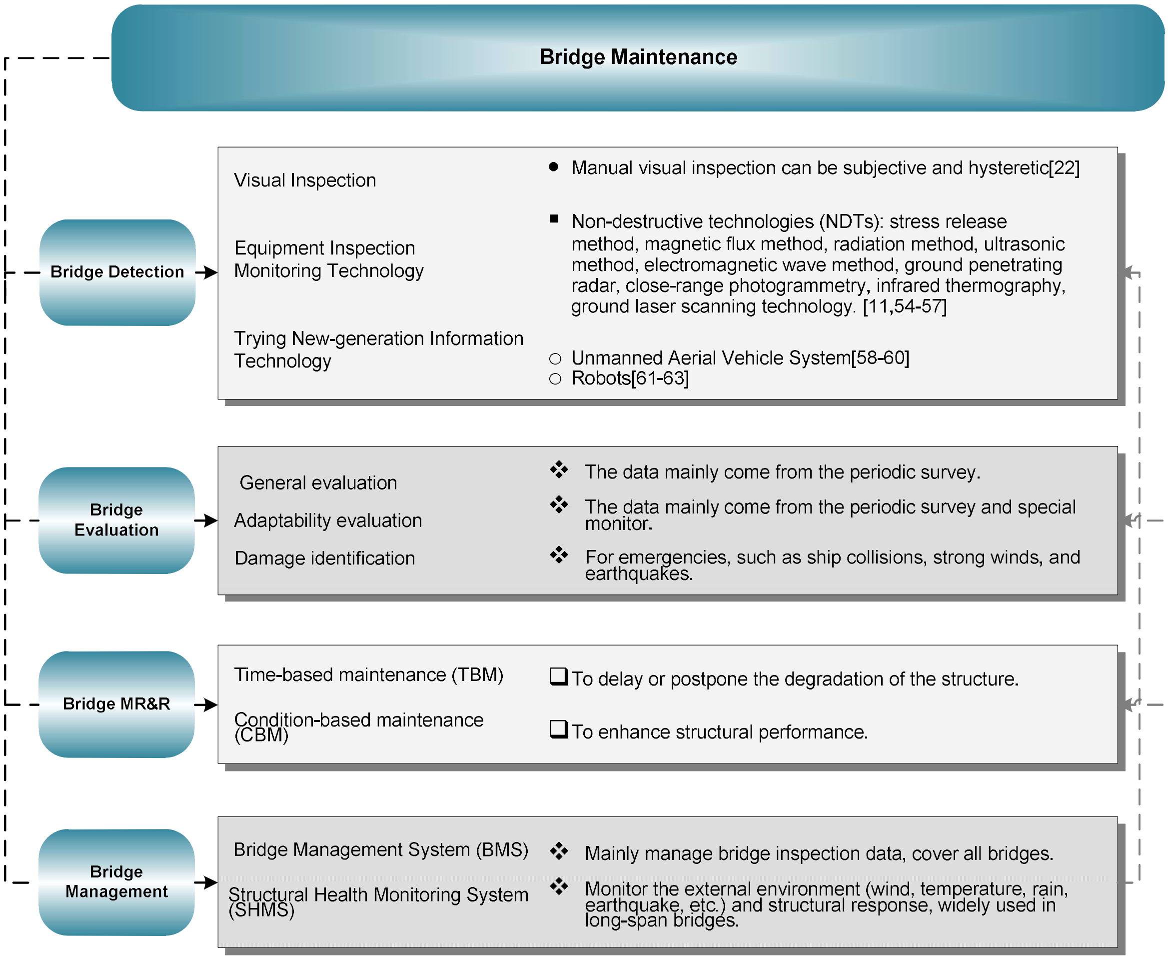


Fig. 13. Bridge maintenance system.

Bridge evaluation is used to assess the condition of the structure by comprehensively describing the defects of each component. In addition, it can provide decision support for bridge MR&R [64]. Bridge evaluation is divided into general evaluation and adaptability evaluation. General evaluation refers to the comprehensive assessment of each component's technical condition to determine the bridge's level of technical condition. The data mainly come from the periodic survey. Adaptability assessment refers to the evaluation of the actual bearing capacity, traffic capacity and flood resistibility of bridges by combining the test and structural stress analysis. The data are mainly from periodic surveys and special monitors. In addition, some studies defined bridge evaluation as the observation and evaluation of the state of the built structure, including damage identification [65,66]. The purpose of damage identification is to find possible local damage, which is used in emergencies, such as ship collisions, strong winds, and earthquakes. At present, an evaluation standard system matching the existing detection technology level has been formed for small and medium-sized bridges.

Bridge MR&R refers to the regular maintenance and repair operations for the normal use of bridges. More precisely, tasks are carried out to prevent and repair catastrophic damage to bridges and improve bridge quality and service levels [10]. Bridge maintenance activities are typically divided into two categories [67,68]: time-based maintenance (TBM) or regular maintenance. It is protective maintenance behaviour to delay or postpone the degradation of the structure; the other is condition-based maintenance (CBM), which is reinforcement maintenance behaviour to enhance structural performance. Due to the conventional hazards of bridge structures, a relatively mature MR&R technique has been formed. These methods have been widely used in the repair and reinforcement of small- and medium-sized bridges [69-71].

Bridge maintenance involves both technology and data/information management. Storing the data/information can better serve the follow-up maintenance behaviours. The bridge management system (BMS) [72] and structural health monitoring system (SHMS) [73] are the two most developed systems in bridge maintenance. SHM has been widely used in the maintenance and management of long-span bridges. The BMS coverage can be extended to all bridges, including small- and medium-span bridges. The combination of the two systems can provide full coverage of the bridge network.

The complexity of bridge maintenance is reflected in the fact that the system has massive data and rich knowledge to work with; it involves various information from multiple sources, and a large number of stakeholders and organisations collaborate throughout its entire lifecycle. When massive data, information, equipment and people are intertwined, it is concluded that there are several critical issues that need to be addressed, including (1) equipment constraints and subjective surveys; (2) data and information silos; (3) superficial data mining; and (4) lack of holistic decisions.

Equipment constraints and subjective surveys – With the existing equipment constraints, it is still not easy to have the most cost-effective technical solutions or equipment for a large amount of data acquisition. The data collected often lack good quality, and the data acquisition accuracy is low. Structural defects are identified and classified manually by engineers and inspectors who need to control the entire process from hazard discovery, testing, recording and entry of results, and the entire process is highly error prone and unreliable.

Data and information silos –The whole lifecycle bridge maintenance involves many different hardware and software systems to work together; the data interoperability issues are still critical, as there are no mature solutions to help to overcome data and information silos. For example, BMS is used to manage bridge survey data, and the generated information regarding bridge structural condition is stored in the inspection reports. SHMS is used for monitoring the external environment and structural response, and it can deal with large-capacity data measurement, transmission and storage. However, these two systems work mostly independently; hence, the survey cannot be timely and effectively shared through different working stages and systems. The intuitionistics of manual inspection and real-time health monitoring are not sufficiently integrated.

Superficial data mining – The current maintenance is more focused on collecting rather than utilising data. Over the years, bridge systems have collected a large amount of survey data, but only a small part of those are utilised successfully for bridge maintenance decision-making. Various types of data have a low degree of correlation and lack connectivity analysis, which means that the potential scientific value of the obtained data has not been fully explored. The diversification of data formats (e.g., structured data, unstructured data) also increases the difficulty of information sharing and integration.

Lack of holistic decision-making – Generally, the knowledge and information in the whole process of bridge maintenance are dispersed among different teams. People with different skills and professional backgrounds perform various tasks, and different engineers tend to focus on their deliverables and operate in silos. As a result, information and knowledge are not easily shared between different departments. In the absence of effective computer-aided tools, it is difficult for a single person or team to master multidomain knowledge. Therefore, decision-makers tend to rely on subjective experience to make critical solutions, which are often not holistic or comprehensive.

4.2 Data Acquisition Technologies

For critical issues in bridge maintenance, embracing advanced technologies and methods has become essential. First, advanced techniques can collect rich data to accurately reflect bridge conditions and serve as a basis for maintenance decision-making. Second, analytical methods are developed to deeply mine the raw data, derive meaningful data, and make maintenance decisions. In practice, maintenance data are mainly captured by sensors or NDTs. Some data that are difficult to collect with sensors and NDTs can be obtained from second-hand sources, e.g., some environment and social data that need to be collected from databases of relevant agencies [1]. **Table 5** summarises mainstream data types for bridge maintenance. Data collected by sensors are divided into three groups: environment data, traffic data and structure response data. Structural data, acceleration, strain, and stress are the most common types because they are the basis for most structure analyses [74]. Major data types collected by NDTs include bridge profiles, point cloud data, photo images, acoustics, radar, infrared images, electrical data and chemical data. Bridge profiles are the most common meaningful data, followed by structure response data. Moreover, due to the strict requirements on equipment, environment, and operators to generate point clouds [75], more studies choose to create point clouds from photos [76,77].

Table 5. Mainstream data types for bridge maintenance.

Data acquisition manner	Data type	Instances
Sensors	Environment data	Temperature Wind speed Humidity Topography and geology Hydrology

	Traffic data	Traffic volume Vehicle load Vehicle speed
	Structure responses	Strain and stress Displacement and deflection Cracks and deformation Acceleration Vibration and frequency
NDTs	Bridge profile	Properties of components, e.g. geometry, number, material properties, and connection of components
	Point clouds Photo images	Bridge structure features: 1) both local features, e.g. girder cracks, and global features, e.g. holistic bridge geometry. 2)only reflect surface conditions.
	Acoustics and ultrasonic Radar Infrared images	Local features: reflect both surface and subsurface conditions.
	Electrical and chemical	Structural corrosion

For data collection sensors, a SHM system is the dominant method. Various sensors and bridge structures are fused as a whole system through IoTs, which may gather the various sensor data of bridges regularly or in real time to provide a scientific basis for decision-making in bridge maintenance [78,79]. However, SHM systems are only installed on the superstructures of critical bridges in practice, while other parts are ignored. Therefore, many studies have optimised sensor placement problems based on intelligent algorithms [53,80] to consider the quality and cost-effectiveness of data acquisition. The current optimal placement methods of sensors include the effective independent method, MinMAC (Minimise Modal Assurance Criterion), modal matrix summation and integration method, origin residual method, modal matrix QR decomposition method, SVD (Singular Value Decomposition), GRM (Guyan Reduction Method), etc. Moreover, the sensor network can be wired or wireless. It is recognised that wireless sensor networks (WSNs) are easier to maintain, more stable, and more cost-effective in the long term [12,81]. However, the reliability of WSNs is affected by several technical challenges, e.g., the lack of a power supply and unstable sensor communication. In practice, the wired system is still implemented more widely, although its data transferring relies on traditional cables rather than on wireless communication techniques.

For data collection devices of NDTs, the application of unmanned aerial vehicles (UAVs) or drones, mobile detection terminals, and wall-climbing robots has greatly improved the safety, efficiency, and intelligence of data acquisition. For example, a drone can conveniently access hard-to-reach areas to capture data efficiently using sensors (e.g., infrared cameras) that it carries. However, these devices require additional calibration, path planning, and control to avoid being blocked by barriers [74]. Another research hotspot is the intelligent detection equipment loaded with image recognition technology, and then the computer vision technology is used to process data for timely analysis to determine the crack profile, width, length, and propagation direction [5]. Hence, the demand for data processing in real-time is met. In addition, facing the strategic needs of emergency rescue in major natural disasters and access to transportation facilities, research on rapid diagnostic technology of bridge performance after disasters has attracted the attention of scholars [83].

Existing studies on data acquisition technologies mainly focus on the innovation of modern inspection devices. Modern inspection devices can still be inefficient, as they require sending staff onsite to collect data [84]. Inspectors need to develop the skill to operate modern inspection devices. The advent of intelligent virtual assistants (IVA) technology helps data collection from the human factors perspective. IVA is an AI-powered agent that integrates machine learning, AR, VR, data science and other technologies to perform tasks or services based on user commands or questions [85]. Li et al. [86] presented a VR-based training and assessment system to assist bridge inspectors in controlling drones. This study demonstrated that IVA has the ability to identify needs of individuals in detail and help them develop the skill in bridge inspection. **Table 6** lists the advantages and disadvantages of data acquisition techniques. Furthermore, the development trend and the key performance indicators (KPIs) targeted by technologies in data acquisition are summarised in **Fig. 14**. With the improvement of hardware and software technologies, the quality and cost-effectiveness of data acquisition is improved. The volume and integrity of maintenance data have increased at the same time.

Table 6. Advantages and disadvantages of data acquisition technologies.

Technologies	Advantages	Disadvantages
Technologies of sensors	All-around data; High quality; Getting data in real-time; Getting data in the long-term;	Placement problems; Technical challenges; Only for critical bridges;
Technologies of NDTs	High accuracy; High intelligence; Unmanned; Reducing data processing time; Accessing to most blind spots;	Strict pre-commissioning operations of devices; Staff needing to be onsite;

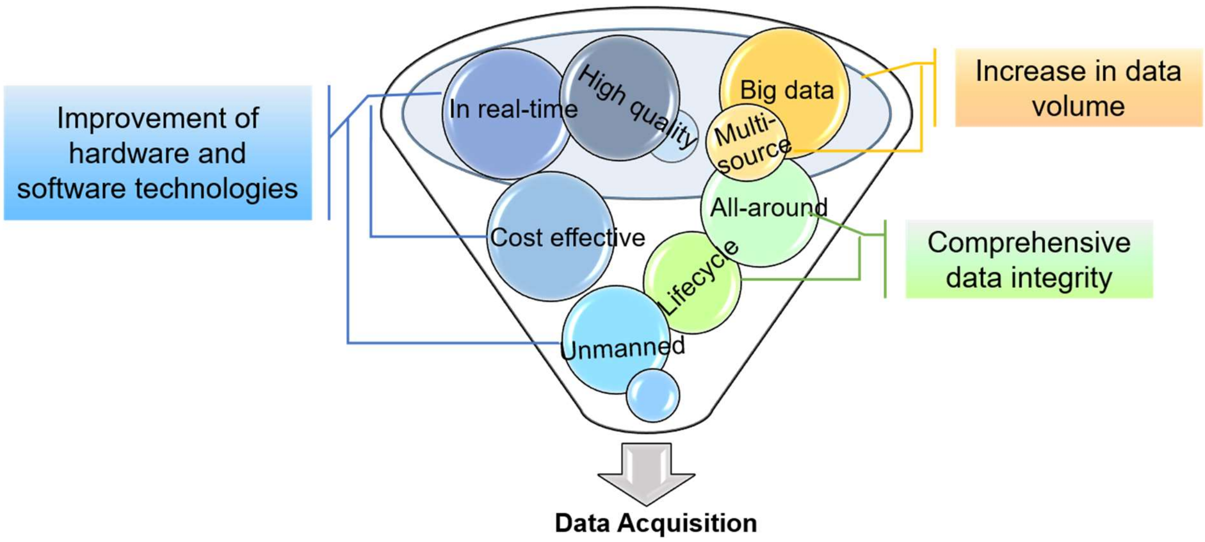


Fig. 14. Trend and KPIs in data acquisition.

4.3 Data and Information Mining Technologies

In this section, the similarity between characteristics of bridge maintenance data and big data is analysed **(Fig. 15**). Maintenance data have low-value density and time variability and are in line with the 4V characteristics of big data, which are large in volume, diverse in variety, frequently changing in velocity, and of great value but low in value density [87.88]. Bridge maintenance data have the characteristics of big data.

The collection of a large amount of data can be turned into a vast base for knowledge mining to go for knowledge-driven approaches. Thus, it is important to adopt big data analysis methods to deeply leverage the raw data. What is converted from raw data is meaningful data, which is also called information.

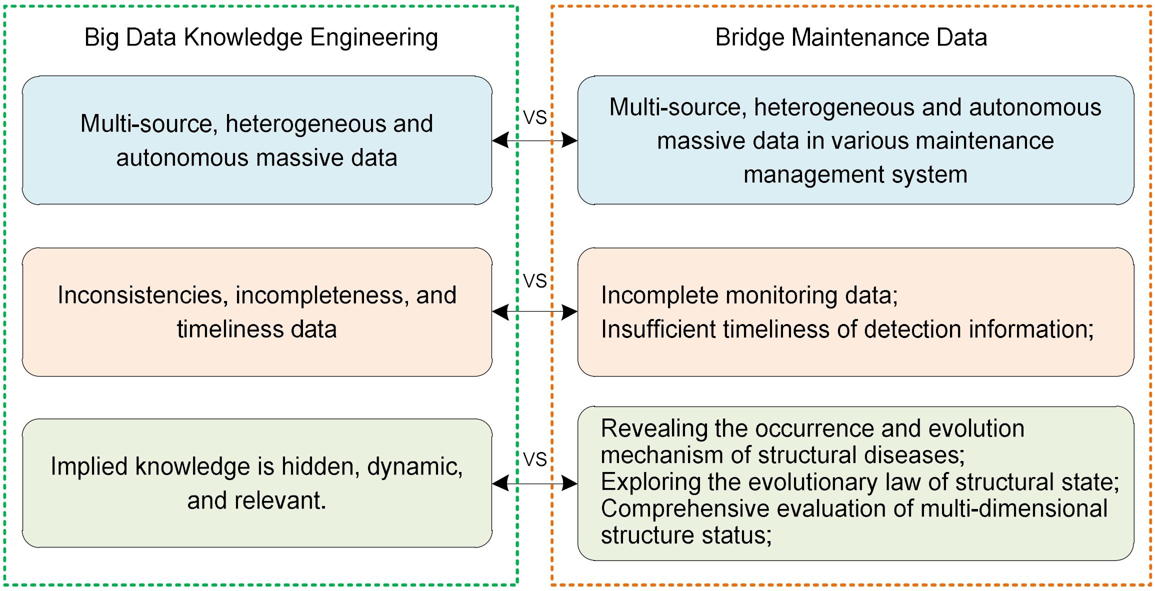


Fig. 15. Similarity analysis between characteristics of bridge maintenance data and big data.

To derive meaningful data from raw data, all kinds of methods are adopted to carry out data preprocessing, data fusion, feature extraction, pattern recognition and other processes step-by-step. Various data types are processed with various technologies, e.g., electrical signals are converted to digital signals [89], traffic load data are converted to structure strain and stress [90], and displacement and strain data are fused together to gain more comprehensive results [91]. The analysis technology of unstructured data is relatively complicated. A considerable amount of data under the condition of the bridge and maintenance actions is buried in the textual bridge inspection reports and not utilised [92]. Information extraction (IE) methods can automatically recognise and extract information from unstructured textual bridge inspection reports and represent them in a structured format. IE methods used in papers can be classified into two primary categories [93-95]: rule-based methods and machine learning ML-based methods. Rule-based methods use manually coded rules for text processing. ML-based methods use ML algorithms for training text processing models based on the text features of a given training text. However, compared to other IE efforts, e.g., IE from social media text, automated IE from bridge reports is more challenging because bridge inspection reports written by different organisations from various locations are highly variable in terms of text characteristics and patterns. To capture the variability in text patterns, IE methods require the development of a comprehensive set of rules specifically for bridging the reports domain. This process is time-consuming and requires a great amount of human effort. Therefore, a few ontology-based IE algorithms have been studied [96,97]. For example, semantic modelling and semantic natural language processing (NLP) techniques were used to facilitate automated textual regulatory document analysis (e.g., code analysis).

Then, the processed data can be used to analyse structural conditions, including current condition evaluation, failure probability computation, and life expectancy prediction. For current condition evaluation, condition indexes [98] can be calculated directly based on sensors or survey data to indicate if damages happen and the if structure is out of service, e.g., discrete indexes are estimated by mapping detected damages and abnormal responses to discrete values to evaluate the current condition [11,99]. for the mechanism for failure probability computation includes two aspects: deterioration severity computation and load computation. The former estimates the probability that deterioration (e.g., loss of stiffness) exceeds the limit [100,101]. The input data mainly come from the survey data, including the bridge profile, damage data (e.g., the size of crack), and environmental data. The latter estimates the probability that the load exceeds the design capacity [102,103]. The input data mainly come from the sensor data, including the bridge profile, traffic data, structure responses (e.g., vibration and displacement) and environment data. Then, life expectancy can be predicted as the time that the failure probability and a condition index decline below a threshold [104-106].

Whether assessing the load rating or reliability of deterioration during the service life of structures, time variables are always the first issue to be considered in many studies, e.g., the prediction model deteriorating in time due to corrosion and live load increase [107], the lifetime performance indicators for the deteriorating structures [108]. The main analytical methods are “model-based” and “data-driven” [22]. The model-based method is essentially a process of bridge structure finite element modelling, model modification, and system parameter inversion. It has high requirements for the accuracy of the theoretical model and the quality of the data. The data-driven method identifies the changing pattern of the structural state by studying the changing trends and probability distributions of the data itself. It is widely used in structural health monitoring. However, only a small part of the maintenance data is used for the analysis process, and its performance improvement is often limited when used on large datasets [22]. In fact, there are many studies on the combined use of the above two methods, e.g., developing stochastic deterioration models for bridge elements [109-112]. Stochastic models capture the uncertainty and randomness of the facility deterioration process as one or more random variables. Stochastic approaches are more in line with the degraded state of the bridge in the real environment, e.g., physics-based stochastic models, Markov chains or Weibull distribution models [113,116]. With the development of artificial intelligence (AI) technology, many research efforts have developed different AI models to better predict and understand bridge deterioration. For example, an artificial neural network (ANN) model is used to develop an application model for estimating the future condition of bridges [117]. Artificial neural networks (ANNs) and k-nearest neighbours (KNNs) are used to build two computational machine learning models to predict deck conditions [118].

At the same time, the digital twin (DT) concept proposed by Michael Grieves [119] has been gradually introduced into the bridge maintenance field with the development of intelligent technology. The DT concept has shown pivotal potential in security prewarning [120]. DT can make full use of data (such as physical models, sensor data (real-time data), operating history (real data), and related derived data generated through mining to integrate multidisciplinary, multiphysical, multiscale, and multiprobability simulation processes. Comparing the application of the BIM and DT models in bridge maintenance work [6], the DT model pays more attention to how to capture and store the historical data of the bridge and, based on that, to predict the future behaviour of the bridge. Data, such as accumulated damage history and repair history can be directly exported, which provides important support for project maintenance teams and decision-making agents to respond appropriately in time when the bridge fluctuates suddenly [121].

Table 7 lists the advantages and disadvantages of analytical methods. These methods can be collectively referred to as data and information mining technologies, which are the combination and improvement of methods represented by various terms. Specifically, these terms encompass various algorithms, such as classification, clustering, association analysis, and regression. However, stressing the use of a certain method alone is not enough to determine the success of big data analysis from knowledge mining to turn to knowledge-driven approaches. The final analysis result is often the intersection of the effects that can be achieved by each link in the process.

Table 7. Advantages and disadvantages of analytical methods

Analytical Methods	Advantages	Disadvantages
IE methods for text files	Automatically reorganization and extraction information;	Time-consuming; An amount of human effort;
The model-based method for evaluation	Easy for engineers; Well-established methodology;	High requirements for models and the data;
The data-driven method for evaluation	Mining hidden patterns in data; Widely used in structural health monitoring;	Only using a small part of data;
Stochastic approaches for evaluation	High accuracy; In line with the degradation state of the real bridge;	Difficult to simulate random variables;
Digital Twin technology for evaluation	Making full use of data; Integration multi-disciplinary, multi-physical, multi-scale, and multi-probability simulation processes;	Unclear methodology in bridge maintenance;

4.4 Holistic decision-making approaches

Maintenance decision-making involves multifactor (e.g., structure safety, costing issues, sustainability) and multidomain knowledge (e.g., structure engineering, material perspectives, environmental perspectives). It is difficult to describe the relationship between variations of factors and the decision-making objective with precise mathematical and mechanical methods. Knowledge-based and artificial intelligence-supported reasoning, which is characterised as a knowledge-based approach, has received increasing attention. Prioritisation indices (PIs) are a need-based bridge maintenance approach that allows short-term maintenance decisions to be made [122]. A PI of Valenzuela et al. [123] considers the structural condition, hydraulic vulnerability and seismic risk, in addition to the importance of the bridge within the road network and the productive system. Echaveguren et al. [124] proposed a systematic method for maintenance decisions and their associated costs by using a PI based on bridge conditions, strategic importance and vulnerability. Additionally, decision-making can be treated as a special case of reinforcement learning (RL) by using a family of efficient sampling algorithms, such as the bootstrapping TD (temporal difference) method, the Monte-Carlo tree search (MCT) method, the deep neural network (DNN) method, and the convolutional neural network (CNN) method [125]. Recently, an important trend has been using semantic web technology (SWT) to address issues related to knowledge representation and decision-making [126-128]. For example, the bridge hazard knowledge base was created to realise hazard classification management. A specific bridge ontology was developed to solve the intelligent retrieval of massive data and knowledge reasoning that is difficult to achieve with traditional approaches [18].

Bridge maintenance supported by knowledge-driven approaches also needs to define the data needed for different decision-making scenarios and how to use technologies to complete the retrieval and service in a smart way [1]. Currently, most data needs are defined in bridge inspection manuals. For instance, primary inspection only requires structure photos, general evaluations and a description of damages, and detailed inspection can require accurate measurement of components' structural performance (e.g., concrete strength) and surface and subsurface damages. A few studies also attempt to define data needs for operation and maintenance applications, e.g., defining the data needs for bridge life estimation [129] and investigating information requirements of stakeholders (e.g., the owner and maintenance teams) [130]. However, comprehensive data requirements have not yet been defined.

Although not defined, online databases and cloud servers reduce hardware dependency and provide the opportunity for accessing unified and up-to-date models, as well as their associated data that could be easily accessed through mobile devices. Hadoop is a software framework that supports distributed applications. It is used to build a distributed platform and use other program groups to perform specific functions, such as storage and calculation, which is the "Hadoop ecosystem", including MapReduce, Spark, cloud computing, etc [22,131]. Cloud computing is another research hotspot. Its architecture can respond to the needs of heterogeneous big data storage in maintenance projects and efficient information sharing and transmission across participants, disciplines, and project stages. Bridge managers assess data during the bridge operation phase from the cloud platform in real-time and understand the health conditions of bridges [132,133]. At the same time, facing the real-time computing requirements of maintenance data, the powerful computing power of cloud computing makes it possible to execute complex algorithms online [13].

Database technology holds considerable potential in the bridge maintenance field. The use of a database allows valuable information to be captured, stored, sorted, and extracted according to a predetermined set of selection criteria [134]. Relational database (RDB) systems and NoSQL (Not-Only SQL) database systems are often employed as the primary data storage for bridge maintenance applications [135,136]. One of the most cutting-edge database technologies is to build an integrated information platform for bridge construction, management and maintenance based on building information modelling (BIM). In bridge maintenance, BIM research has been an additional research hotspot for a long time. Its main objectives are twofold: (1) Enabling an integrated bridge database [137-139]. A wide array of information about the bridge, including the 3D geometry, project management information, such as time schedules and costs or operation and maintenance metrics, are stored in a central, object-oriented database. (2) Developing electronic data exchange standards to facilitate information sharing and collaboration [140-143], such as how the incoming and outgoing information is handled and how project participants build, use and manage this information. The application of BIM further promotes the openness, sharing and multiparty collaboration of data. However, its centralised paradigm is degraded by the risk of data manipulation [144].

Blockchain technology and InterPlanetary file system (IPFS) are emerging solutions to prevent the problems caused by centralisation. Blockchain is a type of distributed ledger technology (DLT) that uses a decentralised architecture based on distributed computing, crypto-chain block structures to store data, node consensus algorithms to verify data and smart contracts to program data [145]. A recent research trend has presented the feasibility of integrating blockchain with BIM, involving methods of blockchain-BIM integration [146-148] and methods of BIM data storage in the blockchain [149,150]. The IPFS, which is a peer-to-peer network, is regarded as an appropriate technical complement to blockchain for storing large files [151]. Tao et al. [152] presented a framework for secure BIM design collaboration in which an IPFS network is responsible for storing large design files (e.g., BIM models), while a blockchain network is leveraged to keep and exchange design information (e.g., design changes). Similar to other emerging technologies in their first years, research on blockchain and IPFS related to bridge engineering is still new and fragmented, but in the future, it may have the potential to play a critical role [153,154]. Finally, the development of technologies, such as Web3D, VR and mixed reality (MR) has greatly promoted the process of information visualisation. Three-dimensional models are displayed to clients using these techniques. More importantly, the maintenance data (e.g., monitoring data, inspection maintenance data, construction management data) are visually displayed and interact with a three-dimensional model as the carrier [155].

The development trend and KPIs in smart bridge maintenance are summarised in **Fig. 16**. Bridge management workers are changing their mindset. They consider the heterogeneity of massive data, attach importance to the implicit relationship between data, and promote the improvement of data analysis results. In addition, they pay more attention to the real-time and powerful analysis and unified storage of dynamic incomplete big data/information, as well as needs for multi-source information sharing and transmission across participants, disciplines, and project phases. The critical review hence reveals the trends of moving from data to knowledge-driven smart bridge maintenance, and a proactive, holistic and smart lifecycle approach is needed to comprehend the complexity of bridge structural conditions.

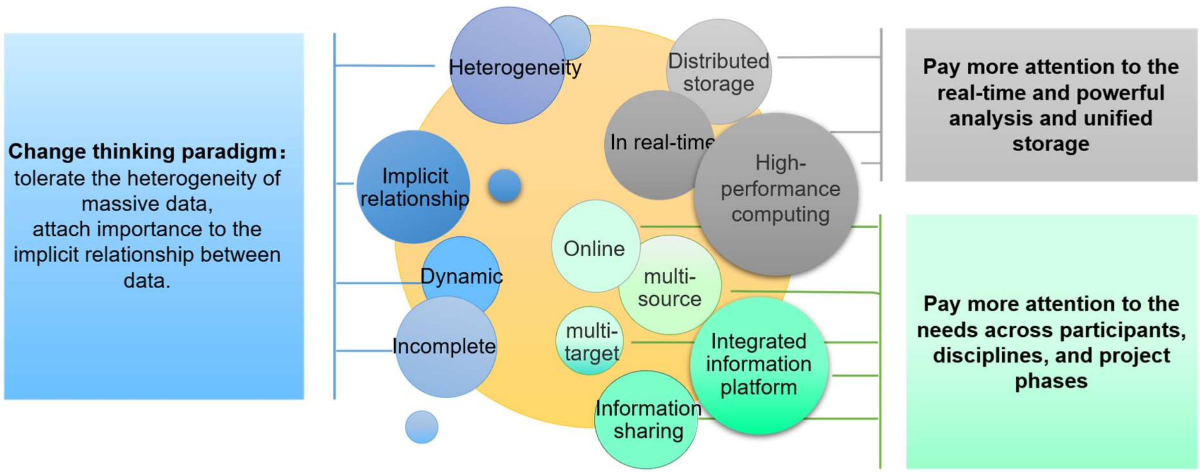


Fig. 16. Trend and KPIs in smart bridge maintenance.

5. A framework facilitating knowledge-driven smart bridge maintenance

Knowledge-driven bridge maintenance supported by big data mining ideally needs to address several challenges. **Table 8** lists a broader range of challenges identified by many researchers to further classify them into two different categories: (1) technical challenges in the data-driven manner and (2) challenges in the transition towards knowledge-driven approaches.

Table 8. Challenges identified by previous researchers.

Challenges in the data-driven manner
● Lack of higher performance hardware to handle large volumes of data; ● Lack of data integration; ● Limitation and isolation of distinct types of data sources; ● Lack of a standard neutral exchange format and schema; ● Poor interoperability of heterogeneous software and platforms; ● Poor interoperability and information sharing among software and technology; ● Poorly developed theory and method for structural state evaluation; ● Unclear method to create accuracy analytical model; ● Poorly developed MR&R technologies;
Challenges in the transition towards knowledge-driven approaches
● Lack of the definitions of data flow requirements; ● The differences and lack of fully adopted work flow; ● Lack of standard procedures; ● Lack of standard data needs; ● Inadequacy of representation of semantics and geometrics for data models; ● Poor collaboration between academia and industry;

(1) Technical challenges in the data-driven manner

Many technology-related challenges prevent data-driven approaches from meeting the growing demands of smart bridge maintenance. A major challenge is the lack of unified data formats for bridge maintenance covering the entire lifecycle data exchange and across different sectors. As the data formats cannot be unified, the big data collected cannot be effectively exchanged and shared in different sectors. Thus, only a small portion of those have been utilised successfully for maintenance decision-making. Currently, there are various examples of integrating different types of datasets and data formats, e.g., expanding the industry foundation classes (IFC) architecture. However, IFC provides a rich, redundant yet ambiguous schema for interoperability of heterogeneous software and platforms, leading to the lack of semantic clarity in mapping entities and relationships. Moreover, the standards for the component classification in the bridge operation and maintenance phase are different from those in the design and construction phases, which means that engineers must do a great amount of work to fully expand the common data standards throughout the lifecycle of bridges. Thus, no unified data formats have been fully extended to encompass the major types of bridge maintenance projects.

The technology-related challenges may be mitigated by improvements to the technology over time, but data-driven approaches are still not sufficient to solve tasks of bridge maintenance decision-making. Bridge maintenance is a complex task that requires the cooperation of different stakeholders. The coordination of work among different teams and organisations in this type of task is important, while is a complicated process. Hence, it requires more holistic and smart lifecycle approaches.

(2) Challenges in the transition towards knowledge-driven approaches

An ideal smart maintenance system can determine data/information requirements and identify by whom and when the data/information should be provided throughout the project lifecycle according to different decision-making scenarios. During this process, data exchange, as one of the important requirements, should be exhaustive in representation of semantics, as well as geometrics. Currently, there are several studies integrating blockchain and IPFS technologies with BIM software to address challenges, such as interoperability and information sharing among software and technology and the definitions of data flow requirements. However, the focus is only on the model level. These BIM systems lack efficient semantic query and reasoning capabilities. There is still a lack of such a holistic and comprehensive semantic-level knowledge system that can provide enough semantic interoperability and representation of the knowledge. This may be because numerous concepts and their logical relationships defined in maintenance standards require engineers to perform manual extraction rather than directly be recognised by computer programs to form a complete knowledge system. It requires manual labour and a high-quality collaboration of experts among different teams and organisations. In addition, it is difficult to reuse or expand existing knowledge bases. These knowledge bases that are built for the same purpose may have different terms and structures. The problem of collaboration between knowledge bases established for different purposes is also difficult to solve. The above challenges hinder the transition towards knowledge-driven approaches.

Fig. 17 shows a proposed framework, which is knowledge driven and targets the development of suitable knowledge networking mechanisms to drive numerous tools. Specifically, this roadmap uses semantic web technology, BIM, and IoTs to integrate maintenance data with embedded big data methods support to enable smart reasoning and holistic maintenance decision-making. The framework includes three key components: 1) A dynamic semantic knowledge base. In a knowledge-driven manner, a dynamic semantic knowledge base is used for intelligent semantic recognition, data and information integration, numerical-based and logical-based reasoning, and holistic decision-making. 2) A database. In a data-driven manner, a database is used for real-time data/information mining with high-performance computing power. 3) Data acquisition system. Big data are collected in a large volume and comprehensively throughout the whole bridge lifecycle. The collaboration of these three crucial components allows the whole framework to work seamlessly and effectively.

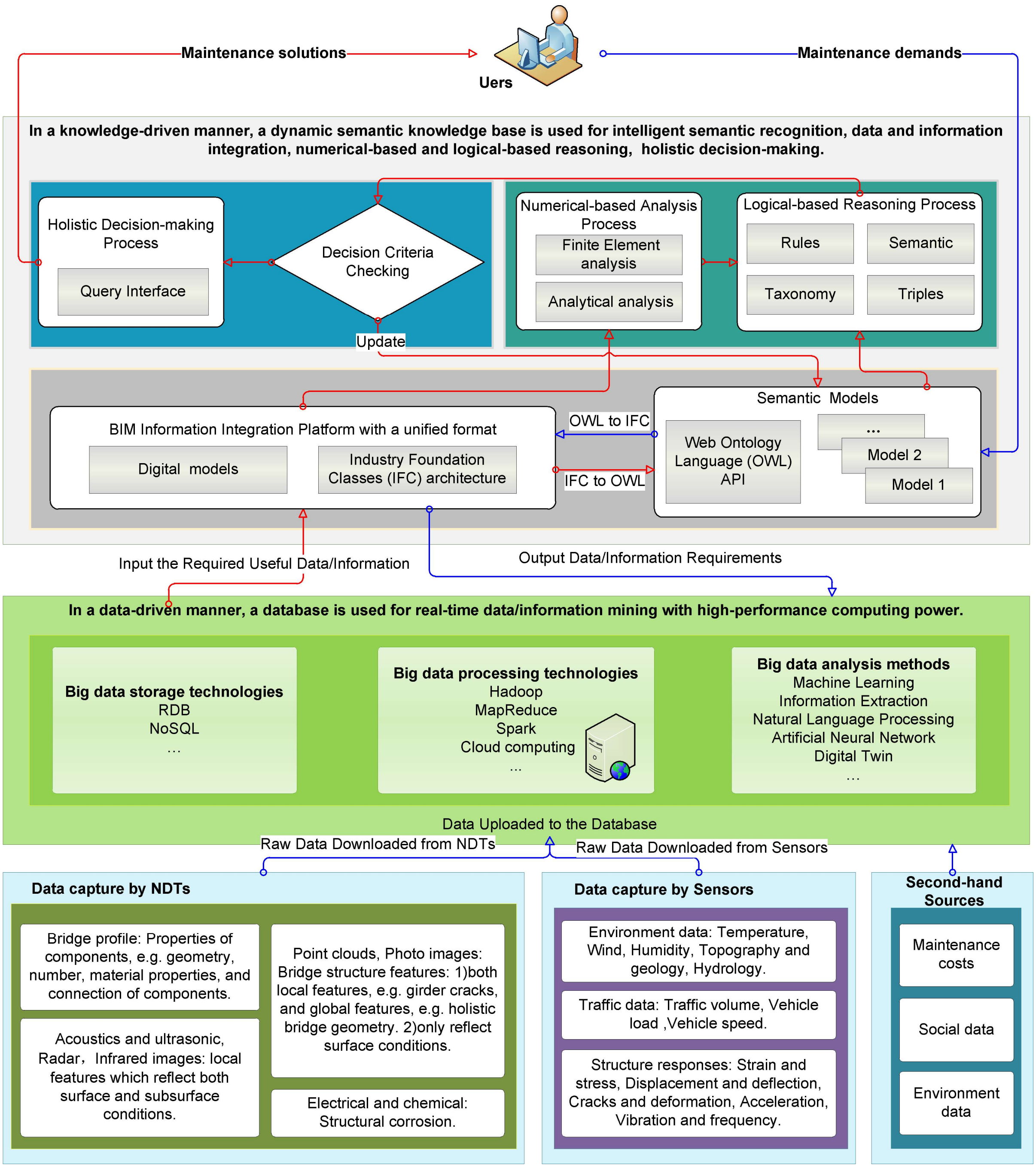


Fig. 17. A knowledge framework to implement smart bridge maintenance.

The workflow is provided as follows: First, bridge maintenance personnel input their needs. Semantic models of the knowledge base match the corresponding maintenance scenarios that define the required data/information and their details. These details are passed into the BIM platform through the translation between the semantic web standard language (Web Ontology Language) and the industry foundation classes architecture. Then, the BIM information integration platform with a unified data format drives the database to call the data collected by the corresponding source in a targeted manner. The process can be called and released in real-time (shown in blue lines). Furthermore, big data storage and processing technologies and big data analysis methods are jointly used to obtain the required useful data/information from raw data in real-time online analysis mode. They are unified and coordinated by the BIM platform. Some of them are used to build finite elements or mathematical models for numerical-based analysis. Some are transformed into semantic models for logic-based reasoning. The results of numerical-based analysis can be embedded in logic-based reasoning to support holistic decision-making. The correctness of the results is determined according to certain criteria. The results that meet the requirements are fed back to engineers at the query interface to assist them in making maintenance decisions, which are further updated into the knowledge base as facts (shown in red lines).

The framework is an open, computable, and evolvable knowledge network based on maintaining big data. Openness means that the sources of the data are diverse. Big data comes from massive, heterogeneous and autonomous sources. Computability means that the knowledge network can use various methods to explore complex and evolving relationships between maintenance data, and it can perform reasoning calculations on knowledge itself. Evolvability means that the network can continuously infer the latest knowledge and update itself. At the same time, knowledge in other networks can be transformed into a standard form and absorbed into the network.

6 Conclusion

This paper presents a critical review and comprehensive literature analysis to investigate state-of-the-art methods used in smart bridge maintenance, which reveals the need for a knowledge-driven approach supported by large survey/monitoring data mining. First, 2,732 papers collected from the WoS core collection database are visually analysed using the CiteSpace software, including four perspectives: literature quantity analysis, journal co-citation analysis, document co-citation analysis, and keywords clustering and burst analysis.. Second, the result of visualisation analysis helps to pinpoint 323 papers for further critical review, focusing on three areas: bridge maintenance tasks and issues, advanced technologies supporting smart maintenance, and holistic decision-making approaches. The analysis informs that bridge engineers need to change their mindset from traditional experience oriented to holistically consider the heterogeneity of maintenance big data, to understand the implicit relationship and knowledge among different data and information streams. Based on the concluded technical challenges in the data-driven manner and challenges in the transition towards knowledge-driven approaches, this paper proposes a novel framework and methodology in the end with an aim to leverage the underused large amounts of bridge maintenance big data by using knowledge-driven approaches, including three key components: smart raw data acquisition, data and information unification through BIM, and dynamic ontological knowledge processing, to facilitate future developments towards smart bridge maintenance.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] C. Wu, P. Wu, J. Wang, R. Jiang, M. Chen, X. Wang, Critical review of data-driven decision-making in bridge operation and maintenance, Struct. Infrastruct. E. (2020) 1-24, https://doi.org/10.1080/15732479.2020.1833946.

[2] X. Zhou, X. Zhang, Thoughts on the Development of Bridge Technology in China, Engineering 5 (6)

(2019) 1120-1130, https://doi.org/10.1016/j.eng.2019.10.001.

[3] Y. Chen, X. Xue, Advances in the structural health monitoring of bridges using piezoelectric transducers, Sensors 18 (12) (2018) 4312, https://doi.org/10.3390/s18124312.

[4] Z. Liu, T. Guo, X. Yu, X. Huang, J. Correia, Corrosion fatigue and electrochemical behaviour of steel wires used in bridge cables, Fatigue Fract. Eng. M. (2020), https://doi.org/10.1111/ffe.13331.

[5] C. Shim, N. Dang, S. Lon, C. Jeon, Development of a bridge maintenance system for prestressed concrete bridges using 3D digital twin model, Struct. Infrastruct. E. 15 (10) (2019) 1319-1332, https://doi.org/10.1080/15732479.2019.1620789.

[6] W. Locke, J. Sybrandt, L. Redmond, I. Safro, S. Atamturktur, Using drive-by health monitoring to detect bridge damage considering environmental and operational effects, J. Sound Vib. 468 (2020), https://doi.org/10.1016/j.jsv.2019.115088.

[7] Important traffic news from the Ministry of Transport of the People's Republic of China, [Online]. Available https://www.mot.gov.cn/jiaotongyaowen/202111/t20211111_3625593.html

[8] LGA responds to RAC Foundation press release on substandard bridges, [Online]. Available https://www.local.gov.uk/about/news/lga-responds-rac-foundation-press-release-substandard-bridges

[9] Local bridge collapses up 70%, [Online]. Available https://www.localgov.co.uk/Local-bridge-collapses-up-70/53924

[10] T. Hong, M. Hastak, Evaluation and determination of optimal MR&R strategies in concrete bridge decks, Automat. Constr. 16 (2) (2007) 165-175, https://doi.org/10.1016/j.autcon.2006.03.002.

[11] S. Abu Dabous, S. Yaghi, S. Alkass, O. Moselhi, Concrete bridge deck condition assessment using IR Thermography and Ground Penetrating Radar technologies, Automat. Constr. 81 (2017) 340-354, https://doi.org/10.1016/j.autcon.2017.04.006.

[12] C. Yun, S. Cho, H. Park, J. Min, J. Park, Smart wireless sensing and assessment for civil infrastructure, Struct. Infrastruct. E. 10 (4) (2014) 534-550, https://doi.org/10.1080/15732479.2013.769011.

[13] X. Tong, H. Yang, L. Wang, Y. Miao, The development and field evaluation of an IoT system of Low-Power vibration for bridge health monitoring, Sensors 19 (5) (2019) 1222, https://doi.org/10.3390/s19051222.

[14] A. Costin, A. Adibfar, H. Hu, S.S. Chen, Building Information Modeling (BIM) for transportation infrastructure - Literature review, applications, challenges, and recommendations, Automat. Constr. 94 (2018) 257-281, https://doi.org/10.1016/j.autcon.2018.07.001.

[15] C.V. Dung, H. Sekiya, S. Hirano, T. Okatani, C. Miki, A vision-based method for crack detection in gusset plate welded joints of steel bridges using deep convolutional neural networks, Automat. Constr. 102 (2019) 217-229, https://doi.org/10.1016/j.autcon.2019.02.013.

[16] H. Kim, E. Ahn, M. Shin, S. Sim, Crack and noncrack classification from concrete surface images using machine learning, Structural Health Monitoring 18 (3) (2018) 725-738, https://doi.org/10.1177/1475921718768747.

[17] S. Krohn, J. Tromp, E.M. Quinque, J. Belger, F. Klotzsche, S. Rekers, P. Chojecki, J. de Mooij, M. Akbal, C. Mccall, A. Villringer, M. Gaebler, C. Finke, A. Thone-Otto, Multidimensional evaluation of virtual reality paradigms in clinical neuropsychology: Application of the VR-Check framework, J. Med. Internet Res. 22 (4) (2020), https://doi.org/10.2196/16724.

[18] G. Ren, R. Ding, H. Li, Building an ontological knowledgebase for bridge maintenance, Adv. Eng.

Softw. 130 (2019) 24-40, https://doi.org/10.1016/j.advengsoft.2019.02.001.
[19] S. Abu Dabous, S. Feroz, Condition monitoring of bridges with non-contact testing technologies, Automat. Constr. 116 (2020) 103224, https://doi.org/10.1016/j.autcon.2020.103224.
[20] S. Agnisarman, S. Lopes, K. Chalil Madathil, K. Piratla, A. Gramopadhye, A survey of automation-enabled human-in-the-loop systems for infrastructure visual inspection, Automat. Constr. 97 (2019) 52-76, https://doi.org/10.1016/j.autcon.2018.10.019.
[21] Y. Fujino, D.M. Siringoringo, Y. Ikeda, T. Nagayama, T. Mizutani, Research and implementations of structural monitoring for bridges and buildings in japan, Engineering 5 (6) (2019) 1093-1119, https://doi.org/10.1016/j.eng.2019.09.006.
[22] L. Sun, Z. Shang, Y. Xia, Development and Prospect of Bridge Structural Health Monitoring in the Context of Big Data. China Journal of Highway and Transport 32 (11) (2019) 1-20. https://doi.org/10.19721/j.cnki.1001-7372.2019.11.001.
[23] S. Banerjee, B.S. Vishwanath, D.K. Devendiran, Multihazard resilience of highway bridges and bridge networks: A review, Struct. Infrastruct. E. 15 (12) (2019) 1694-1714, https://doi.org/10.1080/15732479.2019.1648526.
[24] G. Kabir, R. Sadiq, S. Tesfamariam, A review of multi-criteria decision-making methods for infrastructure management, Struct. Infrastruct. E. 10 (9) (2014) 1176-1210, https://doi.org/10.1080/15732479.2013.795978.
[25] Dan M. Frangopol, D. Saydam, S. Kim, Maintenance, management, life-cycle design and performance of structures and infrastructures: a brief review, Struct. Infrastruct. E. 8(1) (2012) 1-25, https://doi.org/10.1080/15732479.2011.628962.
[26] A. Bradley, H. Li, R. Lark, S. Dunn, BIM for infrastructure: An overall review and constructor perspective, Automat. Constr. 71 (2016) 139-152, https://doi.org/10.1016/j.autcon.2016.08.019.
[27] R. Vanderstraeten, F. Vandermoere, Inequalities in the growth of Web of Science, Scientometrics 126 (10) (2021) 8635-8651, https://doi.org/10.1007/s11192-021-04143-2.
[28] Z. Irani, M.M. Kamal, Intelligent systems research in the construction industry, Expert Syst. Appl. 41 (4) (2014) 934-950, https://doi.org/10.1016/j.eswa.2013.06.061.
[29] J. Song, H. Zhang, W. Dong, A review of emerging trends in global ppp research: analysis and visualization, Scientometrics 107 (3) (2016) 1111-1147, https://doi.org/10.1007/s11192-016-1918-1.
[30] J. Han, H. Kang, M. Kim, G.H. Kwon, Mapping the intellectual structure of research on surgery with mixed reality: bibliometric network analysis (2000–2019), J. Biomed. Inform. 109 (2020) 103516, https://doi.org/10.1016/j.jbi.2020.103516.
[31] C. Chen, Citespace ii: detecting and visualizing emerging trends and transient patterns in scientific literature, Journal of the American Society for Information Science and Technology 57 (3) (2006) 359-377, https://doi.org/10.1002/asi.20317.
[32] C. Chen, F. Ibekwe-Sanjuan, J. Hou, The structure and dynamics of cocitation clusters: a multiple-perspective cocitation analysis, Journal of the American Society for Information Science and Technology 61 (7) (2010) 1386-1409, https://doi.org/10.1002/asi.21309.
[33] C. Chen, S. Morris, Visualizing evolving networks: Minimum spanning trees versus pathfinder networks, IEEE Symposium on Information Visualization 2003, IEEE, Seattle, WA, (2003) 67–74, https://doi.org/10.1109/INFVIS.2003.1249010
[34] X. Zhao, A scientometric review of global bim research: analysis and visualization, Automat. Constr. 80 (2017) 37-47, https://doi.org/10.1016/j.autcon.2017.04.002.

[35] D.M. Frangopol, Life-cycle performance, management, and optimisation of structural systems under uncertainty: accomplishments and challenges 1, Struct. Infrastruct. E. 7 (6) (2011) 389-413, https://doi.org/10.1080/15732471003594427.

[36] D.M. Frangopol, Y. Dong, S. Sabatino, Bridge life-cycle performance and cost: analysis, prediction, optimisation and decision-making, Struct. Infrastruct. E. 13 (10) (2017) 1239-1257, https://doi.org/10.1080/15732479.2016.1267772.

[37] D.M. Frangopol, M. Liu, Maintenance and management of civil infrastructure based on condition, safety, optimization, and life-cycle cost, Struct. Infrastruct. E. 3 (1) (2007) 29-41, https://doi.org/10.1080/15732470500253164.

[38] D.M. Frangopol, J.S. Kong, E.S. Gharaibeh, Reliability-based life-cycle management of highway bridges, J. Comput. Civil Eng. 15 (1) (2001) 27-34, https://doi.org/10.1061/(ASCE)0887-3801(2001)15:1(27).

[39] D.M. Frangopol, M. Soliman, Life-cycle of structural systems: recent achievements and future directions, Struct. Infrastruct. E. 12 (1) (2016) 1-20, https://doi.org/10.1080/15732479.2014.999794.

[40] R.E. Melchers, Progress in developing realistic corrosion models, Struct. Infrastruct. E. 14 (7) (2018) 843-853, https://doi.org/10.1080/15732479.2018.1436570.

[41] N.M. Okasha, D.M. Frangopol, Lifetime-oriented multi-objective optimization of structural maintenance considering system reliability, redundancy and life-cycle cost using ga, Struct. Saf. 31 (6) (2009) 460-474, https://doi.org/10.1016/j.strusafe.2009.06.005.

[42] F. Biondini, D.M. Frangopol, Life-cycle performance of deteriorating structural systems under uncertainty: review, J. Struct. Eng. 142 (9) (2016), https://doi.org/10.1061/(ASCE)ST.1943-541X.0001544.

[43] S. Sabatino, D.M. Frangopol, Y. Dong, Sustainability-informed maintenance optimization of highway bridges considering multi-attribute utility and risk attitude, Eng. Struct. 102 (2015) 310-321, https://doi.org/10.1016/j.engstruct.2015.07.030.

[44] S. Kim, D.M. Frangopol, M. Soliman, Generalized probabilistic framework for optimum inspection and maintenance planning, J. Struct. Eng. 139 (3) (2013) 435-447, https://doi.org/10.1061/(ASCE)ST.1943-541X.0000676.

[45] P. Bocchini, D.M. Frangopol, Generalized bridge network performance analysis with correlation and time-variant reliability, Struct. Saf. 33 (2) (2011) 155-164, https://doi.org/10.1016/j.strusafe.2011.02.002.

[46] P. Bocchini, D.M. Frangopol, A probabilistic computational framework for bridge network optimal maintenance scheduling, Reliab. Eng. Syst. Safe. 96 (2) (2011) 332-349, https://doi.org/10.1016/j.ress.2010.09.001.

[47] H. Furuta, T. Kameda, K. Nakahara, Y. Takahashi, D.M. Frangopol, Optimal bridge maintenance planning using improved multi-objective genetic algorithm, Struct. Infrastruct. E. 2 (1) (2006) 33-41, https://doi.org/10.1080/15732470500031040.

[48] J.M. van Noortwijk, D.M. Frangopol, Two probabilistic life-cycle maintenance models for deteriorating civil infrastructures, Probabilist. Eng. Mech. 19 (4) (2004) 345-359, https://doi.org/10.1016/j.probengmech.2004.03.002.

[49] M Liu, D.M. Frangopol, Probability-based bridge network performance evaluation, J. Bridge Eng. 11(5) (2006) 633-641, https://doi.org/10.1061/(ASCE)1084-0702(2006)11:5(633).

[50] P.J. Rousseeuw, Silhouettes: a graphical aid to the interpretation and validation of cluster analysis,

J. Comput. Appl. Math. 20 (1987) 53–65, https://doi.org/10.1016/0377-0427(87)90125-7.

[51] J. Kleinberg, Bursty and Hierarchical Structure in Streams. Data Mining and Knowledge Discovery 7 (2003) 373–397, https://doi.org/10.1023/A:1024940629314.

[52] B.M. Phares, G.A. Washer, D.D. Rolander, B.A. Graybeal, M. Moore, Routine highway bridge inspection condition documentation accuracy and reliability, J. Bridge Eng. 9 (4) (2004) 403-413, https://doi.org/10.1061/(ASCE)1084-0702(2004)9:4(403).

[53] D. Zymelka, K. Togashi, T. Kobayashi, Concentric array of printed strain sensors for structural health monitoring, Sensors-Basel 20 (7) (2020) 1997, https://doi.org/10.3390/s20071997.

[54] H. Azari, A. Ghorbanpoor, S. Shams, Development of robotic nondestructive testing of steel corrosion of prestressed concrete bridge girders using magnetic flux leakage system, Transportation Research Record: Journal of the Transportation Research Board 2674 (8) (2020) 466-476, https://doi.org/10.1177/0361198120925471.

[55] S. Hsieh, H. Wang, C. Hu, C. Wang, Ultrasonic velocity tomography for inspecting the condition of a bridge pylon, Insight 62 (4) (2020) 192-198, https://doi.org/10.1784/insi.2020.62.4.192.

[56] S. Tang, C. Ramseyer, P. Samant, L. Xiang, X-ray-induced acoustic computed tomography of concrete infrastructure, Appl. Phys. Lett. 112 (2018), https://doi.org/10.1063/1.5009936.

[57] G. Washer, N. Bolleni, R. Fenwick, Thermographic imaging of subsurface deterioration in concrete bridges, Transportation Research Record: Journal of the Transportation Research Board 2201 (1) (2010) 27-33, https://doi.org/10.3141/2201-04.

[58] D. Erdenebat, D. Waldmann, Application of the DAD method for damage localisation on an existing bridge structure using close -range UAV photogrammetry, Eng. Struct. 218 (2020), https://doi.org/10.1016/j.engstruct.2020.110727.

[59] P. Liu, A.Y. Chen, Y. Huang, J. Han, J. Lai, S. Kang, T. Wu, M. Wen, M. Tsai, A review of rotorcraft Unmanned Aerial Vehicle (UAV) developments and applications in civil engineering, Smart Struct. Syst. 13 (6) (2014) 1065-1094, https://doi.org/10.12989/sss.2014.13.6.1065.

[60] T. Omar, M.L. Nehdi, Remote sensing of concrete bridge decks using unmanned aerial vehicle infrared thermography, Automat. Constr. 83 (2017) 360-371, https://doi.org/10.1016/j.autcon.2017.06.024.

[61] F. Xu, Q. Jiang, Dynamic obstacle-surmounting analysis of a bilateral-wheeled cable-climbing robot for cable-stayed bridges, Industrial Robot: the international journal of robotics research and application 46 (3) (2019) 431-443, https://doi.org/10.1108/IR-07-2018-0152.

[62] H. Yun, S. Kim, L. Wu, J. Lee, Development of inspection robots for bridge cables, The Scientific World Journal 2013 (2013) 1-17, https://doi.org/10.1155/2013/967508.

[63] S. Phillips, S. Narasimhan, Automating data collection for robotic bridge inspections, J. Bridge Eng. 24 (2019), https://doi.org/10.1061/(ASCE)BE.1943-5592.0001442.

[64] Y.N. Yang, M.M. Kumaraswamy, H.J. Pam, G. Mahesh, Integrated qualitative and quantitative methodology to assess validity and credibility of models for bridge maintenance management system development, J. Manage. Eng. 27 (3) (2011) 149-158, https://doi.org/10.1061/(ASCE)ME.1943-5479.0000051.

[65] Y. An, E. Chatzi, S. Sim, S. Laflamme, B. Blachowski, J. Ou, Recent progress and future trends on damage identification methods for bridge structures, Struct. Control Hlth. 26 (2019), https://doi.org/10.1002/stc.2416.

[66] Y.B. Yang, J.P. Yang, State-of-the-Art review on modal identification and damage detection of

bridges by moving test vehicles, Int. J. Struct. Stab. Dy. 18 (2018), https://doi.org/10.1142/S0219455418500256.
[67] S. Li, S. Wei, Y. Bao, H. Li, Condition assessment of cables by pattern recognition of vehicle-induced cable tension ratio, Eng. Struct. 155 (2018) 1-15, https://doi.org/10.1016/j.engstruct.2017.09.063.
[68] J.M. van Noortwijk, A survey of the application of gamma processes in maintenance, Reliab. Eng. Syst. Safe. 94 (1) (2009) 2-21, https://doi.org/10.1016/j.ress.2007.03.019.
[69] W. Lin, N. Taniguchi, T. Yoda, Novel method for retrofitting superstructures and piers in aged steel railway bridges, J. Bridge Eng. 22 (2017), https://doi.org/10.1061/(ASCE)BE.1943-5592.0001120.
[70] A. Parghi, M.S. Alam, Seismic behavior of deficient reinforced concrete bridge piers confined with FRP - a fractional factorial analysis, Eng. Struct. 126 (2016) 531-546, https://doi.org/10.1016/j.engstruct.2016.08.011.
[71] W. Ren, L.H. Sneed, Y. Gai, X. Kang, Test results and nonlinear analysis of RC t-beams strengthened by bonded steel plates, International Journal of Concrete Structures and Materials 9 (2) (2015) 133-143, https://doi.org/10.1007/s40069-015-0098-3.
[72] D. Isailović, V. Stojanovic, M. Trapp, R. Richter, R. Hajdin, J. Döllner, Bridge damage: Detection, IFC-based semantic enrichment and visualization, Automat. Constr. 112 (2020) 103088, https://doi.org/10.1016/j.autcon.2020.103088.
[73] A. Li, Y. Ding, H. Wang, T. Guo, Analysis and assessment of bridge health monitoring mass data—progress in research/development of “Structural Health Monitoring”, Science China Technological Sciences 55 (8) (2012) 2212-2224, https://doi.org/10.1007/s11431-012-4818-5.
[74] A. Miyamoto, A. Yabe, Development of practical health monitoring system for short- and medium-span bridges based on vibration responses of city bus, Journal of Civil Structural Health Monitoring 2 (1) (2012) 47-63, https://doi.org/10.1007/s13349-012-0017-0.
[75] C. Koch, S.G. Paal, A. Rashidi, Z. Zhu, M. König, I. Brilakis, Achievements and challenges in machine Vision-Based inspection of large concrete structures, Adv. Struct. Eng. 17 (3) (2014) 303-318, https://doi.org/10.1260/1369-4332.17.3.303.
[76] G. Morgenthal, N. Hallermann, J. Kersten, J. Taraben, P. Debus, M. Helmrich, V. Rodehorst, Framework for automated UAS-based structural condition assessment of bridges, Automat. Constr. 97 (2019) 77-95, https://doi.org/10.1016/j.autcon.2018.10.006.
[77] A. Khaloo, D. Lattanzi, K. Cunningham, R. Dell'Andrea, M. Riley, Unmanned aerial vehicle inspection of the Placer River Trail Bridge through image-based 3D modelling, Struct. Infrastruct. E. 14 (1) (2018) 124-136, https://doi.org/10.1080/15732479.2017.1330891.
[78] R. Sandoval, A. Garcia-Sanchez, F. Garcia-Sanchez, J. Garcia-Haro, Evaluating the More Suitable ISM Frequency Band for IoT-Based Smart Grids: A Quantitative Study of 915 MHz vs. 2400 MHz, Sensors 17 (12) (2017) 76, https://doi.org/10.3390/s17010076.
[79] L.Y. Sui, Z.H. Chen, W. Li, L.X. Wang, Study on Monitoring and Safety Early Warning Technology of Bridge Health Based on Internet of Things Technology, Applied Mechanics and Materials 556-562 (2014) 5994-5998, https://doi.org/10.4028/www.scientific.net/AMM.556-562.5994.
[80] M. Aguero, A. Ozdagli, F. Moreu, Measuring Reference-Free total displacements of piles and columns using Low-Cost, Battery-Powered, efficient wireless intelligent sensors (LEWIS2), Sensors 19 (7) (2019) 1549, https://doi.org/10.3390/s19071549.
[81] G. Zhou, M. Xie, T. Yi, H. Li, Optimal wireless sensor network configuration for structural monitoring

using automatic-learning firefly algorithm, Adv. Struct. Eng. 22 (4) (2019) 907-918, https://doi.org/10.1177/1369433218797074.

[82] Y. Xu, Y. Turkan, BrIM and UAS for bridge inspections and management, Engineering, Construction and Architectural Management 27 (3) (2019) 785-807, https://doi.org/10.1108/ECAM-12-2018-0556.

[83] E. Merschman, M. Doustmohammadi, A.M. Salman, M. Anderson, Postdisaster decision framework for bridge repair prioritization to improve road network resilience, Transportation Research Record: Journal of the Transportation Research Board 2674 (3) (2020) 81-92, https://doi.org/10.1177/0361198120908870.

[84] B.C. Croop, P. Thompson, T. Ahlborn, C.N. Brooks, J. Puckett, M. Fyrster, T.P. Murphy, M. Lopez, D.M. Banach, The Use of Element Level Data & Bridge Management Software in the Network Analysis of Big Bridges, No. 0R14-022. 2017. [Online]. Available https://trid.trb.org/view/1506624

[85] P. Sprengholz, C. Betsch, Ok google: using virtual assistants for data collection in psychological and behavioral research, Behavior Research Methods 54 (3) (2022) 1227-1239, https://doi.org/10.3758/s13428-021-01629-y.

[86] Y. Li, M.M. Karim, R. Qin, A virtual-reality-based training and assessment system for bridge inspectors with an assistant drone, IEEE T. Hum.-Mach. Syst. 52 (4) (2022) 591-601, https://doi.org/10.1109/THMS.2022.3155373.

[87] H. Hemingway, F.W. Asselbergs, J. Danesh, R. Dobson, N. Maniadakis, A. Maggioni, G. van Thiel, M. Cronin, G. Brobert, P. Vardas, S.D. Anker, D.E. Grobbee, S. Denaxas, Big data from electronic health records for early and late translational cardiovascular research: Challenges and potential, Eur. Heart J. 39 (16) (2018) 1481-1495, https://doi.org/10.1093/eurheartj/ehx487.

[88] E. Menditto, D.G.A. Bolufer, C. Cahir, A. Marengoni, S. Riegler, G. Fico, E. Costa, A. Monaco, S. Pecorelli, L. Pani, A. Prados-Torres, Scaling up health knowledge at European level requires sharing integrated data: An approach for collection of database specification, Clinicoecon Outcomes Res 8 (2016) 253-265, https://doi.org/10.2147/CEOR.S97548.

[89] D. Agdas, J.A. Rice, J.R. Martinez, I.R. Lasa, Comparison of visual inspection and Structural-Health monitoring as bridge condition assessment methods, J. Perform. Constr. Fac. 30 (2016), https://doi.org/10.1061/(ASCE)CF.1943-5509.0000802.

[90] R. Ma, S. Xu, D. Wang, A. Chen, Vehicle models for fatigue loading on steel box-girder bridges based on weigh-in-motion data, Struct. Infrastruct. E. 14 (6) (2018) 701-713, https://doi.org/10.1080/15732479.2017.1359308.

[91] R. Soman, M. Kyriakides, T. Onoufriou, W. Ostachowicz, Numerical evaluation of multi-metric data fusion based structural health monitoring of long span bridge structures, Struct. Infrastruct. E. 14 (6) (2018) 673-684, https://doi.org/10.1080/15732479.2017.1350984.

[92] K. Liu, N. El-Gohary, Ontology-based semi-supervised conditional random fields for automated information extraction from bridge inspection reports, Automat. Constr. 81 (2017) 313-327, https://doi.org/10.1016/j.autcon.2017.02.003.

[93] P. Tierney, A qualitative analysis framework using natural language processing and graph theory, International review of research in open and distance learning 13 (5) (2012) 173-189, https://doi.org/10.19173/irrodl.v13i5.1240.

[94] H. Xu, S.P. Stenner, S. Doan, K.B. Johnson, L.R. Waitman, J.C. Denny, MedEx: A medication information extraction system for clinical narratives, J. Am. Med. Inform. Assn. 17 (1) (2010) 19-24,

https://doi.org/10.1197/jamia.M3378.

[95] Q. Li, H. Zhai, L. Deleger, T. Lingren, M. Kaiser, L. Stoutenborough, I. Solti, A sequence labeling approach to link medications and their attributes in clinical notes and clinical trial announcements for information extraction, J. Am. Med. Inform. Assn. 20 (5) (2013) 915-921, https://doi.org/10.1136/amiajnl-2012-001487.

[96] J. Zhang, N.M. El-Gohary, Semantic NLP-Based information extraction from construction regulatory documents for automated compliance checking, J. Comput. Civil Eng. 30 (2) (2016), https://doi.org/10.1061/(ASCE)CP.1943-5487.0000346.

[97] E. Soysal, I. Cicekli, N. Baykal, Design and evaluation of an ontology based information extraction system for radiological reports, Comput. Biol. Med. 40 (11-12) (2010) 900-911, https://doi.org/10.1016/j.compbiomed.2010.10.002.

[98] Z. Sun, H. Sun, Jiangyin Bridge: An Example of Integrating Structural Health Monitoring with Bridge Maintenance, Struct. Eng. Int. 28 (3) (2018) 353-356, https://doi.org/10.1080/10168664.2018.1462671.

[99] B. McGuire, R. Atadero, C. Clevenger, M. Ozbek, Bridge Information Modeling for Inspection and Evaluation, J. Bridge Eng. 21 (4) (2016), https://doi.org/10.1061/(ASCE)BE.1943-5592.0000850.

[100] N. Hoang, K. Liao, X. Tran, Estimation of scour depth at bridges with complex pier foundations using support vector regression integrated with feature selection, Journal of Civil Structural Health Monitoring 8 (2018) 431-442, https://doi.org/10.1007/s13349-018-0287-2.

[101] Z. Kala, Global sensitivity analysis of reliability of structural bridge system, Eng. Struct. 194 (1) (2019) 36-45, https://doi.org/10.1016/j.engstruct.2019.05.045.

[102] Y.F. Liu, X.P. Fan, Dynamic reliability prediction for the steel box girder based on multivariate Bayesian dynamic Gaussian copula model and SHM extreme stress data, Structural Control and Health Monitoring 27 (6) (2020), https://doi.org/10.1002/stc.2531.

[103] J.S. Kong, D.M. Frangopol, Life-Cycle Reliability-Based Maintenance Cost Optimization of Deteriorating Structures with Emphasis on Bridges, Journal of structural engineering 129 (6) (2003) 818-828, https://doi.org/10.1061/(ASCE)0733-9445(2003)129:6(818).

[104] S. Kim, D.M. Frangopol, Efficient multi-objective optimisation of probabilistic service life management, Struct. Infrastruct. E. 13 (1) (2017) 147-159, https://doi.org/10.1080/15732479.2016.1198405.

[105] S. Sabatino, D.M. Frangopol, Y. Dong, Life cycle utility-informed maintenance planning based on lifetime functions: optimum balancing of cost, failure consequences and performance benefit, Struct. Infrastruct. E. 12 (7) (2016) 830-847, https://doi.org/10.1080/15732479.2015.1064968.

[106] S. Kim, D.M. Frangopol, Multi-objective probabilistic optimum monitoring planning considering fatigue damage detection, maintenance, reliability, service life and cost, Structural and Multidisciplinary Optimization 57 (2018) 39-54, https://doi.org/10.1007/s00158-017-1849-3.

[107] D. Saydam, D.M. Frangopol, Time-dependent performance indicators of damaged bridge superstructures, Eng. Struct. 33 (9) (2011) 2458-2471, https://doi.org/10.1016/j.engstruct.2011.04.019.

[108] S. Yang, D.M. Frangopol, L.C. Neves, Optimum maintenance strategy for deteriorating bridge structures based on lifetime functions, Eng. Struct. 28 (2) (2006) 196-206, https://doi.org/10.1016/j.engstruct.2005.06.024.

[109] G. Jia, P. Gardoni, Stochastic life-cycle analysis: Renewal-theory life-cycle analysis with state-

dependent deterioration stochastic models, Struct. Infrastruct. E. 15 (8) (2019) 1001-1014, https://doi.org/10.1080/15732479.2019.1590424.

[110] A. Manafpour, I. Guler, A. Radlinska, F. Rajabipour, G. Warn, Stochastic analysis and Time-Based modeling of concrete bridge deck deterioration, J. Bridge Eng. 23 (2018), https://doi.org/10.1061/(ASCE)BE.1943-5592.0001285.

[111] R. Kumar, D.B.H. Cline, P. Gardoni, A stochastic framework to model deterioration in engineering systems, Struct. Saf. 53 (2015) 36-43, https://doi.org/10.1016/j.strusafe.2014.12.001.

[112] G. Jia, P. Gardoni, State-dependent stochastic models: A general stochastic framework for modeling deteriorating engineering systems considering multiple deterioration processes and their interactions, Struct. Saf. 72 (2018) 99-110, https://doi.org/10.1016/j.strusafe.2018.01.001.

[113] G. Jia, P. Gardoni, Simulation-based approach for estimation of stochastic performances of deteriorating engineering systems, Probabilist. Eng. Mech. 52 (2018) 28-39, https://doi.org/10.1016/j.probengmech.2018.03.001.

[114] S. Ranjith, S. Setunge, R. Gravina, S. Venkatesan, Deterioration prediction of timber bridge elements using the markov chain, J. Perform. Constr. Fac. 27 (3) (2013) 319-325, https://doi.org/10.1061/(ASCE)CF.1943-5509.0000311.

[115] P.D. Thompson, E.P. Small, M. Johnson, A.R. Marshall, The pontis bridge management system, Struct. Eng. Int. 8 (4) (1998) 303-308, https://doi.org/10.2749/101686698780488758.

[116] Z. Tao, R.B. Corotis, J.H. Ellis, Reliability-based bridge design and life cycle management with Markov decision processes, Struct. Saf. 16 (1) (1994) 111-132, https://doi.org/https://doi.org/10.1016/0167-4730(94)00030-T.

[117] Y. Huang, Artificial neural network model of bridge deterioration, J. Perform. Constr. Fac. 24 (6) (2010) 597-602, https://doi.org/10.1061/(ASCE)CF.1943-5509.0000124.

[118] R. Assaad, I.H. El-Adaway, Bridge infrastructure asset management system: Comparative computational machine learning approach for evaluating and predicting deck deterioration conditions, J. Infrastruct. Syst. 26 (2020), https://doi.org/10.1061/(ASCE)IS.1943-555X.0000572.

[119] Z. Hu, X. Fang, J. Zhang, A digital twin-based framework of manufacturing workshop for marine diesel engine, The International Journal of Advanced Manufacturing Technology 117 (2021) 3323-3342, https://doi.org/10.1007/s00170-021-07891-w.

[120] D. Dan, Y. Ying, L. Ge, Digital twin system of bridges group based on machine vision fusion monitoring of bridge traffic load, IEEE T. Intell. Transp. (2021) 1-16, https://doi.org/10.1109/TITS.2021.3130025.

[121] J. Kang, K. Chung, E.J. Hong, Multimedia knowledge-based bridge health monitoring using digital twin, Multimed. Tools Appl. 80 (2021) 34609-34624, https://doi.org/10.1007/s11042-021-10649-x.

[122] T. Echaveguren, P. Dechent, M. Giuliano, J. Sepulveda, Proposal of a condition index for maintenance of runway beams, Proceedings of the Institution of Civil Engineers - Structures and Buildings 167 (6) (2014) 369-379, https://doi.org/10.1680/stbu.11.00078.

[123] S. Valenzuela, H. de Solminihac, T. Echaveguren, Proposal of an integrated index for prioritization of bridge maintenance, J. Bridge Eng. 15 (3) (2010) 337-343, https://doi.org/10.1061/(ASCE)BE.1943-5592.0000068.

[124] T. Echaveguren, P. Dechent, D.C. Universidad, Allocation of bridge maintenance costs based on prioritization indexes, Revista de la construcción (Universidad Católica de Chile) 18 (3) (2019)

568-578, https://doi.org/10.7764/RDLC.18.3.568.

[125] S. Wei, Y. Bao, H. Li, Optimal policy for structure maintenance: A deep reinforcement learning framework, Struct. Saf. 83 (2020) 101906, https://doi.org/10.1016/j.strusafe.2019.101906.

[126] S. Hou, H. Li, Y. Rezgui, Ontology-based approach for structural design considering low embodied energy and carbon, Energ. Buildings 102 (2015) 75-90, https://doi.org/10.1016/j.enbuild.2015.04.051.

[127] J. Zhang, H. Li, Y. Zhao, G. Ren, An ontology-based approach supporting holistic structural design with the consideration of safety, environmental impact and cost, Adv. Eng. Softw. 115 (2018) 26-39, https://doi.org/10.1016/j.advengsoft.2017.08.010.

[128] K. Meng, C. Cui, H. Li, An ontology framework for pile integrity evaluation based on analytical methodology, IEEE Access 8 (2020) 72158-72168, https://doi.org/10.1109/ACCESS.2020.2986229.

[129] R. Helmerich, B. Kühn, A. Nussbaumer, Assessment of existing steel structures. A guideline for estimation of the remaining fatigue life, Struct. Infrastruct. E. 3 (3) (2007) 245-255, https://doi.org/10.1080/15732470500365562.

[130] C. Shim, H. Kang, N. S. Dang, D. Lee, Development of BIM-based bridge maintenance system for cable-stayed bridges, Smart Structures and Systems, 20(6) (2017) 697–708, https://doi.org/10.12989/sss.2017.20.6.697.

[131] C. Yang, Q. Huang, Z. Li, K. Liu, F. Hu, Big Data and cloud computing: Innovation opportunities and challenges, Int. J. Digit. Earth 10 (1) (2017) 13-53, https://doi.org/10.1080/17538947.2016.1239771.

[132] Y.F. Duan, Y.L. Xu, Q.G. Fei, K.Y. Wong, K.W.Y. Chan, Y.Q. Ni, C.L. Ng, Advanced finite element model of tsing ma bridge for structural health monitoring, Int. J. Struct. Stab. Dy. 11 (02) (2011) 313-344, https://doi.org/10.1142/S0219455411004117.

[133] H. Yang, M. Guo, L. Wang, Y. Hou, Q. Zhao, D. Cao, B. Zhou, D. Wang, Investigation on the factors influencing the performance of piezoelectric energy harvester, Road Mater. Pavement 18 (2017) 180-189, https://doi.org/10.1080/14680629.2017.1329873.

[134] P. Forsythe, Proactive construction safety systems and the human factor, Proceedings of the Institution of Civil Engineers - Management, Procurement and Law 167 (5) (2014) 242-252, https://doi.org/10.1680/mpal.13.00055.

[135] K. Grolinger, W.A. Higashino, A. Tiwari, M.A. Capretz, Data management in cloud environments: NoSQL and NewSQL data stores, Journal of cloud computing : advances, systems and applications 2 (1) (2013) 22-24, https://doi.org/10.1186/2192-113x-2-22.

[136] S. Lee, Y. Jeong, A system integration framework through development of ISO 10303-based product model for steel bridges, Automat. Constr. 15 (2) (2006) 212-228, https://doi.org/10.1016/j.autcon.2005.05.004.

[137] J. Bien, Modelling of structure geometry in Bridge Management Systems, Arch. Civ. Mech. Eng. 11 (3) (2011) 519-532, https://doi.org/10.1016/S1644-9665(12)60099-5.

[138] P. Huthwohl, I. Brilakis, A. Borrmann, R. Sacks, Integrating RC Bridge Defect Information into BIM Models, J. Comput. Civil Eng. 32 (3) (2018), https://doi.org/10.1061/(ASCE)CP.1943-5487.0000744.

[139] R. Sacks, A. Kedar, A. Borrmann, L. Ma, I. Brilakis, P. Hüthwohl, S. Daum, U. Kattel, R. Yosef, T. Liebich, B.E. Barutcu, S. Muhic, SeeBridge as next generation bridge inspection: Overview, Information Delivery Manual and Model View Definition, Automat. Constr. 90 (2018) 134-145,

https://doi.org/10.1016/j.autcon.2018.02.033.

[140] K. Afsari, C.M. Eastman, D. Castro-Lacouture, JavaScript Object Notation (JSON) data serialization for IFC schema in web-based BIM data exchange, Automat. Constr. 77 (2017) 24-51, https://doi.org/10.1016/j.autcon.2017.01.011.

[141] C.M. Eastman, Y.S. Jeong, R. Sacks, I. Kaner, Exchange model and exchange object concepts for implementation of national BIM standards, J. Comput. Civil Eng. 24 (1) (2010) 25-34, https://doi.org/10.1061/(ASCE)0887-3801(2010)24:1(25).

[142] Y. Ji, A. Borrmann, J. Beetz, M. Obergrießer, Exchange of parametric bridge models using a neutral data format, J. Comput. Civil Eng. 27 (6) (2013) 593-606, https://doi.org/10.1061/(ASCE)CP.1943-5487.0000286.

[143] Y. Lee, C.M. Eastman, W. Solihin, Logic for ensuring the data exchange integrity of building information models, Automat. Constr. 93 (2018) 388-401, https://doi.org/10.1016/j.autcon.2018.06.002.

[144] X. Tao, Y. Liu, P.K. Wong, K. Chen, M. Das, J.C.P. Cheng, Confidentiality-minded framework for blockchain-based bim design collaboration, Automat. Constr. 136 (2022) 104172, https://doi.org/10.1016/j.autcon.2022.104172.

[145] J. Xu, H. Liu, Q. Han, Blockchain technology and smart contract for civil structural health monitoring system, Comput.-Aided Civ. Inf. 36 (10) (2021) 1288-1305, https://doi.org/10.1111/mice.12666.

[146] M. Das, X. Tao, J.C.P. Cheng, Bim security: a critical review and recommendations using encryption strategy and blockchain, Automat. Constr. 126 (2021), https://doi.org/10.1016/j.autcon.2021.103682.

[147] N.O. Nawari, S. Ravindran, Blockchain and the built environment: potentials and limitations, Journal of Building Engineering 25 (2019), https://doi.org/10.1016/j.jobe.2019.100832.

[148] A.S. Erri Pradeep, T.W. Yiu, Y. Zou, R. Amor, Blockchain-aided information exchange records for design liability control and improved security, Automat. Constr. 126 (2021), https://doi.org/10.1016/j.autcon.2021.103667.

[149] R. Zheng, J. Jiang, X. Hao, W. Ren, F. Xiong, Y. Ren, Bcbim: a blockchain-based big data model for bim modification audit and provenance in mobile cloud, Math. Probl. Eng. 2019 (2019) 1-13, https://doi.org/10.1155/2019/5349538.

[150] F. Xue, W. Lu, A semantic differential transaction approach to minimizing information redundancy for bim and blockchain integration, Automat. Constr. 118 (2020), https://doi.org/10.1016/j.autcon.2020.103270.

[151] N. Nizamuddin, K. Salah, M. Ajmal Azad, J. Arshad, M.H. Rehman, Decentralized document version control using ethereum blockchain and IPFS, Computers & Electrical Engineering, 76 (2019) 183-197, https://doi.org/10.1016/j.compeleceng.2019.03.014.

[152] X. Tao, M. Das, Y. Liu, J.C.P. Cheng, Distributed common data environment using blockchain and interplanetary file system for secure bim-based collaborative design, Automat. Constr. 130 (2021), https://doi.org/10.1016/j.autcon.2021.103851.

[153] M. Cheng, G. Liu, Y. Xu, M. Chi, When blockchain meets the aec industry: present status, benefits, challenges, and future research opportunities, Buildings 11 (8) (2021) 340, https://doi.org/10.3390/buildings11080340.

[154] V. Plevris, N.D. Lagaros, A. Zeytinci, Blockchain in civil engineering, architecture and

construction industry: state of the art, evolution, challenges and opportunities, Frontiers in Built Environment 8 (2022), https://doi.org/10.3389/fbuil.2022.840303.

[155] T. Guzsvinecz, V. Szucs, C. Sik-Lanyi, Suitability of the kinect sensor and leap motion controller—a literature review, Sensors 19 (5) (2019) 1072, https://doi.org/10.3390/s19051072.