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School of Engineering, Design and Built Environment

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Development of Bridge Information Model (BrIM) for Digital Twinning and Management Using TLS Technology

By:

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May 2023

Certificate of Authorship/Originality

I confirm that the work in this thesis has not previously been submitted for a degree or as part of degree requirements, except as fully acknowledged within the manuscript. I also certify that this thesis has been written by myself. Any assistance that I have received in my research study and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated and acknowledged.

Masoud Mohammadi [redacted]

May 2023

Abstract

In the current modern era of information and technology, the concept of Building Information Model (BIM), has made revolutionary changes in different aspects of engineering design, construction, and management of infrastructure assets, especially bridges. In the field of bridge engineering, Bridge Information Model (BrIM), as a specific form of BIM, includes digital twining of the physical asset associated with geometrical inspections and non-geometrical data, which has eliminated the use of traditional paper-based documentation and hand-written reports, enabling professionals and managers to operate more efficiently and effectively. However, concerns remain about the quality of the acquired inspection data and utilizing BrIM information for remedial decisions in a reliable Bridge Management System (BMS) which are still reliant on the knowledge and experience of the involved inspectors, or asset manager, and are susceptible to a certain degree of subjectivity. Therefore, this research study aims not only to introduce the valuable benefits of Terrestrial Laser Scanning (TLS) as a precise, rapid, and qualitative inspection method, but also to serve a novel sliced-based approach for bridge geometric Computer-Aided Design (CAD) model extraction using TLS-based point cloud, and to contribute to BrIM development. Moreover, this study presents a comprehensive methodology for incorporating generated BrIM in a redeveloped element-based condition assessment model while integrating a Decision Support System (DSS) to propose an innovative BMS. This methodology was further implemented in a designed software plugin and validated by a real case study on the Werrington Bridge, a cable-stayed bridge in New South Wales, Australia. The finding of this research confirms the reliability of the TLS-derived 3D model in terms of quality of acquired data and accuracy of the proposed novel slice-based method, as well as BrIM implementation, and integration of the proposed BMS into the developed BrIM. Furthermore, the results of this study showed that the proposed integrated model addresses the subjective nature of decision-making by conducting a risk assessment and utilising structured decision-making tools for priority ranking of remedial actions. The findings demonstrated acceptable agreement in utilizing the proposed BMS for priority ranking of structural elements that require more attention, as well as efficient optimisation of remedial actions to preserve bridge health and safety.

Keywords: Bridge Information Model (BrIM), Bridge Management System (BMS); Bridge Condition Assessment; Decision Support System (DSS); Terrestrial Laser Scanning (TLS); Digital Twinning; Digital infrastructure; Digital transformation

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Anthology of Dissemination

This dissertation is based on a compilation of journal papers that were written and published over the course of this study based on the aims and objectives of this research topic. To fulfil the Western Sydney University (WSU) requirement of a PhD by publication, the thesis includes four published articles, and one published international conference paper supporting different chapters, as follows:

1) Literature review: "A Decade of Modern Bridge Monitoring Using Terrestrial Laser Scanning: Review and Future Directions", Remote Sens. 2020, 12(22), 3796; https://doi.org/10.3390/rs12223796. Q1 with Impact Factor (IF) 4.2 in 2020.

2) Preliminary analysis: "Quality Evaluation of Digital Twins Generated Based on UAV Photogrammetry and TLS: Bridge Case Study", Remote Sens. 2021, 13(17), 3499; https://doi.org/10.3390/rs13173499. Q1 with IF. 4.8 in 2021.

3) Methodology and results: "Application of TLS Method in Digitization of Bridge Infrastructures: A Path to BrIM Development", Remote Sens. Journal, 2022, 14(5), 1148; https://doi.org/10.3390/rs14051148. Q1 with IF. 5.3 in 2022.

4) Methodology and results: "Integration of TLS-Derived Bridge Information Modeling (BrIM) with a Decision Support System (DSS) for Digital Twinning and Asset Management of Bridge Infrastructures", Computers in Industry, 2023, 147; https://doi.org/10.1016/j.compind.2023.103881, Q1 with IF 11.24 in 2023.

Based on the findings of this research project, the following conference paper was prepared and orally presented at the SHMII conference in Potro, Portugal.

5) Preliminary analysis: "Case study on accuracy comparison of digital twins developed for a heritage bridge via UAV photogrammetry and terrestrial laser scanning", Proceedings of the 10th International Conference on Structural Health Monitoring of Intelligent Infrastructure (SHMII), Porto, Portugal, 30 June - 2 July 2021, 1713-1720; https://hdl.handle.net/1959.7/uws:62196.

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Nomenclature

BIM	Building Information Model
BrIM	Bridge Information Model
SHM	Structural Health Monitoring
BMS	Bridge Management System
TLS	Terrestrial Laser scanning
UAV	Unmanned Aerial Vehicle
CAD	Computer-Aided Design
LoD	Level of Detail
RGB	Red-Green-Blue
FEM	Finite Element Model
STD	Standard Deviation
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
C2C	Cloud-to-Cloud
AI	Artificial Intelligence
IoT	Internet of Thing
PRCI	Priority Rating Condition Index
DSS	Decision Support System
AHP	Analytical Hierarchy Process
SMART	Simple Multi-Attribute Rating Technique

Chapter 1

(Introduction)

1.1. General

This chapter presents a general overview of the proposed topic on development of Bridge Information Model (BrIM) and Bridge Management System (BMS) for bridge health monitoring using Terrestrial Laser Scanning (TLS) as the state-of-the-art emerging technology. This includes a summary of the research background, significance of research topic, research methodology as well as research motivations, and objectives. Moreover, the research outlines of the proposal are presented at end of the chapter.

1.2. Introduction

Within the past decade, the need for inspection, assessment, and management in the construction industry has been significantly increased. A Large number of Infrastructures, particularly bridges, were constructed after the Second World War in the late 1940s, longer than 50 years ago while still being operated (Riveiro and Lindenbergh, 2019). Most of these bridges were designed based on old standards and needed to be rehabilitated during their lifetime. Based on the most recent infrastructure report of the American Society of Civil Engineering (ASCE), more than 40% of the American bridges are older than 50 years and more than 13.6% are functionally obsolete (American Society of Civil Engineering (ASCE), 2017). A large proportion of the United Kingdom's bridge assets were constructed from the late 1950s (Rashidi and Gibson, 2012). Similar trends were also found in other countries such as Australia, Japan and European nations (Rashidi et al., 2016a, Žnidarič et al., 2011, Fujino and Siringoringo, 2008), Fig. 1-1.

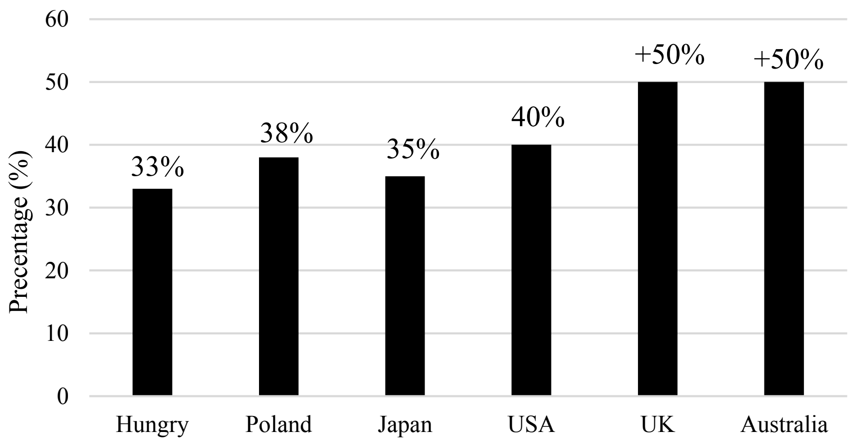


Figure 1-1 Bridges with more than 50 years old around the world

The catastrophic Morandi Bridge collapse in 2018 in Italy with cost of 44 lives of individuals and also River Bridge collapse, the third busiest bridge in Minnesota, the USA in 2007 with killing 13 people and 145 injured people are two highlighted examples of the negligence in having effective maintenance strategy for leady ways of a transport system. Considering an average service life of 70 years, excessive usage, increasing traffic load, overloading, and aggressive environmental effects are influential conditions which significantly cause adverse impacts on the bridge operation/performance. However, such conditions are considered in new standards, employing conservative management and accurate inspection methods can be undeniably effective. Although several management methods have been implemented in traditional work frames, a newer method has been well developed by the use of Bridge Information Modelling (BrIM) during the last decade (Kaewunruen et al., 2020, Andriasyan et al., 2020, Woetzel et al., 2017). BrIM pertains to specific application of Building Information Modelling (BIM) in terms of bridge engineering, referring to creation of three-dimensional Computer-Aided Design (CAD) model with additional geometrical and non-geometrical information, cost estimation, energy consumption, management and assessment methods, as well as maintenance strategies, etc. (Eastman et al., 2018). In this respect, the development of the Building Information Model (BIM) in recent years, has led to a transformation in the digitalization of structural assets and their information in form of a digital twin. This information can then be widely disseminated amongst the stakeholders involved, assisting bridge manager, assessors, and their future decisions. Despite the fact that BrIM is an innovative method for storing varied information, two challenges remain in terms of: 1) creating an accurate visual representation and collecting reliable information in a timely manner, and 2) utilizing this data for management purposes in a reliable Bridge Management System (BMS).

To address the first challenge in this research study, the Terrestrial Laser scanning (TLS) technology was utilized as a reliable, and fast inspection method for capturing detailed geometrical information of the bridge structure. During this research study, the capabilities of using TLS technology in terms of quality and accuracy of data were compared to technologies such as areal photogrammetry in actual bridge case studies. Furthermore, a novel sliced-based method was also developed to use TLS data and generate a TLS-derived 3D model and BrIM.

Moreover, in response to the second concern, this research study provides a thorough methodology to not only use the valuable benefits of having a detailed TLS-derived BrIM but also present a multi-criteria decision support tool that integrates a BMS, targeting a powerful bridge asset management system with more reliable bridge management decisions in remediation strategy planning using BrIM data. During this study, a redeveloped approach for calculating the Priority Rating Condition Index (PRCI) of all bridge element types is elaborated. This approach is then expanded to a Decision Support System (DSS) for optimising major bridge maintenance plans within acceptable safety, functionality, and sustainability boundaries. This methodology is further illustrated and validated using a real bridge case study, Werrington Bridge, a cable-stayed bridge in New South Wales, Australia.

1.3. Background

Over the last decade, the possibility of extracting detailed geometric information/conditions as the basis of creating a precise 3D computer model has made TLS a high-potential instrument for structural texture mappings (Sánchez-Aparicio et al., 2018, Sánchez-Aparicio et al., 2014), surface quality inspections (Teza et al., 2009, Mizoguchi et al., 2013), structural assessments (Hermida et al., 2020, Yang et al., 2019, Miśkiewicz et al., 2019, Kushwaha et al., 2019, Bassier et al., 2019), and managements (Kaewunruen et al., 2020, Andriasyan et al., 2020, Woetzel et al., 2017). During this time, the utilization of highly accurate laser scanning data, for capturing the geometry information of bridges as an input bridge information has meaningfully increased (Tang et al., 2007, Riveiro and Lindenbergh, 2019, Tang et al., 2010). In terms of bridge inspection and assessment, Fuchs et al. (2004) were among the key researchers who employed a laser-based instrument for bridge assessments of several highway bridges in the United States of America in 2004. In their research study, they employed the former technology of laser scanning to measure the deflections of bridge girders under static loading.

Besides, for many years bridge management approaches and condition assessments have been based on long-established manual paperwork and information retained from on-site inspectors and engineers (Rashidi et al., 2020b). These approaches have been primarily paper-based and significantly limit the ability to be readily transferred to asset managers or be referred after a few years. In this regard, Tang et al. (2007) were among the first researchers who suggested the application of laser scanning for not only bridge inspection but also management. In an effort, Tang et al. (2010) comprehensively reviewed the significance of using laser scanner in collecting information and bridge management. Moreover, Chan et al. (2016) emphasized that it is currently essential for bridge owners to make use of Bridge Information Model (BrIM) as a bridge database to store various sources and types of information such as bridge drawings, inspection reports, rehabilitation activities, condition state of elements, and history of decisions. In this respect, Sacks et al. (2016) presented an integrated bridge inspection/mapping system named SeeBridge. In the SeeBridge, a pre-existing bridge model is linked to engineers' data are used as references in a BrIM. Similarly, Dang et al. (2018) presented an updatable BrIM with the aims of bridge mapping for maintenance, including the 3D representation of the bridge link to the record records. In a recent study, Ying et al. (2019) described the advantage of using TLS as a valuable surveying instrument in conducting quality control of bridge element. In this research, the virtual pre-splicing of two steel beams using TLS was carried out for Fujiang Bridge in Tongnan, China. Similarly, Arashpour et al. (2019), developed a framework for quality control of off-site construction of structural components, in order to reduce on-site assembly discrepancy. All of this indicates that TLS can be a valuable asset not only for bridge geometrical inspection and digital twining, but also as a reference for BrIM development and management. The digital data can subsequently be widely disseminated among the stakeholders involved, supporting bridge managers in obtaining more reliable data as an input for management systems.

1.4. Research Motivations

Maintenance strategies are mainly depended on adopted monitoring and inspection methods, and employing traditional methods of monitoring such as general inspection by trained on-site inspectors are quite laborious, expensive, time-consuming and potentially unsafe. Besides that, any maintenance negligence or delayed actions may result in significant future costs. This can be of more significance when the structure is of especial usage or importance. The vital components of the road network system, especially bridges, are among the most susceptible and yet important structures that need to be accurately inspected and well-maintained. These important structures are often located in rugged terrains and built in places where access to them is difficult. Therefore, implementing an effective inspection method and periodic maintenance/rehabilitation strategy, and also having a reliable record of these information is essentially required. In this respect, adoption of a cost-effective method is another important factor that needs to be considered. In relation to cost-related matters, the most recent report of Roads and Maritime Service (RMS) of New South Wales (NSW) of Australia, currently known as Transport for NSW (TfNSW), in June 2019 (Transport for NSW office, 2019) announced that more than 28% of the NSW government budget were spent on managing and maintaining infrastructure assets, especially roads and bridges. All of this motivates the author to employ advanced technologies such as TLS and aerial photogrammetry not only to create an updatable reference 3D digital format of the bridge but also to create a BrIM for management purposes. Having this information in the long term not only reduces the excessive costs of traditional methods, but it is also possibly safe and reliable. Furthermore, integrating TLS-derived BrIM with a management system can assist engineers to gain a better understanding of the condition of the health of the bridge structure and enable them to make better decisions in bridge management or maintenance.

1.5. Research Aims and Objectives

This research study aims to address the two major research gaps/challenges in terms of, first, producing an accurate 3D representation of the bridge in a timely manner, and then, using this information for management purposes, by proposing a new method of BrIM creation based on TLS point cloud. In addition, in response to the second challenge, and in contrast to traditional paper-and-inventory-based Bridge Management Systems (BMSs), which rely on frameworks that are subject to subjectivity due to the varying experience and skill of the engineers involved. Instead, this research proposes a comprehensive methodology that not only leverages the advantages of a detailed TLS-derived BrIM but also incorporates a multi-criteria decision support tool, which integrates a BMS. This method aims to enhance bridge asset management and reduce subjectivity in decision-making. This system is expected to make more reliable management decisions in terms of remediation strategy planning using BrIM data. The overall objectives of this research study are highlighted as follows:

1- Evaluate the implication of TLS and TLS-based point clouds in terms of quality and accuracy for bridge inspection in comparison to other advanced technologies such as aerial photogrammetry.

2- Propose a practical methodology for 3D solid model reconstruction of bridges using point cloud data captured by TLS.

3- Develop a comprehensive methodology for Bridge Information Model (BrIM) creation having the bridge 3D solid model as geometrical information and connecting additional non-geometrical information to each bridge substructure.

4- Develop a BMS leveraging the created BrIM, integrating a redeveloped condition assessment model and decision support tool targeting a powerful bridge asset management system with more reliable bridge management decisions in remediation strategy planning.

5- Prove the soundness of the proposed methods in form of a real bridge case study and validate the outcomes by comparing the quality of TLS data, CAD model versus the as-designed CAD drawings, and illustrating the outcome in a BrIM-oriented BMS.

1.6. Research Methodology

To achieve the research aims and objectives mentioned, the proposed research study is divided into four major phases listed below:

1- Background reading based on a thorough literature search on utilizing new technologies, specifically TLS on bridge health monitoring, in terms of inspection, assessment, and management.

2- Conduct preliminary analysis, scan trials, and research on implication of TLS including experimental tests, data quality evaluation, and comparisons.

3- Utilizing the TLS point cloud in 3D CAD model extraction of bridge using innovative sliced-based approach and assigning non-geometrical information such as maintenance records and so on, to develop a BrIM.

4- Using BrIM data to establish a comprehensive Bridge Management System (BMS) including a redeveloped condition assessment model and a Decision Support System (DSS) for optimising major bridge maintenance plans within acceptable safety, functionality, and sustainability boundaries. The following flowchart, shown in Fig 1-2, summarises the outlines of this research study.

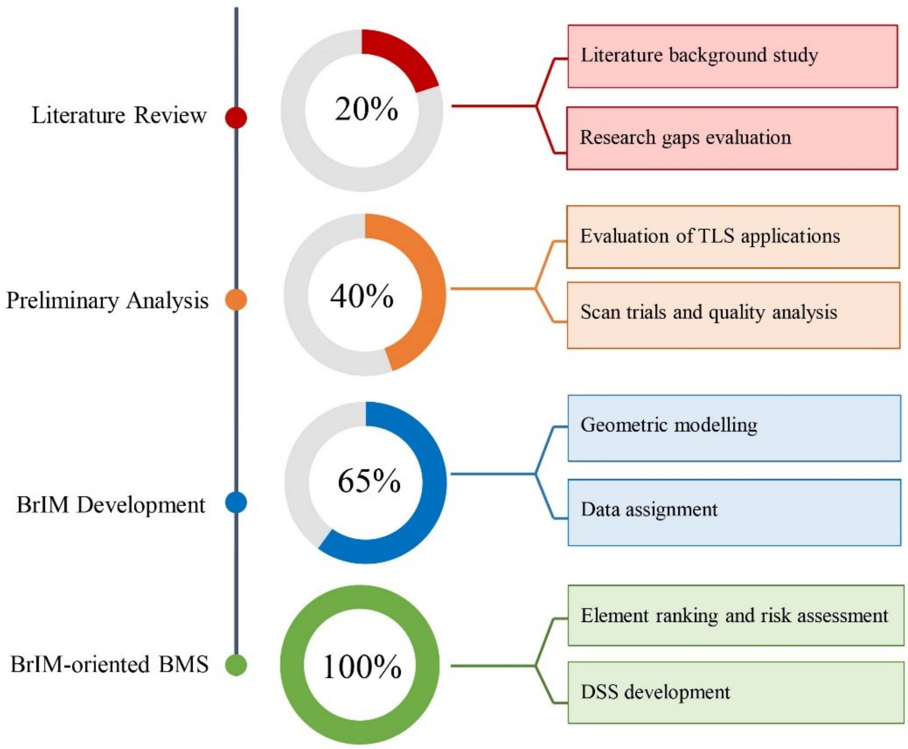


Figure 1-2 Summary of research methodology flowchart

1.7. Layout of thesis

As presented in Fig 1-3, the layout of this thesis is as follows:

Chapter 1 introduces the significance of bridge asset management, and the benefits of existing advanced technologies such as TLS and their applications in development of BrIM platforms for bridge inspection and management. Research background research gaps, aims and objectives of this study as well as research methodology, have been discussed throughout this chapter.

Chapter 2 reviewed the application of 3D laser scanning, as an emerging technology, for bridge engineering by means of a mixed scientometric and state-of-the-art review methods. This chapter investigates the application of TLS in bridge engineering to uncover the research experiences and identify the current research gaps and future directions. This chapter's contents have already been published as a journal paper and until November 2022, has been cited in over 57 papers worldwide.

Chapter 3 includes preliminary analysis and research on the implementation of TLS in terms of qualitative point cloud creation for detailed bridge inspection. This chapter provides a comprehensive methodology along with a thorough bridge case study to evaluate two digital point clouds developed from an existing Australian heritage bridge via both airborne photogrammetry and TLS. This chapter's contents have already been published as a journal paper in 2021 and have been cited in over 20 papers worldwide until November 2022.

Chapter 4 presents a novel sliced-based approach for bridge geometric Computer-Aided Design (CAD) model extraction, to be used as part of BrIM development. In this chapter, a practical methodology for TLS-derived BrIM development using detailed 3D model and connecting additional non-geometrical information are elaborated. This methodology was further verified and demonstrated via a case study on a cable-stayed bridge called Werrington Bridge, located in New South Wales (NSW), Australia. This chapter's contents have already been published as a journal paper in 2022.

Chapter 5 presents comprehensive methodology for using BrIM in a redeveloped element-based bridge condition assessment model, while integrating a Decision Support System (DSS) to make a reliable Bridge Management System (BMS). This method is further implemented in a designed plugin software and validated using a real bridge case study for Werrington Bridge.

Chapter 6 summarizes the key findings of this research study, including the results of the literature search, preliminary analysis, BrIM and BMS development, and their evaluations, as well as the future directions.

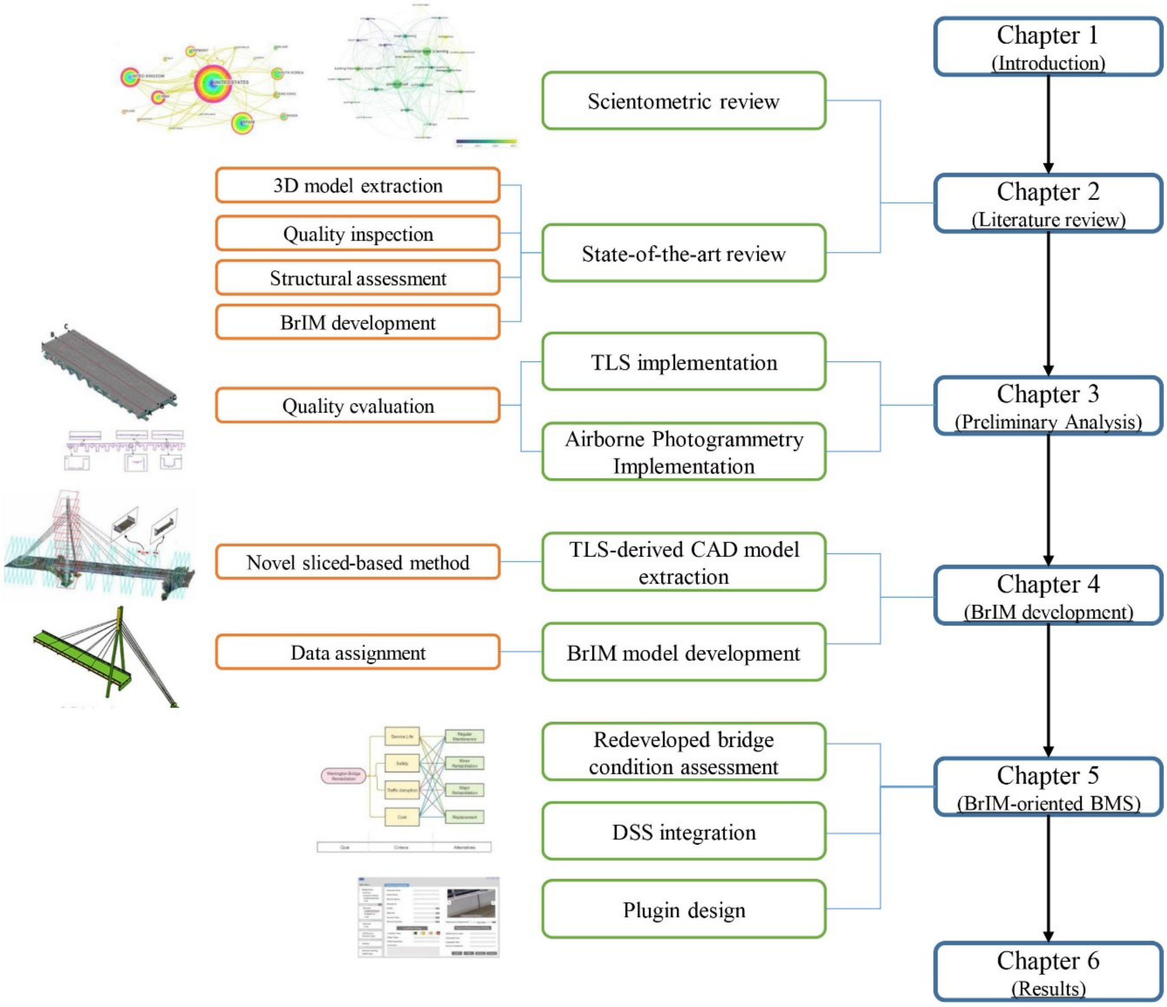


Figure 1-3 Layout of thesis

Chapter 2

(Literature Review)

A portion of the content of this chapter has been published as a journal paper titled "A Decade of Modern Bridge Monitoring Using Terrestrial Laser Scanning: Review and Future Directions", Remote Sens. 2020, 12(22), 3796; https://doi.org/10.3390/rs12223796. Q1 journal with an Impact Factor (IF) of 4.2 in 2020, and over 50 citations by other research studies worldwide until November 2022

2.1. Introduction

This chapter covers a thorough literature review on using laser scanning for bridge engineering and asset management by means of a mixed scientometric and stat-of-the-art review methods. It also investigates the application of terrestrial laser scanning (TLS) in different phases of bridge construction, operation and maintenance to explore recent research and identify the current research gaps and future directions. Following a brief overview of TLS development and capabilities, over 1500 research publications are collected, analysed and discussed through a scientometric literature search. The review is extended with a state-of-the-art review on applications of TLS in bridge engineering and asset management according to four major categories including (1) generation of 3D geometric model, (2) quality inspection, (3) structural assessment, and (4) Bridge Information Model (BrIM).

2.2. Overview of Terrestrial Laser Scanners

Terrestrial Laser Scanners, as its name implies, are ground-based surveying instruments which emit laser beams (electromagnetic light waves) onto the points of objects' surface, and make use of laser range finding to assign three-dimensional coordinates to each of the points reflected (Liu, 2010). In Oxford Dictionary (Bradbery and Lea, 2020), the rangefinder is defined as "an instrument for estimating how far away an object is", and according to Zámečníková et al. (2014), laser scanners determine distances based on the beam's wavelength electronically. Therefore, Terrestrial laser scanner (TLS) has an ancestor in the form of radar (stands for Radio detection and ranging), an electronic tool developed in the 1930s for estimating the object's location by measuring the time taken for a radio wave to be transmitted, reflected and return to the provider (Ou et al., 2020, Trim, 2002). Although radars were accurate enough to measure the location of vehicles, etc. as their general use, surveying and mapping requirements demand far greater precision. Since then, radar technology has improved such that it is now possible to use miniature radars to identify and scan small parts of an object (Riveiro and Lindenbergh, 2019).

Research studies and improvements on TLS as an advance technology, providing precise information, dates back to almost two decades ago, through the first and second decades of the 21st century. During this time, TLS units became lighter, more precise, less voluminous, and reflecting better ergonomics (Staiger, 2011). Moreover, a significant increase in data acquisition speed and accuracy enhancement were of great benefits concurrently occurred. Four generations of TLS development are as follows:

-1st generation, from 1997: Units are bulky and pulse-based, can capture data points between 1000 to 5000 per second with a range of 50 m to 200 m. Power source and data storage are external. Some representatives are RIEGL LMS Z210, CYRAX 2200 (Staiger, 2011).

-2nd generation, from 2002: Units operate with faster speed than the previous generation counterparts, some phase-based units are developed, however, the power source and data storage are still external from the scanner. Some general representatives are CALLIDUS, CYRAX 2500, ZOLLER + FRÖHLICH IMAGER 5003 (Staiger, 2011).

-3rd generation, from 2006: Units possess further improvement in measurement speed and ability to capture objects further away in greater ranges. The power source and data storage is integrated into the instrument, and the data combined with the digital photos. Adoption of some traditional surveying systems and techniques such as Global Positioning System (GPS) and forced centring, start to become advanced landscapes of TLS units. Some typical representatives are FARO PHOTON, LEICA SCAN STATION, RIEGL LMS Z-420i, ZOLLER + FRÖHLICH IMAGER 5006 (Staiger, 2011).

-4th generation, from 2010: Units possess further improvement in terms of measurement speed and range again. The camera and captured digital photos integrated into the data treatment process. Moreover, the power supply and data storage are fully integrated into the instrument. Some commercially available representatives are FARO FOCUS, RIEGL, VZ 400, Z + F IMAGER 5010 (Staiger, 2011).

-5th generation, from 2015: Units possess further improvement in terms of measurement speed and range again. The high-resolution camera combined with internal lightening for capturing photos in dark environments, and also positioning system are more improved and fully integrated into the instrument. In overall, TLS features such as internal storage capacity, power supply, wireless connections are further developed, improved and optimized. Some typical representatives are LEICA RTC 360, Z + F IMAGER 5010x, and 5016.

The latest in the technological development of TLS can be gauged from the specifications of ZOLLER + FRÖHLICH IMAGER 5016, which is considered to be used in this research study. The Z + F IMAGER 5016, shown in Fig. 2-1, can capture more than 1 million data points per second, has a range of 0.4 m to 360 m away from the object, a horizontal field of view of 360º, and vertical field of view 320º. Features integrated into the TLS unit includes a full High Dynamic Range (HDR) panorama camera (80 Mpixel) with high speed, last generation of positioning systems, automatic real-time registration and, resolution/accuracy up to 0.8 mm at a subject distance of 10 m (Zoller + Fröhlich GmbH, 2021). As a tangible example, the time required for a full 360ºx320º scan with a resolution of 6 mm at a distance less than 10 m (high resolution), plus photographs, is less than 3:30 minutes. Fig. 2-2 shows the evaluation of Z+F products during the last two decades.

(a)

(b)

Figure 2-1 Z+F IMAGER 5016 (a) a close-up view and dimensions; (b) mounted on a tripod.

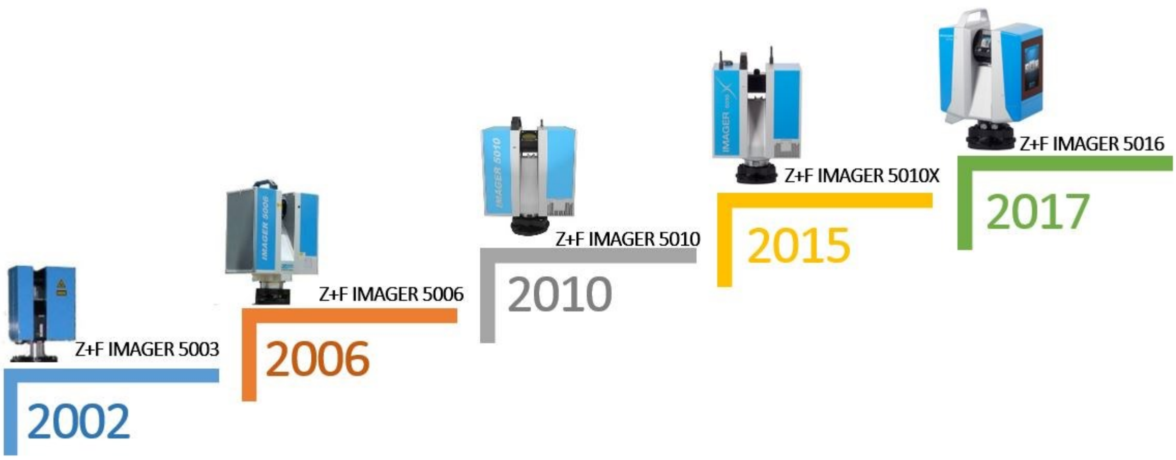
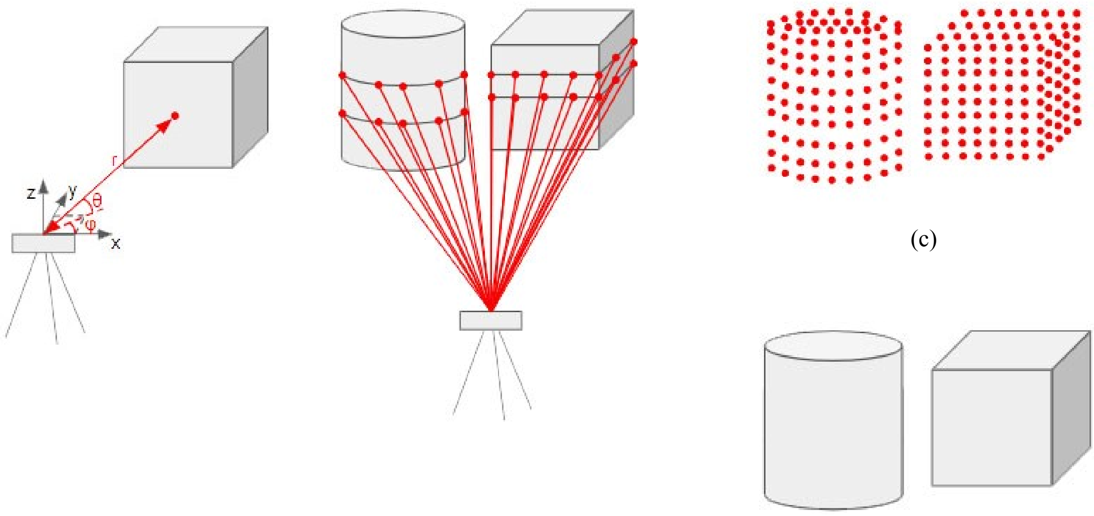


Figure 2-2 Evaluation of Z+F laser scanner products.

2.3. Terrestrial laser scanning

In a scanning process, the terrestrial laser scanner (TLS) captures and stores data of the object's points in x, y, and z coordinates associated with attributions such as the intensity of the laser beam reflected from the observed object and colour range. TLS generates millions of 3D data points, each one corresponding to a different location of the observed object by sending and receiving a laser beam and determining the distance (r) and angles (θ, and ϕ) between the unit and objects Fig. 2-3(a, b). These data can be amassed to form a raw set of data points named point cloud, shown in Fig 2-3(c). From a point cloud captured of an observed object by TLS, a digital 3D representation of that object can be generated, Fig. 2-3(d), Rooms (2018). Generation of 3D models from the acquired TLS data points, point cloud, is an important consideration for various applications. Therein, TLS can be a right alternative for traditional inspection and measurement tools. However, unlike 3D Computer-Aided Design (CAD) programs, which typically show objects as they should be built (commonly known as as-designed), TLS can be utilized to capture and generate 3D models of objects in their as-is/as-built conditions including flaws and all details with high speed and precision. Furthermore, combination of collected data points with RGB (Red, Green, and Blue) range of colours in new generations, has made TLS as a valuable advanced technology for inspection and maintenance. These TLS capabilities are of significance in the realm of civil engineering when drawings are not available or many changes over the years are not recorded. With TLS, it is now possible to accurately record complex geometries, such as cultural heritage buildings, bridges, roads, tunnels, etc. This study mainly focused on the application of TLS in bridge engineering.



(a) (b) (d)

Figure 2-3 3D model generation: (a) laser measurement; (b) laser emission; (c) point cloud; (d) 3D model (Rooms, 2018)

2.4. Application of TLS in bridge engineering and asset management

To give an overview of using laser scanning for bridge engineering, this research attempts to explore application of TLS in bridge engineering by means of a combined scientormetirc and state-of-the-art review. The aim of this research is to investigate the different applications of TLS in bridge engineering and asset management and evaluate current works, research gaps and further directions in this area of research.

2.4.1. Scientometric review

The scientometric review is defined as a quantitative investigation of the current research on the forming of science, which considers the impact of journals, institutions, and the network of countries in a specific area of research. This reviewing method can provide a deeper understanding, including a comprehensive summary of the currently published papers and measures the impact of research regarding the citation processes (Pollack and Adler, 2015, Chen, 2006).

In the current study, a quantitative analysis is proposed for assessing the published papers related to the applications of laser scanning in bridge engineering and asset management. Bibliometric techniques are applied to published literature by this methodology and are used to map the structure and development of various concerns and objectives based on the collected large-scale academic data sets (Chen, 2006). In the following, analyzing the intellectual landscape of the current research area and perceiving relevant questions that researchers may try to respond are comprehensively presented by a network modelling and visualization (Su and Lee, 2010). Visualizing the whole field of laser scanning in bridges will facilitate readers to gain a comprehensive view of research trends and patterns in this field of study.

The identification of prominent researchers that mainly affect the structure of this field of study is obtained by analyzing keywords and abstracts which describe the research contents. Moreover, research patterns are obtained by the following methodologies: the co-occurrence of keywords analysis, co-author analysis considering the countries of origin (Song et al., 2016, Cobo et al., 2011). Subsequently, VOSviewer and CiteSpace (Chen et al., 2010) as two practical computer programs were employed for bibliometric mapping.

2.4.1.1. Scientometric search methodology

During the past decade, a massive amount of research outputs has been published in both conference proceedings and scientific journals; however, the literature search has mainly relied on high-ranked journals and reputed conferences in the area of civil engineering, construction management, and structural health monitoring. For the literature search, the main source of information was considered to be Scopus launched in 2004, which contains more than 75 million records of articles and books (Elsevier, 2020). Moreover, a supplementary literature search was also conducted in Google Scholar, PubMed, and Web of Science. Fig. 2-4 shows an overview of the literature search methodology. At the beginning stage of the literature search, a two-fold general keywords including the capturing tool (3D point cloud, Laser scanner or Laser scanning or 3D scanning or scanning) and the application area (Construction and Civil engineering) were used. A total of 2140 papers were identified at the beginning stage. Some of the papers were from other subject areas such as physics, astronomy, medicine, and mathematics and not related to the research topic. Therefore, two types of criteria were applied during this stage. At first, a subject area exclusion was considered for the chosen papers and then the year of publication was restricted to 2010 to 2020. The first criterion led to the removal of 511 papers, while the next one eliminated 95 papers. Overall, 606 papers were eliminated, leaving 1534 papers. Fig. 2-5 depicts the number per year of the collected papers in this stage which shows an increasing rate of publication in this area during the last ten years.

In the next stage, the remaining 1534 papers were screened by more specific keywords. Again, the remaining papers were reduced due to specific keywords related to the specific applications of the laser scanning for bridge inspection. At this stage, considering two other keywords of “bridge” and “structure”, 1152 papers were removed. Next, during the eligibility stage, the remaining 410 papers were assessed by looking at the title, leading to the exclusion of 71 papers again. At this stage, the relevance of the remaining 339 papers was skimmed by reading the abstract of the papers. Due to irrelevant focus of the subject matter, 30 more papers were excluded. In the inclusion stage, the full text of all 309 remaining papers were given a quick perusal and the objectives were identified. Fig. 2-5 reveals the historical trend of published studies in this area and demonstrates the low rate of publications specifically focused on bridge engineering, thereby this topic can be considered as a promising subject area to be investigated. During the last decade, publication numbers kept rising, reaching about 42 publications in 2019, confirming the growing interest in the field of bridge engineering.

Considering the multiple objectives of the papers in this field, documents were divided into five subdivisions related to the specific application of 3D laser scanners in bridge engineering.

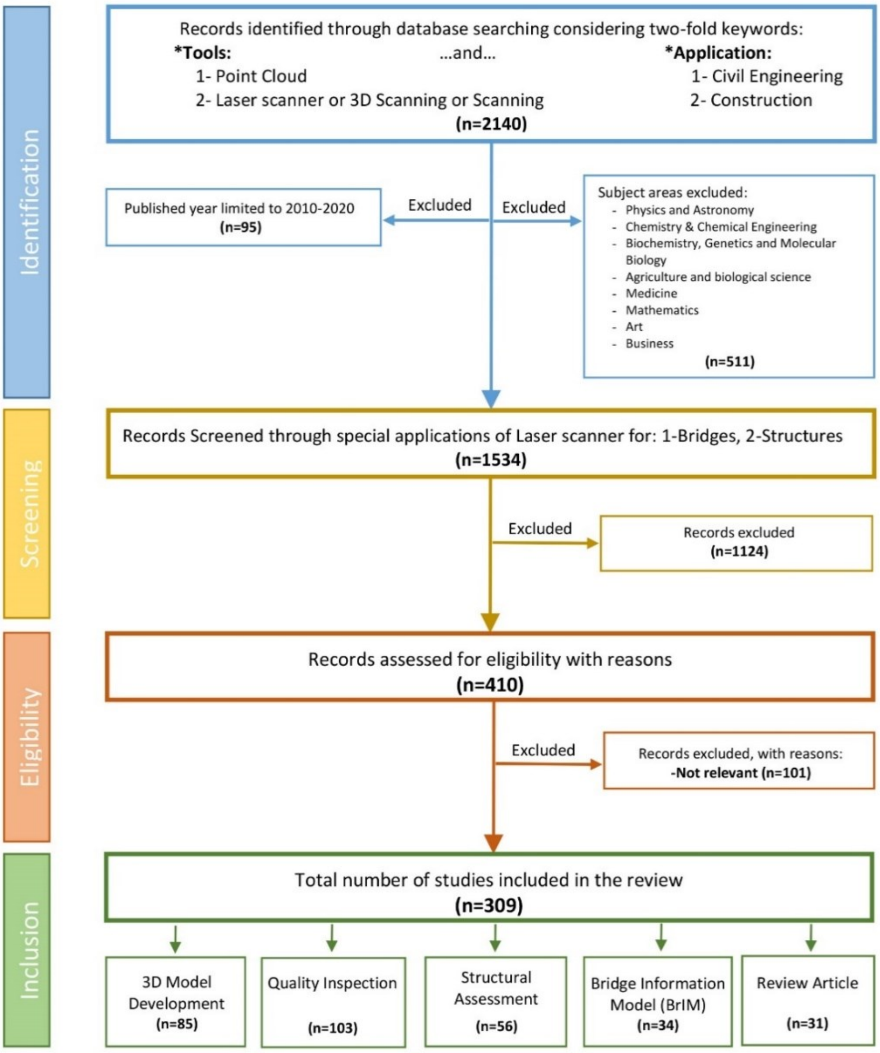


Figure 2-4 Flowchart of the scientometric review process

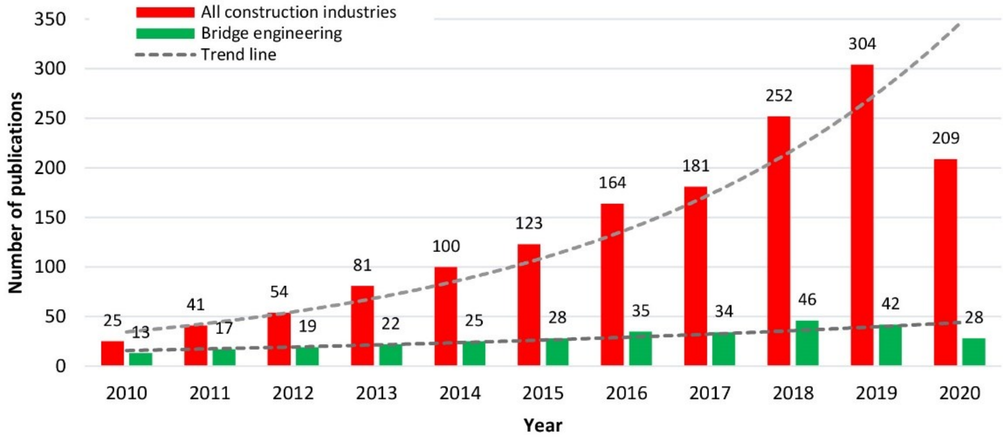


Figure 2-5 Historical trend of published papers using TLS in all construction industries and bridge engineering (2010-2020)

2.4.1.2. Co-occurrence of keywords analysis

Keywords are important to present the fundamental concepts/concerns and subject areas of the published work, and demonstrate a quick overview of the research horizons (Van Eck and Waltman, 2010). In order to construct and investigate the map of the existing knowledge domain in bridge engineering and assessment, the co-occurrence of keywords was evaluated using VOSviewer. The VOSviewer presents the keywords network in a distance-based diagram. Considering the keywords network, the result of the literature search were analyzed and visualized, as presented in Fig. 2-6. This network contains 25 nodes and 172 links, and Table 1 presents details such as the number of occurrences, average year published, number of links, and total link strength. Each keyword in this network is defined as a node and the relationship between each node is considered as a link. The distance between two nodes determines the relationship weakness or strength. The far distance between two keywords/nodes shows a weaker relationship, while a closer distance indicates a stronger connection (Perianes-Rodriguez et al., 2016). The sum of the strength of the links related to a specific node is defined as total link strength. Moreover, the size of the presented nodes indicates the number of documentations in which the keyword was established and several colors indicate diverse years of study (Oraee et al., 2017).

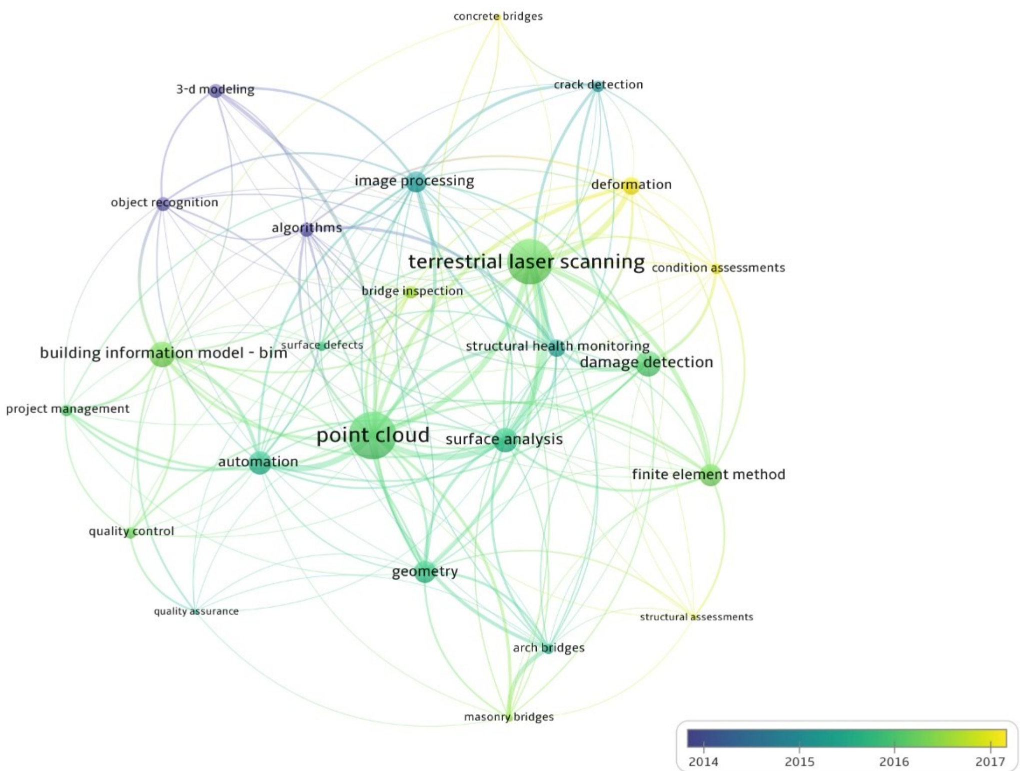


Figure 2-6 Network of co-occurring keywords

Table 2-1 List of keywords and related network data

Keyword	Occurrence	Average year published	Links	Total link strength	% of total occurrence	
3D Model Development						
Point cloud	58	2016	22	105	12%	48%
Terrestrial laser scanning	55	2016	21	78	11%	
Image processing	24	2015	21	56	5%	
Structural health monitoring	20	2015	17	52	4%	
Automation	26	2015	17	49	5%	
Finite element method	25	2016	15	36	5%	
Algorithms	16	2013	18	36	3%	
3D modeling	15	2013	8	20	3%	
Quality Inspection						
Damage detection	30	2016	17	42	6%	27%
Geometry	25	2015	16	43	5%	
Object recognition	15	2013	12	25	3%	
Bridge inspection	14	2016	11	24	3%	
Crack detection	13	2015	11	26	3%	
Arch bridge	11	2015	14	36	2%	
Surface defects	10	2015	13	21	2%	
Concrete bridges	6	2018	8	8	1%	
Masonry bridges	8	2016	11	28	2%	
Structural Assessment						
Surface analysis	28	2015	19	70	6%	13%
Deformation	19	2017	11	36	4%	
Condition assessments	11	2016	11	21	2%	
Structural assessment	5	2016	9	12	1%	
Construction Management						
Bridge information model- BrIM	30	2016	15	45	6%	12%
Project management	13	2016	10	21	3%	
Quality control	12	2014	11	22	2%	
Quality assurance	5	2015	9	13	1%	

The frequency of each keyword is presented by the number of occurrences in Table 1. So, based on this table "point cloud" and "terrestrial laser scanning" are the two main keywords that emerge frequently, showing extensive studies in this area. Additionally, the average year published presents the period that studies are more concentrated on research works/keywords. As an instance, terrestrial laser scanning is a keyword with high frequency during the period 2015-2016. Based on the presented information, the occurrence number of some keywords such as bridge inspection, crack detection, and surface defects reveal that the research undertakings related to bridge assessment and also bridge management are limited; hence, there is an obvious and essential need for further studies in this field.

2.4.1.3. Network of Countries/Regions

In order to demonstrate the contributions of countries/regions in the presented field, a network was created by CiteSpase software, showing the distribution of research publications. 68 nodes and 164 links were included in this network. As shown in Fig. 2-7, the main contributions to the publications in this field of research belonged to the following countries, respectively; the United state (77 papers), Spain (48 papers), United Kingdom (40 papers), South Korea (28 papers), and China (28 papers).

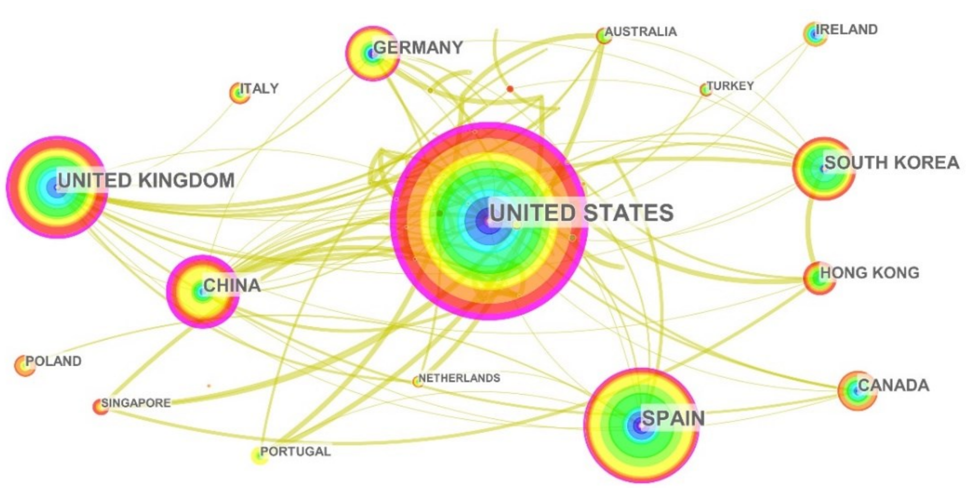


Figure 2-7 Network of countries/regions

2.4.1.4. Overview of the scientometric review

Research studies on using TLS as an emerging quantitative tool, providing precise information, dates back to almost ten years ago for bridge engineering. During the last decade, the historical trends show that the number of publications kept rising from an average of 15 papers/year in 2010 and 2011 to 44 papers/year in 2018 and 2019, which confirm the growing interest in using TLS in the field of bridge engineering as shown in Fig. 2-5. This growing interest demonstrates the publication rates specifically on bridge engineering; however, higher growing rate is observed in the whole construction industry which includes the use of TLS in health monitoring of bridges, buildings, roads, tunnels, etc.

In this study, the co-occurrence of keywords, by means of presenting fundamental themes of published papers, was investigated. The results of keyword mapping, performed in Section 2.4.1.2, highlighted the frequency of keywords presence, indicating concerns and limitations in this field of study. In this regard, 3D model generation and quality inspection are shown to be the more investigated research topics by possessing 48% and 27% of the total keyword occurrences, while structural assessment and construction management are unique and opportune topics that need to be investigated. Moreover, this study considered the relationship between the key countries of research origin and the United States of America is shown to be the lead country in terms of being the main contributor in research undertakings. In particular, the USA maintains strong research links with United Kingdom and Spain, however, weaker research links are reported with countries such as Australia and Germany.

2.4.2. State-of-the-Art Review

Following the review and considering the multiple objectives of the collected papers mentioned in the Scientometric Review section, the methodology of this research was extended to a state-of-the-art review on applications of TLS in bridge engineering and asset management according to four major categories including (1) generation of 3D geometric model, (2) quality inspection, (3) structural assessment, and (4) Bridge Information Model (BrIM).

2.4.2.1. Generation of 3D geometric model

A raw topographic point cloud data generally appears in a form of x-, y-, z-coordinates associated with attribution such as intensity value and colour, which cannot interpret information of the objects' surfaces. The primary and most challenging task is to convert this raw data to meaningful information for subsequent applications, which includes data acquisition and 3D model reconstruction. The output of this task as a solid 3D representation is often the preferred form of embodiment for engineers. The generated 3D model in this task for a civil infrastructure, such as a bridge, could not only provide a better understanding of as-is geometrical conditions/details but also could benefit engineers in making better decisions either in bridge management or assessment.

Based on the aforementioned information to investigate the common approaches/projects in application of a point cloud for bridge engineering, the process can be roughly classified into two phases: (1) data acquisition and (2) 3D model creation. The first phase refers to the onsite data acquisition strategies to maximize the data coverage and optimize the number of scan stations, while the second phase pertains to the process and methods of obtaining a 3D geometric model from the raw captured points. Bridges often face major challenges due to the shape and orientation of the structures in the data acquisition phase, and also contain complex structural components that make difficulties for the second phase. In the following, the two-phases toward 3D model creation of bridges are reviewed.

Data acquisition

Data acquisition is the most crucial and challenging phase to provide sufficient quality and quantity of data point clouds, and plays an important role in deploying the point cloud for bridge engineering applications. This phase is closely aligned with the second phase, where errors in scanning or identifying unsuitable scan stations could provide insufficient quality and quantity data points. Besides that, infrastructures such as bridges, are more diverse and complex in terms of type, orientation, shape, dimensions and surrounding scene, which result in significant challenges in data acquisition. Therefore, preparing a scanning strategy plan to minimize the time on site and maximize the data quality and quantity need to be carefully considered (Riveiro and Lindenbergh, 2019, León-Robles et al., 2019, Cabo et al., 2017, Argüelles-Fraga et al., 2013, Popescu et al., 2019, Frías et al., 2019).

In practice, scanning strategies are usually planned by engineering surveyors after identifying the purpose of data acquisition, site surveying to roughly identify a scanning station network as well as scanning parameters (Mahmood et al., 2020, Lichti et al., 2019, Laefer et al., 2009). Jia and Lichti (2019) developed a hierarchical scanning strategy based on an optimization method to figure out the TLS viewpoint planning problems. In another effort, Lu and Brilakis (2017) presented a top-down scan strategy and tested on more than ten highway bridges. The results showed that the average required scanning time of these bridges is 2.8 hours across 17 scans. Hinks et al. (2015) presented a flight planning strategy of collecting data sets that guarantee the complete coverage with minimal data redundancy of the object structure, but the method was applied to a city building model. Biswas et al. (2015) proposed a novel scientific scanning strategy plan, which could be utilized in construction sectors. Zhang et al. (2016) proposed a practical scanning plan method named “divide-and-conquer” to optimize onsite scans.

Point cloud data are usually acquired based on two parameters: data quality and resolution, which are needed to be adjusted manually based on the smallest targeted object. Negligence in selecting appropriate parameters can cause low-quality or redundant data production, which could negatively affect the scanning time and post-processing procedures. Rebolj et al. (2017) presented the result of a research on these parameters to define an acceptable metric for evaluation of the laser scanning data quality for 3D model reconstruction. These parameters have also been discussed in some other research works and guidelines (G.S.A., 2009, Dai et al., 2013, Gröger et al., 2012).

Data quality setting has a great impact on the data acquisition rate (measured pixel/second) i.e. scanning time and in turn, the amount of redundant data and the range of noise. On the other hand, the resolution setting refers to defining the smallest recognizable object dimension, which is generally in centimetre order for concrete parts of a structure, and in millimetres order for steel components (Riveiro and Lindenbergh, 2019). Steel structural components are usually made of low thickness segments with edges (e.g. I section) causing a serious challenge for TLS to detect sufficient data points in order to describe edges (Anil et al., 2012, Laefer and Truong-Hong, 2017). Moreover, fine resolutions are also needed to be considered for damage detection proposes to investigate at least moderate damages such as visible cracks, spalling, and scalings (Laefer et al., 2014, Valença et al., 2017, Cabaleiro et al., 2017, Suchocki and Błaszczak-Bąk, 2019). Cabaleiro et al. (2017) experimentally investigated the cracks of a timber beam using this technology. Results showed that the TLS could detect cracks with the widths of above 3 mm considering an average resolution of 1 mm.

In general, four main factors could considerably affect the quality of data points including, the weather conditions, surface smoothness and reflectivity properties, scanning geometry, and laser scanner specifications (Soudarissanane et al., 2011, Wang and Kim, 2019). The first factor relates to the atmospheric conditions such as humidity, temperature, and light while the second-factor is mainly relevant to the surface texture of the exposed object. Surface smoothness, roughness, and colour could effectively disturb the laser beams traverse and return with regard to the surface material. Geometry scanning particularly concerns the TLS position and incident angle of the laser beams (Wang and Kim, 2019). Soudarissanane et al. (2011) demonstrate the level of noise less than 2 mm by changing the location of the TLS less than 30 m from the object while considering less than a 40-degree incident angle. Moreover, Laefer et al. (2014) state that the results of crack width detection can highly be affected by the orthogonal distance greater than 12.5 m and 30 degrees of incident angle. In this research, results show the absolute error of 1.37 mm occurring at 5.0-7.0 m orthogonal distance. The last factor refers to the scanner device mechanism which includes hardware properties and general settings.

Although all the aforementioned factors may be significant for capturing the high quality data points, for a large monitoring project, such as a bridge inspection, selecting appropriate surveying equipment, such as high-tech laser scanner, tripod with stabilizer and having a detailed scanning plan could certainly reduce the impact of capturing redundant data.

3D model generation

The objective of this phase is to create 3D model of the bridge structures from the captured raw data points to be utilized for either bridge information modelling (BrIM), bridge assessment and maintenance. The generated virtual 3D model could be used throughout the bridge's lifespan, from the design stage (also known as as-design) to practical purposes of the existing structure (called "as-built" or "as-is"). During the bridge's lifespan, the bridge conditions may undergo changes due to variations in construction and operation phases, which cause a different status comparing to the design documents or the initial status. In such circumstances, only an accurate as-built 3D model derived from a detailed survey can illustrate the actual modifications of the structure (Barazzetti, 2016, Brilakis et al., 2010).

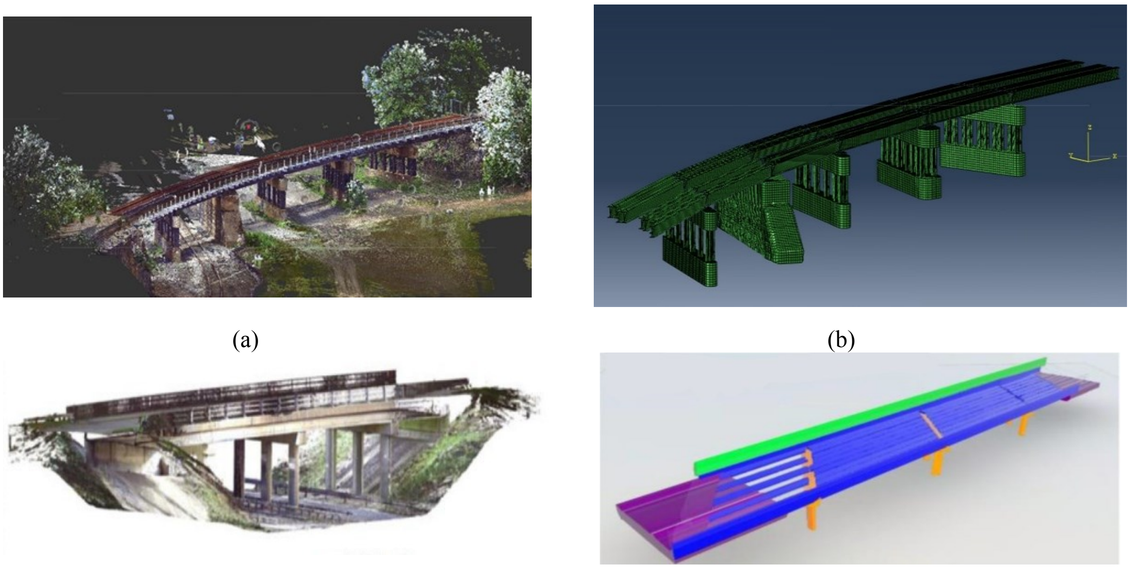
3D model generation phase is containing three steps of pre-processing, segmentation, and Computer-Aided Design (CAD) model creation (Intwala and Magikar, 2016). Pre-processing refers to data clean up and registration of the raw data points. Generally, raw data points acquired by TLS contain noise, which affects the construction of 3D model. This noise can be reduced using various filters such as Angle, Median, and Chordal (Karbacher and Häusler, 1998, Budak et al., 2005) in the data clean-up stage. Besides that, considering multiple scan locations, acquired data point clouds need to be aligned using target points and alignment methods known as the registration stage (Cheng et al., 2018). Recently, pre-processing stages have become a considerable capability for TLS instrument and software, containing intelligent systems to accelerate this phase and reduce the office works (Gómez-García-Bermejo et al., 2013, Zheng et al., 2016). Segmentation is the other step of defining logical divisions for the acquired data points to become interpretable as a geometric shape presenting the detected object's surface (Ma and Liu, 2018, Intwala and Magikar, 2016). Since the number of acquired data points are usually very large, presenting an accurate automatic segmentation method has become a challenge during recent years. To overcome this, Constructive Solid Geometry (CSG) and Boundary representation (B-rep) methods have been adopted (Wu et al., 2018, Wyvill and Kunii, 2005). The CSG method generates 3D solid models based on the combination of volumetric primitives using Boolean operations while the B-rep method gives a way to trigger a collection of surfaces as a 3D object. In CSG, the solid models are described as a series of bounded simple primitives including cone, cylinder, sphere and cuboid in a particular process known as CSG hierarchical tree to generate a solid model (Wu et al., 2018, Han et al., 2023). However, B-rep method tries to extract boundaries from the raw data points representing edges, vertices and surfaces, as the skeleton of the solid model (Valero et al., 2012). Employing the CSG method, all detected components of the bridge structure are divided into a number of simple subsets/primitives extracted from the raw data points. In recent years, many studies have been focused on utilizing the combination of B-rep in CSG method (Wu et al., 2018, Ma and Liu, 2018).

In extracting point clouds of individual surfaces for generating 3D models, researchers tried to develop segmentation algorithms that automatically classify captured data points, meeting the same features into the same subset known as "Feature-based segmentation" or segments based on data points satisfying mathematical models named "Model-based segmentation".

Identification of surface's curvature based on captured data points (Son et al., 2015b, Son et al., 2015a) or comparison of neighbouring points features such as the angle of normal and unit vectors, (Wang et al., 2012) are some of the features developed in algorithms such as region growing (Walsh et al., 2013), ray-tracing (Xiong et al., 2013), cluttering and voxel/cell-based algorithms (Hinks et al., 2013) in the feature-based segmentation. However, in the model-based segmentation, algorithms such as Hough transform (Vosselman and Dijkman, 2001, Patil et al., 2017, Bosché et al., 2015) and RANSAC (Liu et al., 2016, Sanchez and Zakhor, 2012) are often used.

The creation of the 3D CAD model is the last step of generating an integrated geometric model using the segmented data points. There are several approaches, fitting and sweeping are two frequent techniques used in this regard. The former technique refers to fitting simple primitives extracted from the segmented points while the latter indicates a technique of extruding a segmented shape along a path to obtain the 3D CAD model visualization. Examples of these techniques have been developed in existing research works conducted by Walsh et al. (2013), Barazzetti (2016), Xiong et al. (2013), Stull and Earls (2009), Laefer (2020), Yang et al. (2020a), and Han et al. (2023). In these research works, efforts have been made to develop a high-level algorithm or introduce a detailed scanning plan to auto-identify specific sections of a structure, especially bridge structures.

In an effort to develop a fitting technique, Walsh et al. (2013) utilized the region-growing algorithm to segment data points belonging to each surface of a reinforced concrete bridge pier cap. After that, a planar surface was fitted to each segment, and then the completed 3D model was made based on the interactions and orientations of the fitted surfaces. In another effort, Barazzetti (2016) presented a semi-automated method containing NURUBS as a mathematical function for direct geometric modelling of an object with complex surfaces. Xiong et al. (2013) proposed an automatic method of converting raw data points into an as-is BIM using a ray-tracing algorithm to identify occluding objects with block visibility. Cabaleiro et al. (2014) developed a line detecting method using the Hough transform algorithm to obtain an accurate boundary representation of a steel frame component. So far, more studies have been conducted and targeted on the latter technique, sweeping. In an initiative, Laefer and Truong-Hong (2017) proposed an automatic method identifying cross-section of a steel structural component and exploiting the 3D model by sweeping the detected profile along its longitudinal direction. In continuing research in this area, Laefer (2020) elaborated on another method which involves identifying multiple cross-section cuts along the principal direction of a steel component. In this method, more reliable 3D models with an actual representation including longitudinal changes were created (Laefer, 2020). Similarly, Yan et al. (2017) developed a voxel-based mesh generation method consisting of three actions to create a computational 3D model of a structure. This method starts with the extraction of cross-sectional cuts using the voxel-based algorithm and then exploiting the correct map of the components by extruding the detected cuts along their principal axes. In order to test the proposed method, a full-scale bridge was scanned and its geometric 3D model was made, as shown in Fig. 2-8(a-b). In a similar strategy, Lu et al. (2019) proposed a top-down segmentation process for detecting major bridge components such as slab, pier, and girder relying on boundary extraction algorithms to estimate the shape of the structural components by merging multiple sliced models. This method was tested on 10 sets of concrete bridge data in London and one of the slab bridges is shown in Fig. 2-8(c-d), (Zhao et al., 2019, Lu et al., 2019).



(a) (b) (c) (d)

Figure 2-8 Generation of 3D models from the point data sets: (a) Robot City bridge point cloud Pennsylvania; (b) 3D FE model of the Robot City bridge; (c) Dunsley corner bridge point cloud, Cambridge (Zhao et al., 2019, Lu et al., 2019); (d) 3D solid model of Dunsley corner bridge (Zhao et al., 2019).

2.4.2.2. Quality Inspection

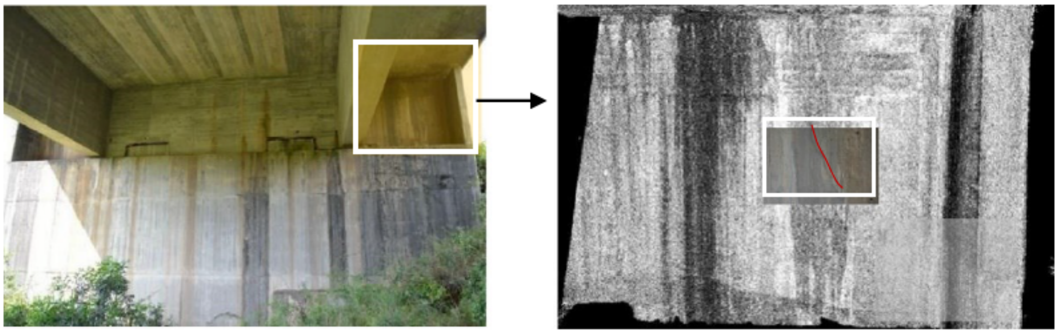
In the last few years, TLS has proven its potential benefits in conducting geometry inspection of damaged infrastructures such as bridges. This section summarizes the research efforts on identifying most probable bridge surface damages such as cracks and mass loss of structural members.

Crack detection

Traditionally, the optical evaluation was considered as a reliable method for crack inspection of bridges, which was performed using a hand-held measuring magnifier or a crack width ruler (Valença et al., 2017). These evaluations could assess only a few accessible areas of the structures, were quite labour-intensive, time-consuming and subjected to human error (Gastineau et al., 2009, Valença et al., 2014, Rashidi et al., 2020a). Mechanical probes and electronic sensors were the next generations. They were more developed than the previous method and able to measure crack features such as length and width (Marazzi et al., 2011, Laflamme et al., 2012, Patricio and Maravall, 2007, Koch et al., 2014). Although those instruments provided high accuracy for crack detection, they suffered from significant limitations, such as limited measurement range, physical access requirements, and considerable costs (Gordon et al., 2004). Alternatively, TLS known as a non-contact method and an efficient tool was able to accurately capture details of structures, which is emerging an alternative unit to overcome the shortcomings of direct visual inspections (Olsen et al., 2010, Truong-Hong et al., 2016). Nowadays, various types of laser scanners are available with a wide range of data acquisition speed (generally 2,000-120,000 points per second) and resolution (generally 0.8–100 mm at 10–300 m).

On the other hand, TLS having some limitations relating to resolution and noise level of the point cloud appears unique challenges in crack detection. Particularly, for small cracks, problems such as noisy data or mixed pixels may result in inaccurate information (Tang et al., 2009). RGB colour model is effectively utilized as an additional attribute for crack detection to solve these problems (Guldur et al., 2015), but it requires high accuracy of mapping RGB colours from images to the point cloud. The dependency of data quality and accuracy on the scan position and scan range are the other drawbacks to be considered while using TLS for crack detection (Valença et al., 2017, Łabędź et al., 2022). In this regard, Anil, et al. (2013) characterized the performance of laser scanners for identifying even the thin cracks (visible cracks as small as 1 mm) in reinforced concrete frames using an automatic method presented by Tang, et al. (2009). In this effort, the effects of parameters such as the sampling interval of the scanner and the range of the laser beam from the surface on the detection of the minimum crack size were investigated.

Considering the significance of regular bridge inspection, crack detection as part of structural assessment plays an important role in planning maintenance strategies and optimizing time-consuming interventions (Valença et al., 2017). In this regard, a fundamental mathematical approach was proposed by Laefer, et al. (2014) to measure the minimum detectable crack width using terrestrial laser scanner in unit-based masonry. In this study, it was indicated that the minimum detectable crack width depends on the technical specification of the scanner and the scan range. Therefore, at the ranges of less than 10 m, TLS can detect vertical cracks of at least 5 mm. Besides, it was presented that the orthogonal distance played a key role in the accuracy of the obtained information. So that at the distances between 5 to 7.5 m the results contained small errors. In another effort, Truong-Hong, et al. (2016) suggested using RGB colours model to identify crack's characteristics (e.g. length and width) by measuring the distance between data points on the crack edges. Similarly, Valença et al. (2017) presented an integrated method of laser scanning and image processing considering colour RGB values for automatically measuring the width, length, and orientation of cracks occurred in a concrete bridge in Portugal as shown in Fig. 2-9. In a similar method, considering an average resolution of 1 mm for TLS, Cabaleiro, et al. (2017) identified the timber beam cracks with widths above 3 mm. Table 5 summarizes different examples of crack detection/mapping for components made of different materials.



(a) (b)

Figure 2-9 Crack characterization using integrated laser scanning and image processing: (a) identified critical region; (b) 3D model of critical region (Valença et al., 2017).

Mass loss, scaling and spalling

Vibration due to dynamic loading conditions caused by traffic and high winds, and/or impact of harsh environmental conditions can generate damages such as mass loss, which can be significant over time (Teza et al., 2009). Therefore, inspection and monitoring the health status of bridge structures at certain time intervals play a significant role in detecting signs of deterioration and planning proper counter measures or restoration (Aktan et al., 2000).

Table 2-2 Examples of crack detections in different components.

Materials	Components	Detected crack		TLS		References
		Width (mm)	Length (mm)	Scan range (m)	Resolution	
Concrete	Wall and Slab					(Xu and Yang, 2019, Bayar and Bilir, 2019, Valença et al , 2017, Sarker et al , 2017, Valença et al , 2016, Giri and Kharkovsky, 2016, Rabah et al , 2013, Cho et al , 2018, Guldur et al , 2015, Anil et al , 2013)
	Façade	2.7 ~ 20	620	2.5	6 mm @ 50 m	(Valença et al , 2017)
		>1.13	>88	20 ~ 35	5 mm @ 100 m	(Laefer et al , 2010)
	Beam					(Guldur Erkal and Hajjar, 2017)
	Pavement					(Yang et al , 2020c, Yu et al , 2014)
	Cylindrical specimen					(Turkan et al , 2018, Giri et al , 2017)
Brick	Wall					
	Façade	1~7	_	5 ~ 12.5	0.4 mm @ 11 m	(Laefer et al , 2014)
		>0.85	>90	20 ~ 35	5 mm @ 100 m	(Laefer et al , 2010)
Timber	Beam					
		3~13	30~590	<7.5	<1 mm @ 10 m	(Cabaleiro et al , 2017)

Teza et al. (2009) were among the first researchers, who proposed an automatic method of recognizing surface damaged areas using TLS observations/information. This method was based on the calculation of some properties of selected surfaces such as Gaussian and mean curvatures. In this study, piers and T-shaped beams of a concrete bridge in Italy were selected as a case study, and the obtained data were compared to the onsite visual observations. Fig. 2-10(a-b) demonstrates surface damages caused by weather conditions in the concrete pier captured by TLS with RGB values. As shown in Fig. 2-10(b), the point cloud was subdivided into small sub-areas and the provided algorithm applied to each sub-area, separately. The findings of this research showed acceptable agreement between the selected damage areas, shown by red colour, and inspected damaged areas using Gaussian curvature computation. In another effort, Liu et al. (2011) applied a damage quantification method on the acquired TLS data to detect the defective areas. In this study, a combination of distance and gradient-based damage quantification methods was used for mass loss detection of the pile caps of a bridge substructure. The result of this research showed realistic quantification, which encouraged the bridge engineers to better quantify bridge damages using TLS.

Mass loss damage can also be generated due to spalling and scaling in concrete surfaces (Mizoguchi et al., 2013, Jana, 2007, Makuch and Gawronek, 2020). In this regard, Mizoguchi, *et al.* (2013) proposed an effective method based on region growing algorithm for quantitative analysis of the scaling on damaged surfaces of concrete structures using laser scanning data. The results of this research showed the effectiveness of the proposed method on bridge case studies shown in Fig. 2-10(c-d). Similarly, a recent technique for detecting such damages presented by Kim, *et al.* (2015) allowing engineers to specify the location of surface damages and quantify the spalling defects. The results of this research indicated that the proposed technique is applicable for detecting surface damages larger than 3 mm in both length and depth.

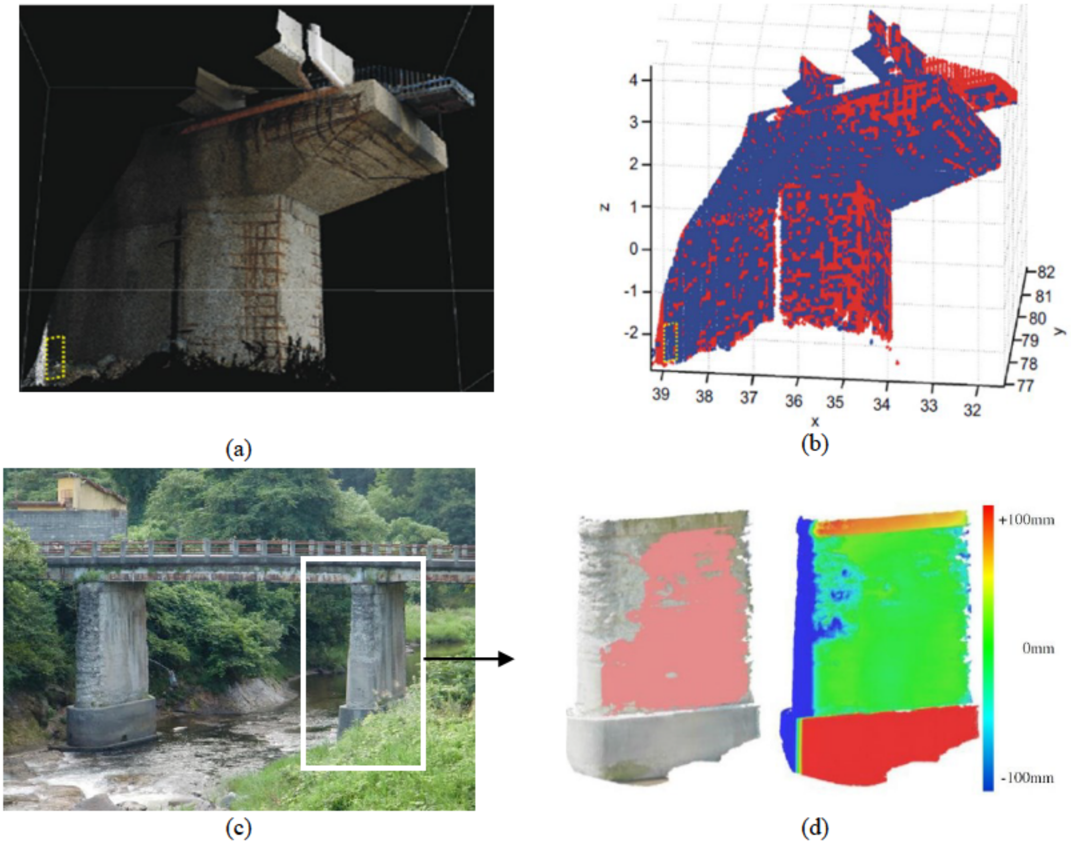


Figure 2-10 Surface damage detection of concrete pier: (a) Point cloud with RGB values; (b) Results of using curvature computation (Teza et al., 2009); (c) Concrete pier with scaling; (d) Evaluated scaling depth (Mizoguchi et al., 2013).

Flatness defect detection is another approach that can be conducted using TLS (Tang et al., 2011, Bosché and Guenet, 2014). In this regard, a series of experiments were carried out by Tang et al. (2011) to investigate the performance of different proposed algorithms and compare the results to obtain the best outcome. In this study, various parameters, including varying types of laser scanners were utilized, and varying scan locations and distance, size and thickness of defect were analysed. The findings of this research indicated that the flatness defects as small as 30 mm across are detectable from a distance of 20 m. Table 3 summarizes different examples of mass loss, scaling and spalling damages detected by TLS.

Table 2-3 Examples of mass loss, scaling and spalling in different components.

Damage type	Components	Detected damage		TLS		References
		Area	Depth	Scan range (m)	Resolution	
Mass loss						(Teza et al , 2009, Liu et al , 2011, Guldur et al , 2015, Guldur Erkal and Hajjar, 2017)
	Concrete pier	>50% of surface	_	80	5 mm @ 50 m	(Teza et al , 2009)
	Concrete girder	8% of surface	_	20	5 mm @ 50 m	(Teza et al , 2009)
	Steel girder	> 50 % of surface	_	<20	2 mm @ 10 m	(Guldur et al , 2015, Guldur Erkal and Hajjar, 2017)
	Timber pier	> 30 % of surface	_	<20	2 mm @ 10 m	(Guldur et al , 2015)
Scaling						(Mizoguchi et al , 2013, Tang et al , 2011)
	Concrete pier	_	<100 mm	10 ~ 30	5 mm @ 600 m	(Mizoguchi et al , 2013)
	Concrete surface	> 30 mm across	>1 mm	3 ~ 20	0.014 ° ~ 0.036 °	(Tang et al , 2011)
Spalling						(Guldur Erkal and Hajjar, 2017, Makuch and Gawronek, 2020, Kim et al , 2015, Guldur et al , 2015)
	Concrete deck	> 10 % of surface	–	<20	2 mm @ 10 m	(Guldur Erkal and Hajjar, 2017, Guldur et al , 2015)
	Concrete panel	<180 mm×180 mm	<30 mm	4 ~ 12	2 mm @ 20 m	(Kim et al , 2015)

2.4.2.3. Structural Assessment

The successful application of laser scanning technology in providing accurate and reliable information about the state of the health of structures in a short time has significantly impressed and attracted civil engineers' attention. The possibility of extracting detailed geometric information as the basis of creating a precise computational model has made TLS a high-potential instrument for structural analysis. This model not only provides a detailed vision of the existing structure, but also allows to obtain resulted simulations close to real behaviour of the structure. As such, in recent years, structural engineers have taken advantage of the constructed geometric models as a basis for assessing structural performance (Hermida et al., 2020, Yang et al., 2019, Miśkiewicz et al., 2019, Bassier et al., 2019, Pérez et al., 2018). That allows improving a decision system for possible actions of the maintenance timely, especially for large-scale complex structures such as bridges (Cha et al., 2019, Gawronek and Makuch, 2019, Liu et al., 2019b). On some occasions, the extracted 3D models were also used as a basis to obtain a calibration for unknown parameters of the structure or components known as inverse engineering (Yang et al., 2019, Yang et al., 2018b).

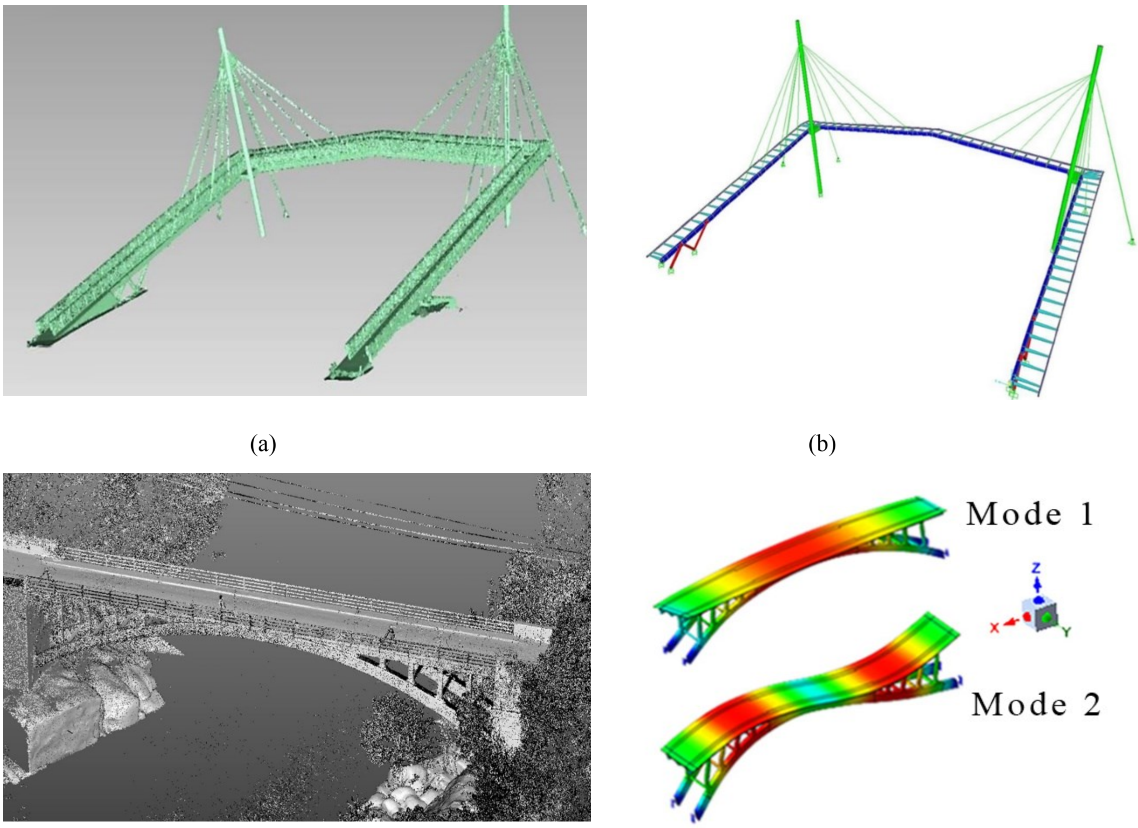
Geometric modelling

Over the past decade, the methodology of utilizing the data point clouds as a basis for extracting suitable solid 3D models, with the purpose of structural assessment, has widely established. During this period, researchers have mainly focused on the development of semi- and/or fully automatic methods, discussed in Section 2.4.2.1, to convert raw data points into a 3D solid model (Bosché, 2010, Brilakis et al., 2010, Laefer et al., 2011, Xu and Neumann, 2020), since discrete points cannot directly be used for structural analysis. Creation of 3D models using these methods can considerably assist structural engineers to carry out the structural analysis using the Finite Element Method (FEM). It can also benefit them from having a precise 3D model and accurate analysis even for large-scale, complex structures such as bridges.

One of the first applications of laser scanning technology in bridge assessment was presented by Stull and Earls (2009). In this study, a damaged composite bridge was modelled based on TLS information and the reserve capacity of the bridge structure was estimated reaching that of the extracted Finite Element Model (FEM). In another effort, Lubowiecka et al. (2009) evaluated an ancient masonry bridge with complex geometry based on finite element analysis. The captured information from TLS was used for defining the updated geometry of the aforementioned bridge. Similarly, Armesto et al. (2010) presented a dimensional and structural analysis of an ancient arch bridge to control its deflection arising from material aging. Moreover, Ming et al. (2013) employed TLS to capture 3D spatial data of a large steel structure. The captured data was then utilized for reconstruction of the 3D model and deformation analysis. Moreover, Sánchez-Aparicio et al. (2014) proposed a workflow to improve the calibration of finite element models converted from the acquired data points. In this study, experimental modal identification was utilized as a non-intrusive system to identify the global properties of the structural system. Similarly, Khaloo and Lattanzi (2015) used such workflow for extracting information from TLS to create a finite element model of a timber bridge. In another effort, Bitelli et al. (2016) developed a semi-automated voxel-based mesh generation method for converting data points directly into the finite element model. In this study, the proposed method was tested on a cultural heritage with the aim of structural analysis. This was an initial concept for other studies in which Castellazzi et al. (2017), Korumaz et al. (2017), and D'Altri et al. (2018) presented a semi-automated strategy that enables the transformation of data point into finite element mesh with the aim of health assessment of historical structures. In another research, Conde-Carnero et al. (2016) proposed another automated approach for direct conversion of data points into a suitable finite element model with regards to structural analysis. In this effort, the presented approach was utilized for the structural assessment of an existing footbridge, shown in Fig. 2-11(a-b), under design loads. Concerning the structural assessment of another historical bridge in Portugal, laser scanning, and some other non-destructive tests were conducted by Bautista-De Castro et al. (2018). The results of these tests were used to calibrate the finite element model suitable for numerical evaluations and bridge condition assessment. Moreover, regarding the importance of assessing safety conditions, static and modal analysis were conducted on the constructed model under conditions of traffic load and vibration, Fig. 2-11(c-d). This study concluded the existence of sufficient bearing capacity, and safety factors were determined based on the current state of this historical bridge (Sánchez-Aparicio et al., 2017).

Deformation measurement

In addition to the aforementioned studies, TLS has also made notable contributions in assessing bridge structures with the aim of capturing vertical deformations. Zogg and Ingensand (2008) were, perhaps, pioneers of utilizing TLS to measure the accurate vertical deflection of a bridge under load. They proposed three different loading scenarios to investigate the application of TLS in evaluation of surface deflection. Similarly, Lovas et al. (2008) also described the advantage of using TLS for deformation monitoring of bridges in comparison to other traditional surveying methods. In another effort, Minehane et al. (2014) evaluated the settlement of two bridge case studies based on their constructed FE model. In this study, the

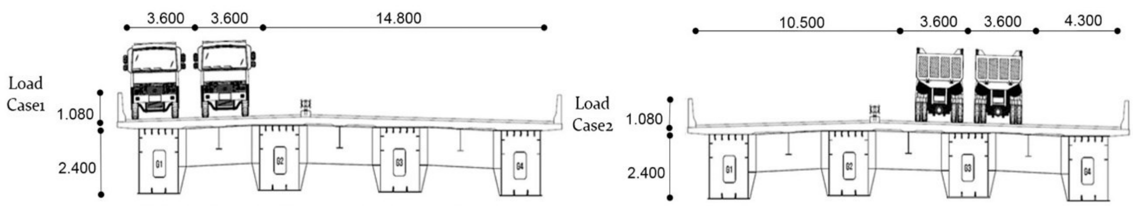


(a) (b)

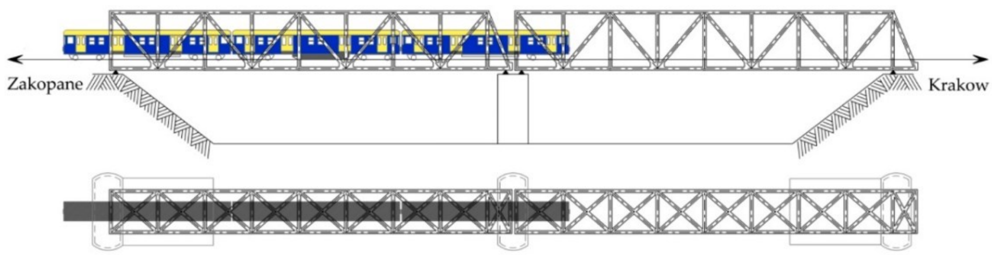
(c) (d)

Figure 2-11 Generation of finite element model from data points for subsequent numerical evaluation: (a) Optimized acquired point cloud of the footbridge (Conde-Carnero et al., 2016); (b) Structural finite element model of the footbridge (Conde-Carnero et al., 2016); (c) Optimized acquired point cloud of the Boco bridge (Bautista-De Castro et al., 2018); (d) Structural modal analysis of the Boco bridge (Bautista-De Castro et al., 2018).

deformation was monitored and assessed according to the BD21/01 guidelines using TLS data points (BD 21/01, 2001). Similarly, Mill et al. (2015) tested the applicability of TLS for identifying the spatial distribution of bridge deformation. Considering this concern, in another effort, Gyetvai et al. (2018) presented a workflow to generate the geometric models for conducting a finite-element-based structural assessment. In this research, the FE model of a wrought-iron bridge was created and assessed under different loading scenarios based on AASHTO guideline (AASHTO LRFD, 2012). In a recent practical study, Cha et al. (2019) presented an efficient shape information model to be utilized in deflection monitoring of bridge structures. This study described two practical tests performed on real cases, considering loading scenarios mentioned in the Korean highway bridge design standard (Korean Highway Bridge Design Code, 2010), as shown in Fig. 2-12(a). In this study, the average vertical deflections from the data points were calculated and compared with LVDT measurement for verification. The results showed a reasonable difference of less than ±1 mm in calculations. In a similar strategy, Gawronek and Makuch (2019) compared the vertical deflection values of an ancient railway bridge using TLS with conventional surveying methods under static loads. In this study, the loading scenario was defined, considering the railway technician consultation, as shown in Fig. 2-12(b). The results indicated a maximum and average deviation of ±3 mm and ±0.3 mm in measurements. However, the available TLS devices on the market offer the possibility to collect high-accuracy data of less than a millimeter. More accurate TLS devices with lower deviations can be a right alternative for electrical and mechanical measuring equipment generally used in the field of bridge engineering (Kermarrec et al., 2020). Table 4 summarizes different examples of using TLS for deflection measurement of bridges.



(a)



(b)

Figure 2-12 Static loading scenarios for deflection assessment: (a) Static loading scenarios for girder bridge (Cha et al., 2019); (b) Static loading scenario for railway bridge (Gawronek and Makuch, 2019).

Inverse engineering and model updating

The possibility of extracting high detailed geometric information of structures from TLS point clouds has made TLS as an alternative unit in providing a valuable source of data to be used for quantitative research approaches. Utilization of laser scanning for geometric identification purposes, and also a combination of this technology with 3D printing have led to the development of a novel process for reproducing historical or key components of structures,

Table 2-4 Examples of deflection measurement using TLS for different types of bridges.

Bridge type	Span (m)	Measured deflection, Maximum (mm)	TLS resolution	Load type	References
Steel girder	100	4.82	35 mm @ 300 m	Static load by trucks	(Cha et al , 2019)
Steel truss	52.7	18.2	1.5 mm @ 10 m	Static load by train	(Gawronek and Makuch, 2019)
Concrete viaduct	156	14	2 mm @ 25 m	Static load by tanks	(Zogg and Ingensand, 2008)
Cable-stayed	307	350	5 mm @ 100 m	Static load	(Lovas et al , 2008)
Concrete cantilever	17.5	35	6 mm @ 50 m	Static load by blocks	(Mill et al , 2015)

called inverse engineering (Xu et al., 2017a, Armesto-González et al., 2010). Laser scanning technology can simply bring the 3D geometric information of an object into a 3D virtual workplace. When generating digital models from TLS point clouds, inverse engineering can be incorporated to create models that accurately represent real structures. As a result, the models could accurately reflect structural behaviour in structural analysis and can rightfully be referred to as a digital twin of the original.

From the engineer's perspective, this source of information can be utilized for calibration of FE models (Riveiro et al., 2018, Xu et al., 2018) discussed in Section 3.3.1 for bridge structures or similar problems containing uncertainties supposed to be estimated through inverse analytical procedures named model updating (Yang et al., 2018b, Mistretta et al., 2019, Yang et al., 2019). In an effort, Conde et al. (2016) proposed an inverse analytical procedure for masonry arch bridges to be investigated for damage conditions. In this effort, an optimization method, using the genetic algorithm, was utilized to obtain a satisfactory convergence between the predictions of numerical modelling and actual deformation measured under different loading scenarios. In a recent study, Yang et al. (2019) experimentally investigated the application of data points acquired by TLS for estimating the uncertain elastic parameters of a small-scale composite arch bridge specimen. In this study, the composite arch specimen was subjected to a monotonic load, and then point clouds of the specimen's deformed shape were captured at each loading step. A finite element simulation considering similar geometric and loading conditions were developed. By presenting a model updating workflow for optimizing the difference between the surface deformation obtained from the real measurement and the simulation, the calibration of parameters was achieved. In this regard, similar strategies were carried out by Lee and Park (2011), Xu, *et al.* (2017b) and Yang, *et al.* (2018a). Although available TLS devices have the potential to provide data with less than a millimetre accuracy, such accuracy can still be improved to achieve more reasonable results in terms of the reverse engineering and model updating. While the accuracy of the TLS device used to scan the structure is critical, it is not the only determinant of the digital model's quality. Instead, it is more important to use inverse engineering and model updating techniques to create a more accurate representation of the actual structure. Using the scanned data, a preliminary digital model is created, which is then refined through iterative processes of model updating and validation, resulting in an accurate representation of the structural behaviour of the original. By combining these techniques, it is possible to create a digital twin that accurately reflects the structural behaviour of the actual structure.

2.4.2.4. Bridge Information Modelling (BrIM)

Although several management methods have been considered in traditional frameworks, employing a conservative management method for bridge health monitoring and maintenance has been well developed by the use of BrIM during the last decade (Kaewunruen et al., 2020, Andriasyan et al., 2020, Woetzel et al., 2017, Li et al., 2023). In recent years, applications of bridge information modelling have provided faster solutions and processes for integrated bridge information in a shared platform. In this regard, Chen and Shirolé (2006) critically compared the valuable benefits of using BrIM as an advanced technology with traditional 2D drafting techniques (Davidson and Skibniewski, 1995). BrIM pertains to the specific form of Building Information Modeling (BIM) application in terms of bridge engineering, referring to the creation of 3D CAD model associated with integrated additional information of time and cost estimation, energy consumption, and etc (Eastman et al., 2018). 3D CAD models are linked to other related tools allowing evaluation of time as the fourth dimension (4D), cost as the fifth dimension (5D), and energy as the sixth dimension (6D) during the different phases of bridge design, fabrication/construction, operation and maintenance. BrIM technology can improve, support, and facilitate simultaneous works by multiple process disciplines while reducing the time-consuming project controls and possible errors in terms of design, construction, and assessment (Azhar, 2011). The bridge model can provide a wide range of information, including, the 3D graphic presentation and all used specifications in the bridge project such as previous analysis, assessments, equipment, control systems, and other related decisions provided in different phases of the project. An accurate and reliable source of data is required for bridge monitoring that can offer a useful starting point for development of bridge management systems (Tang et al., 2007, Weseman, 1995, Javidan and Kim, 2019). BrIM as an integrated platform, can support real-time monitoring/inspection of bridges by providing an interface for "as-is" conditions and remote operating management of the system. Although BrIM provides an ideal platform for various developments, many of these capabilities have not been well-established in this area (Eastman et al., 2018). During the last decade, the utilization of highly accurate laser scanning data, as an emerging technology for capturing the "as-is" geometry conditions of the bridge as a BrIM input has meaningfully increased. In this regard, Tang, et al. (2007) were among the first researchers who investigated the utilization of laser scanning for bridge inspection and management. In this study, a laser scanning approach for geometric bridge inspection was presented using a bridge case study. In another effort, Tang et al. (2010) comprehensively reviewed the significance of using laser scanner raw data for creation of "as-is" BIM in civil engineering projects, commonly called Scan-to-BIM, and surveys developed methods in this regard. However, creation of "as-is" BIM using TLS data is generally a manual time-consuming process. Researchers were mainly focused on development of automatic, or semi-automatic approaches to extract the 3D BIM in a short time with a high level of accuracy from the laser scanned data points with aims of condition assessment and management (Zhao and Vela, 2019, Panushev and Brandt, 2007, Pu and Vosselman, 2009, Sacks et al., 2018, Lu et al., 2019, Zhao et al., 2019, Kwiatkowski et al., 2020a, Zhang and Dung, 2023). As an instance, Zhao and Vela (2019) took an efficient machine learning approach to automate/facilitate the process from a laser scan point cloud to BrIM. In this effort, components of two concrete bridge were segmented, using proposed algorithm, and 3D solid models in Industry Foundation Class (IFC) format were provided. Table 5 summarizes various examples of using TLS based BrIM for bridge modelling, assessment and management.

Table 2-5 Examples of TLS based BrIM for different types of bridges.

Bridge type	Span (m)	TLS		BrIM application	Location	References
		Scans	Resolution			
Concrete Slab	5	18	2 mm @ 10 m	Management	Cambridge, UK	(Lu et al., 2019, Zhao et al., 2019)
Concrete viaduct	24	_	3 mm @ 10 m	Condition assessment	Koszalin, Poland	(Miśkiewicz et al., 2019)
Stone arch	29	12	2 mm @ 10 m	Condition assessment	Alcántara, Spain	(Pérez et al., 2018)
Stone arch	11.5	10	2 mm @ 10 m	3D model & assessment	Mondariz, Spain	(Lubowiecka et al., 2009)
Cable-stayed	27	_	6 mm @ 50 m	3D model & assessment	Vigo, Spain	(Conde-Carnero et al., 2016)
Concrete arch	35	18	2 mm @ 25 m	3D model & assessment	Amares, portugal	(Bautista-De Castro et al., 2018)

Masonry arch	15.5	6	6 mm @ 50 m	Condition assessment	Killorglin, Ireland	(Minehane et al., 2014)
Iron truss	52	2	5 mm @ 50 m	Condition assessment	Dublin, Irland	(Gyetvai et al., 2018)
Concrete girder	25	12	3 mm @ 10 m	Condition assessment	_	(Tang et al., 2007)
Concrete girder	5.2	14	2 mm @ 10 m	Management	Acworth, USA	(Zhao and Vela, 2019, Sacks et al., 2018)
Cast iron cable	21.2	10	2 mm @ 10 m	Condition assessment	Ozimek, Poland	(Kwiatkowski et al., 2020a)

The related research works in this area can be summarized into three main categories of 3D model development, progress tracking, and quality control and management. The 3D model development refers to the construction of 3D solid model, as discussed in Section 2.4.2.1, while other categories indicate the application of constructed 3D model in project management engineering.

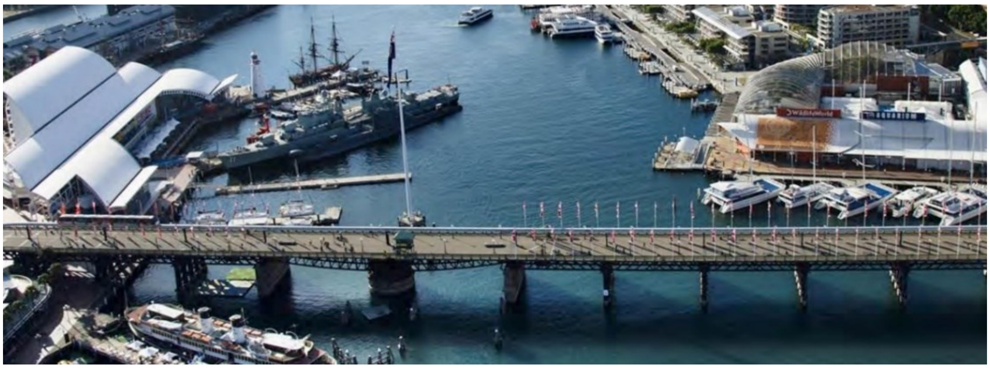
Progress tracking

Choosing an accurate and efficient progress tracking method for construction projects is always a vital consideration for successful management of the projects, as it allows right decisions to be made in a short time. Using conventional progress tracking methods requires manual data collection by daily reports, which is a time-consuming and error-prone procedure. It also can distract project managers from their important task to make in-time and appropriate decisions. In the last decades, researchers tried to employ emerging technologies to improve the output of progress tracking methods using 3D imaging tools and TLS (Puri and Turkan, 2020, Turkan et al., 2012, Turkan et al., 2013b, Bosché et al., 2015, Turkan et al., 2013a, Turkan et al., 2014). In a recent study, Puri and Turkan (2020) proposed a semi-automated methodology for monitoring bridge construction projects, comparing “as-built” and “as-is” data. In this method, the project status was calculated based on the analysis of regularly collected data, using laser scanning technology in a four-dimensional BIM model (3D geometric model + project schedule). Findings of this research were further investigated by application to a bridge replacement case study in Albany. The results showed the benefits of using this method over manual methods of progress tracking. In another effort, Bosche and Haas (2008) proposed an automatic retrieval for 3D CAD objects from the TLS scans to be used for assessing construction progress. In this process, construction progress was tracked, comparing deviations between constructed BIMs during different phases of construction. The authors named the proposed process as Scan-vs-BIM. The results of this research showed the proof of concept, however, further field experiments and other application areas, such as bridge construction, were suggested. In another effort, Turkan *et al.* (2013b) presented another object recognition framework for tracking the secondary and temporary objects, such as formwork, scaffolding and shoring in different phases of construction works. This framework was further developed to analyse/manage other dimensions of the construction project (time and cost) for concrete structures such as bridges (Turkan et al., 2014, Bosché, 2012). Similar attempts on automated construction progress measurement approaches, utilizing TLS for capturing the state of construction, have been developed in existing research conducted by Zhang and Aridit (2013), and Kim, *et al.* (2013).

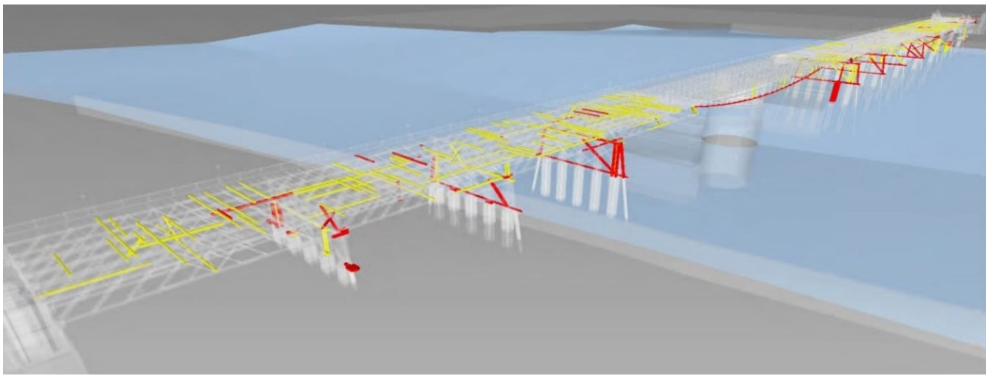
Quality control, management and operation

Application of BIM technology as an integrated platform, facilitates simultaneous works by multiple disciplines in different phases of design, fabrication/construction and operation. Integration of this technology with TLS for rapid and intelligent survey, can be an innovative solution for well managing and controlling different phases of mega projects, such as a complex bridge. In this regard, Ying *et al.* (2019) described the advantage of using TLS as a valuable tool in conducting quality control of bridge components before assembling. In this research, the virtual pre-splicing of two steel beams using TLS was carried out for Fujiang Bridge in Tongnan, China. Similarly, Arashpour *et al.* (2019), developed a framework for quality control of off-site constructions of structural components, in order to reduce on-site assembly discrepancy. In this effort, the point cloud of the prefabricated components was captured using TLS, and the results were compared with the as-designed geometry condition provided in BIM. In this regard, similar efforts have been conducted by Kim et al. (2016), Wang et al. (2016), and Maalek et al. (2019) on integrated BIM and laser scanning for real-time dimensional quality assurance (Liu et al., 2019a, Wang et al., 2015) and decision making systems (Rashidi et al., 2018a, Rashidi et al., 2018b, Zhang and Dung, 2023).

Generation of BIM data can be a valuable source of information for managing, assessing, and forecasting the state of the structure. In this regard, Sacks et al. (2016) presented an integrated bridge inspection system named SeeBridge. In the SeeBridge system, a bridge model is automatically generated and assessed using TLS point cloud data. As a result, this system was validated assessing a girder bridge in the USA; a two slab bridge in the UK; and a girder bridge in Israel (Sacks et al., 2018). Similarly, Dang et al. (2018) presented an updatable BrIM with the aims of bridge management and maintenance, including the digital representation of the bridge components linked to their damage records. In this study, the proposed BrIM system was tested on a highway concrete bridge as a case study. Finally, the initial results showed the acceptable implementation of this system for bridge monitoring and maintenance. In a recent research study, Bolourian and Hammad (2020) presented an automatic approach with the aim of bridge condition assessment, providing the level of criticality based on the point cloud data. This approach was effectively validated by inspecting a concrete bridge in Canada. In a recent project, Sydney Harbour Foreshore Authority of NSW, Australia, developed a BrIM for the historical Pyrmont Bridge in Sydney, to facilitate the managing and operating of this built asset (Sahlman, 2018). Fig. 2-13 shows the current form of this bridge and its maintenance report. However, drawings of this bridge were in particular paper-based, and many changes over the years were not accurately recorded. Having BrIM not only has provided an accurate 3D representation of this bridge, but also has taken a three-month reporting process to less than a day that is now automated and instantaneous.



(a)



(b)

Figure 2-13 Development of BrIM for Pyrmont Bridge, Sydney: (a) Current form; (b) Original/non-original fabrics over time as a BrIM output (Sahlman, 2018).

2.5. Research gaps and Future Directions

In the last decade, the terms of digital twin and smart manufacturing have been introduced to define the promising trends of automation process and digitization in the construction industry, especially bridge engineering. During this period, introducing new technologies such as TLS offer the chance to improve upon the traditional methods of bridge assessment, and management, using the generated 3D model from the acquired data.

Currently, data acquisition, as the most crucial phase of generating a 3D solid model, is heavily performed in a manual way based on surveyors' experiences. Collecting sufficient data with complete coverage for a large and complex structure, such as bridge, is an important consideration and where research is still lacking to identify the required optimum scan locations and parameters. Future research needs to be conducted on the optimization of scan locations and TLS parameters, ensuring the completeness of scan data, thereby minimizing the scan time and avoiding collecting redundant data. Although scan planning procedures have been proposed for buildings in previous studies (Zhang et al., 2016, Biswas et al., 2015), there are some key challenges for complex structures, such as bridges, which need to be addressed. In this regard, obstruction of bridge components and range of access for bridges located in rugged terrains are some of the challenges where research is still lacking and needs to be considered.

The possibility of extracting detailed geometric information, with the aim of structural assessment, is another demand for using TLS as a reliable alternative for electromechanical measuring equipment. Although the available TLS instruments in the market offer the possibility of collecting high-precision data with sub-millimetre accuracy, future research should be conducted to investigate the required data resolution and quality in relation to the project's Level of Detail (LoD). Using TLS in model updating and reverse engineering approaches may necessitate not only a higher LoD, but also novel algorithms in order to have an accurate representation of the actual structure and structural behaviour.

Generation of 3D solid models from the acquired TLS data points is an important consideration for various applications. Although some studies presented segmentation algorithms and proposed methodologies to extract 3D solid models from laser scan data (Cabaleiro et al., 2014, Yan et al., 2017), these studies are not directly focused on the complex components of structures with various orientations. The uniqueness of the shape of bridges is a significant barrier to automation in the 3D reconstruction of infrastructure models from TLS data. Deterministic methods are difficult to develop due to the variety of shapes, and stochastic approaches are challenging due to the need for extensive training data to handle such diversity. Most of the existing research works are focused on point cloud clustering, while these methods are not robust with regard to occlusion. Future research is needed to improve the object detection of complex structural components of bridges in occlusion. Moreover, to date, no commercial software, nor a robust automatic method for direct transformation of raw acquired data into valid geometric model exists. Therefore, further research is suggested to be conducted on practical methodologies that allow conversion of raw point cloud into a valid 3D model.

Identifying the type of construction material, thereby estimating the construction material volume is another demand that can facilitate the maintenance and repair procedures of bridges, which is not robustly addressed in the current research works. However, a limited number of publications have investigated the potential benefits of TLS for visual material classification (Hassan et al., 2017, Valero et al., 2018). Locating and classifying the structural damages along with quantifying the detected deficiencies are other aspects that can be facilitated using TLS, individually or in integration with photogrammetry. Although new generations of TLS instruments support high-resolution images, a few publications investigate the integration of acquired point data and image processing with the aim of quality inspection (Teza et al., 2009, Mizoguchi et al., 2013). Future research works on this topic can potentially provide an efficient way for extracting necessary information for a complex structure such as a bridge, thereby time- and cost-saving.

Successful application of BIM in asset management of structures has made this platform as an advanced alternative for traditional paper-based processes. BrIM as the specific form of this platform for bridge engineering, has great potential to develop rapidly. However, few publications and researches have investigated the application of BrIM (Sacks et al., 2018, Sacks et al., 2016, Hu et al., 2020, Kim et al., 2020). The research is still lacking in developing automated methodologies, using Artificial Intelligence (AI) to inspect and control the design, assembly, and operational processes based on the code conformances and disciplines in case of a bridge. Future research is also suggested on development of the real-time onsite controlling methods, innovative bridge condition assessment procedures (Aflatooni et al., 2015, Aflatooni et al., 2014), and progress tracking approaches for construction and operation phases of a bridge, and providing decision-making algorithms for arisen or anticipated problems.

2.6. Summary and conclusions

This literature study investigated the application of laser scanning as an emerging technology in modern bridge surveying, based on a combined scientometric and state-of-the-art review, not only to evaluate the existing documentation data set, but also to provide a deeper understanding for researchers in this field. A scientometric analysis was conducted based on the collected total number of 1534 publications to explore the status and global research trends of using TLS in the area of bridge engineering. In this regard, based on the selected relevant papers, the four major applications of TLS in bridge engineering were reviewed and categorized. The first category is the generation of 3D models, which refers to the data acquisition phase and reconstruction of the geometry model from the acquired point cloud data. The second is the quality inspection, mainly focused on the most probable bridge surface damages. In addition, the application of TLS in structural assessment, and bridge information modeling, as the other two categories were discussed. Moreover, each category was investigated based on the current landscape of the research, relevant improvements, significant results and recommendations in this area.

Besides an extensive literature review study, this literature study is concluded with a fundamental discussion on the scientometric analysis, ongoing research gaps, and future directions in this research field. Based on the keyword analysis, research topics related to 3D model development and quality inspection, are identified to be trendy subjects, while further investigations are suggested for TLS based structural assessment and management in the field of bridge engineering. Scan location optimization should be further developed considering the minimum occlusion in data acquisition for bridge components. Further research is also suggested on practical methodologies that allow the direct transformation of raw data points into a valid 3D model. Localizing, classifying, and quantifying the structural deficiencies are other aspects of using TLS that can be further investigated with the aim of bridge quality inspection. Future research is also suggested to be investigated for real-time management of the bridge systems using integrated BrIM with intellectual decision support systems, not only to benefit managers to have better understating of the state of health of the structure, but also support them to make better decisions either in bridge management and maintenance.

Chapter 3

(Preliminary Analysis)

** The content of this chapter has been published as a journal paper titled "Quality Evaluation of Digital Twins Generated Based on UAV Photogrammetry and TLS: Bridge Case Study", Remote Sens. 2021, 13(17), 3499; https://doi.org/10.3390/rs13173499 Q1 journal with an Impact Factor (IF) of 4.8 in 2021, and over 20 citations by other research studies worldwide until November 2022 **

3.1. Introduction

Bridge infrastructures are among the expensive and vital components of the road/transport networks that need to be durable and healthy during their lifetime. Over the years, as the bridge is used and exposed to environmental effects, the health of the structure can be deteriorated due to various conditions such as over loadings, material aging, and corrosion environment. Therefore, if the process of deterioration not greatly monitored or regularly maintained, this situation can arise to cease infrastructures' normal operation and service. However, in some critical situations, any negligence in choosing a reliable and accurate monitoring and maintenance system may result in irrepealably structural damages, catastrophes, and future costs (Rashidi et al., 2021). The collapse of Taiwans' Nanfang'ao bridge in 2019 (Horgan, 2019), and the Morandi bridge collapse in 2018 in Italy (Calvi et al., 2019) are some of the recent instances of catastrophe due to a lack of accurate monitoring and maintenance systems. Therefore, records of any structural deficiency and changes in the construction phases to the original as-designed plans and also maintenance actions are valuable pieces of information that needs to be accurately retained for future references. However, amassing this amount of information regularly is a time-consuming and expensive task, especially if the bridge is long with high altitude elements and data collection is performed by a limited number of on-site inspectors manually. According to the National Bridge Inspection Standards (NBIS) introduced in 1971 (Mohiuddin, 2010), development of bridge defects, measurements of changes in geometry and the overall health condition of the bridge infrastructure are needed to be carried out through visual/manual inspections in the frequency of a two years cycle. This process involves elements of subjectivity and is considerably influenced by the inspectors' experience. Given the time and money involved in obtaining the manual on-site bridge inspections, a need for developing modern, efficient and reliable methods of inspection is established (Chen et al., 2018, Kwiatkowski et al., 2020b, Villarino et al., 2014, Pourzeynali et al., 2021).

Over time, advanced technologies such as photogrammetry and laser scanning have widely developed a reputation as methods/tools capable of extracting rapid and precise three-dimensional (3D) digital representation of the object, known as a digital twin, without direct contact (Feroz and Abu Dabous, 2021, Dorafshan and Maguire, 2018, Rashidi et al., 2020b). During this time, researchers have mainly focused on adopting these advanced remote techniques to mitigate the consequence of costly and unsafe methods of manual and direct bridge inspections to satisfy the needs for a modern/computerised, remote, safer, more cost-effective, more accurate and less distributive bridge inspections. Unmanned Aerial Vehicle (UAV) based photogrammetry (Feroz and Abu Dabous, 2021, Dorafshan and Maguire, 2018), and Terrestrial Laser Scanning (TLS) (Rashidi et al., 2020b), are among the common methods used to overcome the challenges involved with manual bridge inspection. The outcome of using these state-of-the-art technologies is a detailed computer-based digital twin as a point cloud that can be virtually revisited any time for any data collection, analysis and measurements (Opoku et al., 2021). In the case of bridge engineering, the application of these remote technologies not only enables safer, more accurate and reliable works but also decreases the overall inspection time and costs.

Camera-based bridge inspection method using permanent analog cameras mounted on the critical points of the bridge structure were among the primary solutions that significantly attracted bridge engineers by not having to travel to the bridge site for inspection (Chen et al., 2019a). This method was further developed by Jahanshahi et al. (2011), who proposed an imagery-based system that enables the use of camera-based images to make a reliable comparison between the current and former conditions of the bridge structure. Along with the successful application of using the camera-based inspection method, and in order to make this method more practical and efficient, cameras were mounted on mobile vehicles such as Unmanned Aerial Vehicles (UAVs), commonly known as drones (Rashidi and Samali, 2021). Nowadays, several research studies have emphasised the valuable benefit of using UAV-based photogrammetry as a reliable robot method for bridge inspection, documentation and surface evaluation (Dorafshan et al., 2019, Dorafshan et al., 2018). In the UAV based photogrammetry, high-resolution areal images are taken remotely from different viewpoints of the proposed object, and then a 3D point cloud is generated based on further post-processing techniques using matched key points through Structure from Motion (SfM) or Multi View Stereropsis (MVS) algorithms (Szeliski, 2011). In a critical review study, Remondino et al. (2012) evaluated the performance of various image-based algorithms when dealing with large and complex data sets in regards to accuracy and data quality. The results of this study for an SfM based lighthouse data set in a Ground Control Point (GCP) analysis indicated 50 mm and 31 mm accuracy in terms of mean and standard deviation, respectively. In a bridge inspection case study, Seo et al. (2018) investigated the capabilities of drones and their effectiveness in activities related to bridge inspection. Following this research, an efficient bridge inspection method presented and tested for an inspection of a three-span timber bridge in the USA. The result showed the acceptable usage of drone-based photogrammetry as an efficient bridge inspection method capable of identifying a variety of surface damages such as corrosion, spalling, cracking, etc. However, drones are designed to be controlled by Global Positioning System (GPS), and the failure or weakness of GPS signals in some places such as the bridge underneath is a concern that needs to be considered by the drone pilot. In another study, Abolhasannejad et al. (2018) evaluated the application of UAV based photogrammetry for bridge deformation measurements proposing an image motion correction algorithm to tackle the camera motions during image data acquisition. In another effort, Pan et al. (2019) presented a semi-automated algorithm for extracting 3D digital model of a bridge via UAV based photogrammetry and evaluated this method for an existing heritage bridge case study in China. In a similar strategy, Chen, *et al.* (Chen et al., 2019a) proposed a bridge inspection procedure using UAV based photogrammetry for 3D model reconstruction and subsequent virtual inspection and damage detection.

The new technology of Terrestrial Laser Scanning (TLS) is another common approach for the rapid and precise collection of spatial information from an object's surface (Rashidi et al., 2020b). However, unlike traditional surveying methods that only capture the specific individual points of the targeted object one after another, TLS constantly captures each detail of the entire scene with the accurate position for each point and stores the data points in a 3D coordinate system, namely the x, y, z, associated with attributions such as colour. Thousands of data points, each corresponding to different locations of the exposed object, can be amassed to create a digital representation of the object, often called a point cloud. Therein, (TLS) has an alternative means to manual onsite inspections in the realm of built structures as it is capable of capturing accurate geometry of complex structures such as bridges within a short time frame (Riveiro and Lindenbergh, 2019). In the case of bridge engineering, this advanced technology has the potential to be used in a variety of applications in terms of as-built/as-is digital model development, quality inspection, structural assessment and management (Rashidi et al., 2020b, Truong-Hong and Laefer, 2019). As an initiative, Fuchs et al. (2004) are among the first researcher who suggested the application of the laser system as a 3D coordinate mapping instrument for inspection and assessment of highway bridges in the USA. In this research study, the capabilities of the laser system were assessed based on several laboratories and in-field evaluations for measuring global rotations on a girder bridge and bridge deflections under static load. Following this research strategy, Tang et al. (2007) reviewed the capabilities of TLS in the 3D model development of bridges; and also in detecting accurate measurements for bridge geometric features such as vertical clearance, etc. (Tang and Akinci, 2012a). In another effort, Mizoguchi et al. (2013) utilized the acquired TLS based point cloud for quantities evaluation of components' deficiency such as level of scaling, spalling, rate of section loss caused by corrosion, etc. Moreover, Minehane et al. (2014) utilized the TLS based bridge point cloud for structural assessment of a bridge in the UK. In another research study, Gyetvai et al. (2018) introduced an algorithm for identifying actual cross-sections of a bridge in Ireland with wrought-iron components. The successful implementation of this algorithm in reconstructing member cross-sections and overall geometric dimensions proved the valuable benefit of TLS in conducting geometric inspection and structural assessment. In a recent research study, Gawronek and Makuch (2019) utilized TLS measurements for assessing the vertical deformation of a truss bridge under a static load in Poland. The result of this practical research indicated ±3 mm maximum deviation in vertical deflection measurements analysis. Similar studies were also carried out in using TLS concerning as-built model development as a basis for reliable bridge structural assessment (Conde-Carnero et al., 2016, Ziolkowski et al., 2018, Mill et al., 2015, Laefer and Truong-Hong, 2017).

Nowadays, the possibility of twinning an existing asset into an accurate digital counterpart using these state-of-the-art technologies, with the aim of health monitoring and management of civil infrastructure assets, has become a strong demand among asset managers and structural engineers (Rashidi and Samali, 2021, Rashidi et al., 2020b). Providing such a detailed source of information as a digital model and application of Artificial Intelligence (AI) enable automation in various aspects of 3D model reconstruction and geometric identification (Laefer and Truong-Hong, 2017), quantitative management and progress tracking (Rashidi et al., 2018a, Tang et al., 2007), as well as damage quality inspection and structural assessment (Conde-Carnero et al., 2016, Gyetvai et al., 2018, Gawronek and Makuch, 2019, Yu et al., 2021). Moreover, this offers the possibility of using low-cost, remote, rapid, and precise computer visions compare to direct inspections and identifications.

State-of-the-art technologies such as UAV based photogrammetry and TLS, have benefits with a rapid, precise, and voluminous collection of remote data. However, the definition of generating a well-detailed as-built model for a bridge case study can be varied in terms of quality, integrity, and geometric accuracy of the point clouds. Although a limited number of research studies investigated the level of geometric accuracy for different point clouds generated (Lu et al., 2020, Kubota et al., 2019, Moon et al., 2019, Mohammadi et al., 2021a), the research is still lacking a reliable methodology for evaluating and comparing the quality of the bridge size point clouds. Therefore, this research study aims to provide a systematic methodology in this chapter as a pathway for engineers to evaluate and compare the quality of such voluminous datasets subjected to implementation of a detailed data capture, quality inspection and precise 3D model reconstruction. To this end, a range of general and specific approaches are proposed to be used for quality, consistency, and accuracy evaluations of such bridge size point clouds. Following the research, the soundness of the proposed methodology is proved in form of a real bridge case study by evaluating and comparing two available point clouds generated based on both UAV based photogrammetry and TLS for a heritage bridge named McKanes Falls Bridge in New South Wales (NSW), Australia. The summarized objectives of this chapter are listed below:

- Developing a systematic methodology for quality evaluation and comparison of bridge size point clouds.
- Proposing ranges of general and specific evaluation approaches.
- Proving the soundness of the proposed methodology and approaches by evaluating and comparing two point clouds for a bridge case study.

3.2. Bridge Case Study

In order to demonstrate the proposed evaluations and comparisons, two field studies using UAV and TLS were performed to collect the point clouds for a heritage-listed bridge named McKanes Falls Bridge, over the Coxs river, located in the city of Lithgow, New South Wales (NSW), Australia, Fig. 3-1. This timber truss bridge is among the four remaining McDonald style bridges in NSW built in 1893 and registered as a cultural heritage in 2000. The bridge structure consists of two timber truss spans in 27 meters length supported by sandstone masonry abutments at each end and a concrete pier at the center. The central pier of the bridge was originally constructed by stone, however, replaced by a reinforced concrete pier following a severe flood in 1986 (Fraser, 2001). The bridge's roadway is about 4.5-meter width and does not have a footway for pedestrians. The bridge deck is comprised of lateral timber beams supported by several longitudinal girders.

This research study is defined as part of an asset management project for upgrading the existing aged bridge with a stronger, safer, and more reliable structure while preserving a similar appearance and aspects as its original. This upgrading project includes restoring the critical timber components, strengthening the bridge structure using new steel and timber elements, and reinforcing the existing foundation and abutments with concrete to increase the bridge's load-bearing capacity and ductility (Mohammadi et al., 2020, Javidan and Kim, 2020), and allow safe use by vehicles up to General Mass Limit (GML) standard (Roads and Maritime Services, 2019). Therefore, after conducting preliminary investigations, risk assessments and some site surveys by experienced engineers and the research group, possible flight plans for UAV and scan positioning for TLS were evaluated and prepared. These strategies were defined in such a way as to collect sufficient data with complete coverage of the whole bridge. In the following, a summary of the data capture using both UAV and TLS methods are presented.

(a)

(b)

Figure 3-1 McKanes Falls Bridge: (a) Bridge satellite view, (b) Bridge status in 2019, Roads and Maritime Services (2019)

3.2.1. UAV Photogrammetry Survey

The McKanes Falls Bridge was surveyed using a close-range photogrammetry technique by capturing high-resolution images from different sides of the bridge. The bridge survey was carried out employing the Sony Alpha 7R digital 36 megapixels digital camera consisting of a 35mm full-frame lens mounted on the Intel® Falcon 8+ UAV system. This UAV system, as its state-of-the-art technology, is designed to be lightweight, quick, easy to operate, support a flight and camera stabilizer technology for challenging environments and harsh weathers such as a strong wind, and a V-frame body that offers a wide range of unobstructed view for data capture. Moreover, the control centre of this technology has the ability to be programmed based on the predesigned flight plan while automatically setting up drones flight speed, altitude, and required images from various positions, and also images' overlap to provide the desired result within the shortest flight time.

The predesigned flight plan was defined for the control center of the UAV system including two take-offs, capturing both sides of the bridge from south to north each in three paths with angles ranging from 0 to 45 degree, and one takes off observing the bridge overhead along the bridge length, all with offset distances less than 20 m. Moreover, to obtain additional details and well-document the blind spot of the bridge, several handheld images were also taken from different locations such as the bridge underneath.

Regarding the post-processing phase, the Structures from Motion (SfM) image processing technique coupled with Dense Multi-View Stereo (DMVS) was employed to convert the captured images into a 3D point cloud using ContextCapture software (Bentley Systems Company, 2021). During this process, the point cloud was generated based on the attached coordinates of each image obtained from the UAV Post Processed Kinematic (PPK) system, and considering the high-resolution setting in a geo-referenced system. The final bridge point cloud containing more than 349 million colorized data points is shown in Fig. 3-2(a).

3.2.2. TLS Survey

In another field test, the McKanes Falls Bridge was surveyed/scanned utilizing the Leica ScanStation P40 terrestrial laser scanner. This laser unit offers great versatility of features including long-range scanning (up to 270 meters away from the unit), fast rating data acquisition (about 1 million points per second), various ranges of resolution/accuracy (up to 0.8 mm at 10 m), wide field of view 360º×320º along with a low range of noise. This unit is equipped with an integrated positioning system that improves post-processing procedures and allows real-time on-site registrations (Leica Geosystems Company, 2018).

Scans were performed from more than 50 scan stations including multiple positions around the bridge sides, deck and bridge underneath in line with the predesigned scan plan considering close positions with an offset less than 20m away from the bridge. Normal resolution (6.3 mm

@ 10 m), normal quality settings and capturing High Dynamic Range (HDR) images were considered as data collection settings of the laser unit in each scan station.

TLS based scan data generally contain an amount of redundant data and a range of noise points which can affect the 3D model reconstruction, measurements, and other related inspection purposes. In this regard, pre-processing filters were applied to the acquired data and then clean data sets were registered/matched and colorized in post-processing procedures using Leica Cyclone software (Leica Geosystems Company, 2018). The outcome as a bridge point cloud with more than 1590 million points was also geo-referenced according to the geographic coordinate system, shown in Fig. 3-2(b).

(a)

(b)

Figure 3-2 Generated McKanes Falls Bridge point cloud based on: (a) UAV photogrammetry, (b) TLS

3.3. Quality Evaluation Methodology

According to the literature study presented, state-of-the-art emerging technologies such as UAV based photogrammetry and laser scanning each has their advantages in the case of bridge monitoring and as-is model reconstruction, however, some considerations/concerns can negatively affect their implementation in generating a precise and qualitative as-is 3D model. Weakness or absence of GPS signal, calibration degradation, inaccurate or insufficient surveying targets, and failure of image matchings in case of UAV based photogrammetry (Dorafshan and Maguire, 2018); and diffusion or poor laser beam reflection, degradation of laser unit's calibration, lacking surveying targets and choosing unstable laser positions in case of TLS are among the concerns that can be triggered to low-quality point cloud and some defects such as noisy data set with non-uniform points density, and inaccurate geometric position (Rashidi et al., 2020b).

Despite the growing popularity and common application of these advanced technologies in terms of inspection and monitoring, there is still a lack of information in assessing the quality and evaluating the occurrence of common defects for such a massive data set based on a specific standard or criteria. However, VDI/VDE 2643 BLATT 3 guideline (Verein Deutscher Ingenieure and Verband Der Elektrotechnik, 2008) initiated to provide various approaches for quality evaluation of measuring 3D objects in terms of accuracy and potential errors. Following this research, considering the approaches presented in the aforementioned guideline and some general/well-known error metrics, a systematic methodology is presented. Moreover, as a real case bridge case study, the quality of McKane Falls Bridge point clouds is evaluated and compared using the proposed approaches/methods. The methodology of this research is presented in Fig. 3-3. This methodology would be useful for bridge surveyors to achieve a systematic and reliable methodology for data quality evaluation of the generated point clouds.

As illustrated in Fig. 3-3, the framework is divided into two main subsections of bridge survey and data quality evaluation. Bridge survey involves three tasks including site survey, data acquisition and post-processing to achieve a well-detailed 3D model. This subsection is not the main concern of this study, however, a summary of the McKane Falls bridge case study as its survey using both TLS and UAV methods are presented in Section 3.2.

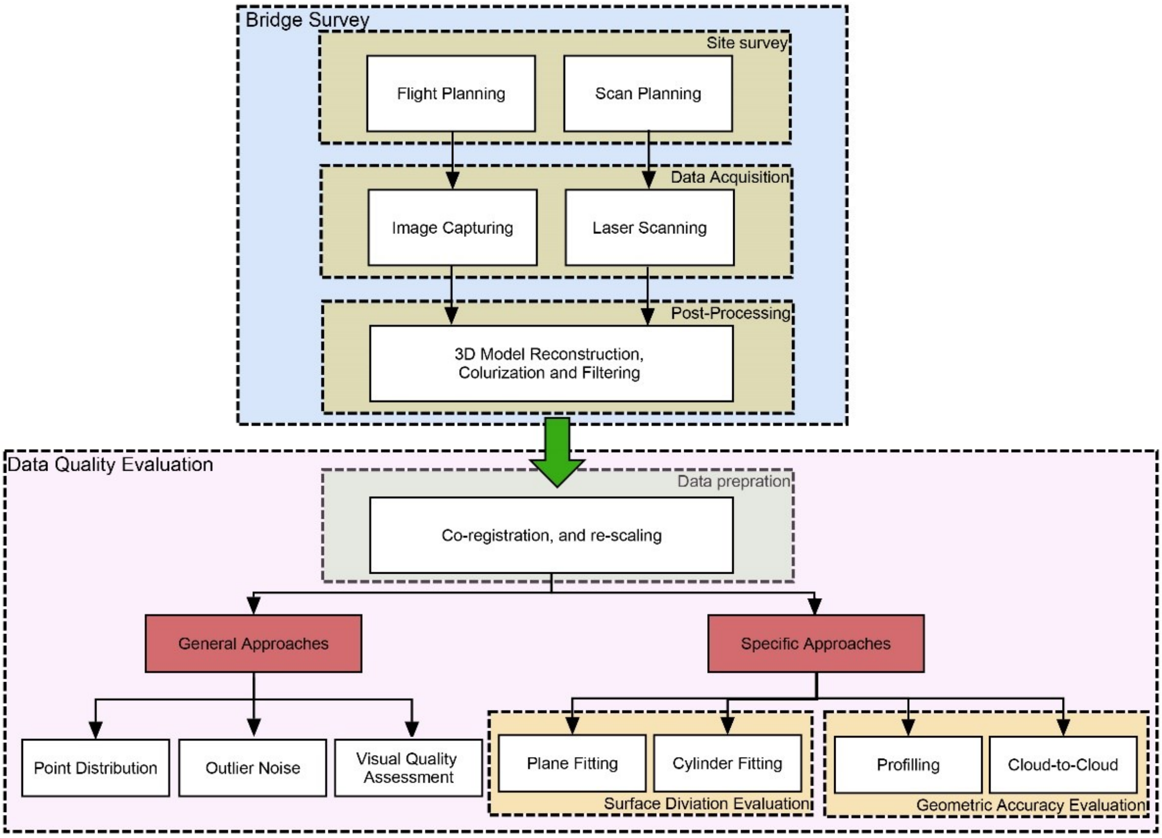


Figure 3-3 Bridge Surveying procedures and methodology of the data quality evaluation

In this study, a series of approaches are presented in the data quality evaluation subsection to be considered for evaluating the possible defect of the generated 3D point clouds. Data preparation, as the first step of data quality evaluation, refers to defining both point clouds being compared in a similar coordinate system. In some circumstances, the generated point clouds are captured, registered and aligned in different local coordinate systems and scales which may lead to an unacceptable/unfair comparison. Therefore, the generated point clouds need to be co-registered and re-scaled based on similar conditions. In this regard, one of the point clouds can be considered as the reference data set and the other point cloud becomes co-registered and re-scaled by transforming the data points to improve the alignment. Let's assume that Xp, Yp, and Zp are the 3D coordinates of a point, ($1 \leq p \leq P$, P is the number of points), that needs to be transformed. The transition of this point to Xj, Yj, and Zj ($1 \leq j \leq P$) can be calculated by Eq. 3-1.

$$\begin{bmatrix} X_j \\ Y_j \\ Z_j \end{bmatrix} = R \cdot S \begin{bmatrix} X_p \\ Y_p \\ Z_p \end{bmatrix} + \begin{bmatrix} T_x \\ T_y \\ T_z \end{bmatrix} \tag{3-1}$$

where R is the rotation matrix based on α, β, and γ as rotation angles along the X, Y and Z axis, respectively, as given in Eq. 3-2; S is the scale matrix as given in Eq. 3-3; and Tx, Ty, and Tz are translations along X, Y and Z axis, respectively.

$$R = R_x \cdot R_y \cdot R_z = \begin{bmatrix} cos\alpha & -sin\alpha & 0 \\ sin\alpha & cos\alpha & 0 \\ 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} cos\beta & 0 & sin\beta \\ 0 & 1 & 0 \\ -sin\beta & 0 & cos\beta \end{bmatrix} \cdot \begin{bmatrix} 1 & 0 & 0 \\ 0 & cos\gamma & -sin\gamma \\ 0 & sin\gamma & cos\gamma \end{bmatrix} \quad (3\text{-}2)$$

$$S = \begin{bmatrix} S_x & 0 & 0 \\ 0 & S_y & 0 \\ 0 & 0 & S_z \end{bmatrix} \quad (3\text{-}3)$$

In order to minimize the differences between point clouds, Iterative Closest Point (ICP) algorithm needs to be applied to refine the alignments (Besl and McKay, 1992). This algorithm is based on a search for pairs of nearest corresponding points in two datasets. Once both point clouds become well-aligned in a similar coordinate system, other steps of data quality evaluation can be performed. Following these steps, some well-known error metrics including Standard Deviation (STD), STD Error, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) are used and presented in Eqs. 3-4, 3-6, and 3-8, respectively.

$$STD = \sqrt{\frac{1}{M-1}\sum_{i=1}^{M}(D_i - \bar{D})^2} \quad (3\text{-}4)$$

where M defines as the number of observed data points of the sample, D_i is the distance value of each point to the corresponding reference point or surface, $\bar{D}$ is the average value of the distance can be calculated by Eq. 3-5.

$$\bar{D} = \frac{1}{M}(D_1 + D_2 + \cdots + D_i) \quad (3\text{-}5)$$

$$STD\ Error = \frac{STD}{\sqrt{M}} \quad (3\text{-}6)$$

$$RMSE = \sqrt{\frac{1}{M}\sum_{i=1}^{M}(D_i)^2} \quad (3\text{-}7)$$

$$MAE = \sqrt{\frac{1}{M}\sum_{i=1}^{M}|D_i|} \tag{3-8}$$

3.3.1. General Approaches

Evaluation of points distribution, the outlier noise and conducting visual quality assessments are among the most reliable general approaches for evaluating the consistency of the acquired data points and the surveying instrument/equipment.

Having insufficient points in a low volume of density may cause some defects regarding future investigation and analysis related to the surface generation, as-is model reconstructions and proper interpretation for having a reliable inspection (Huang et al., 2009). Therefore, evaluating the points distribution can be considered as a valuable approach calculated based on the number of the collected points per unit area of the object surface.

Generated point clouds usually contain outlier noises that refer to deviant/abnormal data points which are different from the remaining data (Salgado et al., 2016, Karami et al., 2021). Although normal noises can be defined as redundant data with minor distance errors, outlier noises are defined as a broader concept that includes discordant data with considerable errors that may arise from false point measurements and reconstruction faults within the point cloud generation process. Edges of the objects are among the most susceptible areas prone to this error either in photogrammetry, and laser scanning (Uchida et al., 2020, Salgado et al., 2016, Wang, 2014). The outlier noise evaluation can give us valuable information concerning the relied methods and systems. The outlier noise can be filtered by establishing a noise removal algorithm or a threshold to control the maximum distance errors. As suggested by Chen, *et al.* (2019a), this threshold, α', can be defined based on Eq. 3-9.

$$\alpha' = \lambda' + 2\beta' \tag{3-9}$$

where λ' is the mean distance error and β' is the standard deviation.

Damage quantification and visual quality assessment of the generated point clouds is another approach for quality evaluation of the point clouds referring to the amount of agreement between the extracted damaged area from the data set and the existing damage in on-site inspections.

3.3.2. Specific Approaches

Surface deviation and geometric accuracy evaluation are among the specific approaches/concepts adopted from VDI/VDE 2643 guidelines (Verein Deutscher Ingenieure and Verband Der Elektrotechnik, 2008, Verein Deutscher Ingenieure and Verband Der Elektrotechnik, 2012, Hosseininaveh Ahmadabadian et al., 2019) for assessing the quality and precision of 3D measuring systems. In the following, these two approaches are described.

3.3.2.1. Surface Deviation Evaluation

In theory, the captured texture of an object with a smooth surface expects to be presented in a layer of points without thickness, however, this is not the reality, and the surface is generally quantified by points with a deviation from its ideal form. In surface metrology, the amount of deviation demonstrates the level of noise obtained and can generally show the reliability of the surveying equipment and system in terms of generating a precise as-is/built 3D model (Verein Deutscher Ingenieure and Verband Der Elektrotechnik, 2008). Therefore, this evaluation recommended to be conducted based on some surface deviation evaluation methods/criteria such as plane fitting, cylinder fittings, etc. The plane fitting evaluation refers to measuring the spatial distribution of the object's points to their best-fitted plane. This process is performed based on defining a fitted plane using Least Squares Fitting (LSF) algorithm (Essa, 2014, Mousavi et al., 2018). Considering a plane equation in 3D Euclidean space, Eq. 10, the LSF algorithm is a regression analysis to find an approximate solution for the plane equation, by minimizing the sum of squares of the normal distance values, *S*, for each point to the corresponding reference point on the approximate plane, D_i, shown in Eqs. 3-11 and 3-12 (Rabbani, 2006).

$$a(x_i - x_0) + b(y_i - y_0) + c(z_i - z_0) = 0 \tag{3-10}$$

where, a, b and c are defined as the normal vectors of the plane, and x_0, y_0, z_0 are points position in a 3D X-Y-Z coordinate system.

$$Sum = \sum_{i=1}^{m} {D_i}^2 \tag{3-11}$$

where, D_i, is defined as follow:

$$D_i = \frac{|a(x_i - x_0) + b(y_i - y_0) + c(z_i - z_0)|}{\sqrt{a^2 + b^2 + c^2}} \tag{3-12}$$

In a similar strategy, considering the surface equation and using LSF algorithm, the best-fitted plane can be estimated.

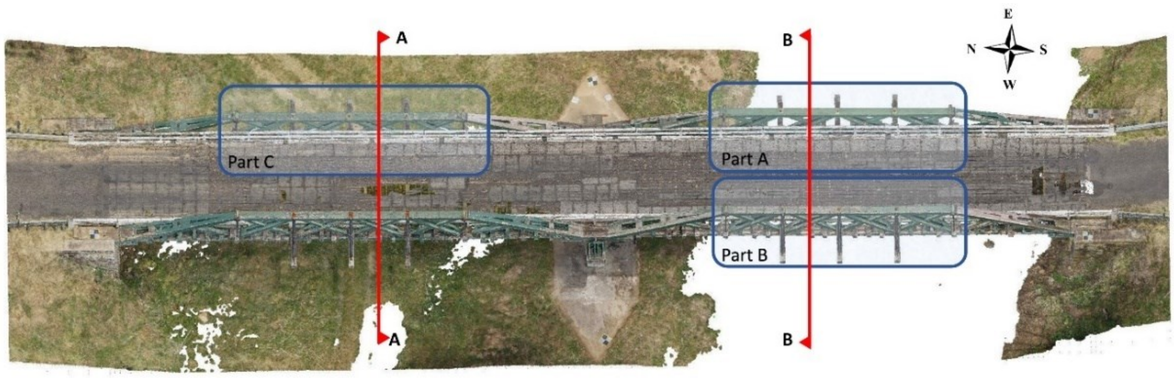
3.3.2.2. Geometric Accuracy Evaluation

The methodology of using extracted point clouds as a basis for detailed quality inspection of infrastructures, especially bridges, has been widely established. However, the capability of employing these data for evaluating different levels of inspections has remained a key problem. Depending on the importance of the project, identifying various surface damages and deformations generally require a high Level of Detail (LoD) inspection, however, a lower LoD is enough for geometry measurements purposes. The relationship between LoD and the accuracy of laser scanning is defined in the ASTM E57.02 Standard Specification for 3D Imaging Data Exchange (ASTM International, 2018), which sets the minimum requirements for 3D imaging data exchange, including the necessary level of detail and accuracy for various applications. Higher levels of inspections, such as Level 3 structural assessment and Level 4 special inspection, require more extensive and detailed inspections for detailed 3D model extraction to be used for the structural assessment. Therein, with an eye on having a geometric accuracy evaluation for the generated point clouds during level 2 partial (routine) inspection, this study recommends three methods of point-to-point, profiling and cloud-to-cloud comparison between the generated point clouds.

The point-to-point comparison refers to measuring the relative distances between a few recognizable feature pairs in different data sets. As presented by Koutsoudis, *et al.* (2014), this criterion with a comprehensive view can be used to evaluate the level of noise, scaling error and the level of geometric accuracy for the generated point clouds. However, this method can be extended by evaluating the relative distance between some fitted planes, known as a plane-to-plane comparison, for a more reliable geometry accuracy evaluation. Evaluating and comparing the extracted cross-sectional profile of an object in the different data sets, known as profiling, can be considered as a valuable source of data for extending the geometric accuracy evaluations. The cross-sectional profile refers to the two-dimensional linear shape of a 3D object sliced perpendicularly. In the profiling method, the corresponding spatial distribution of the extracted cross-sectional profiles can be evaluated and compared in overall or for different subsections of an object. The Cloud-to-Cloud (C2C) comparison refers to measuring the nearest neighboring distance between reference points in a point cloud and their corresponding points in another dataset, using the Hausdorff distance algorithm (Rockafellar and Wets, 1998, Ahmadabadian et al., 2017). However, this algorithm is less sensitive to low dense point clouds and could yield unexpected results. Local modelling strategy is an improved form of this method that is generally faster and could yield more reliable results for clouds with more constant density. The local modelling strategy can compute a local model around the nearest point so as to approximate a surface and get a better estimation of the real distance. This surface can be defined based on various algorithms such as LSF, triangulation, or quadric function (Ahmad Fuad et al., 2018).

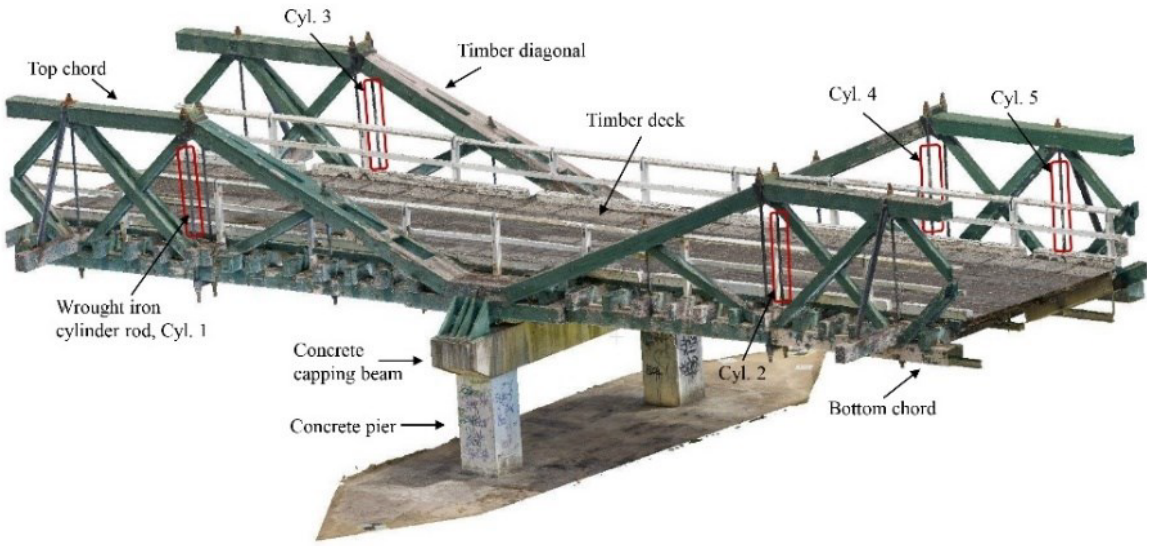
3.4. Results of case study evaluation

In this section, in order to further investigate the application of the proposed methodology, the quality of the McKanes Falls Bridge point clouds captured/scanned via UAV-based photogrammetry and TLS are evaluated and compared. Concerning the first step of data preparation, both point clouds were evaluated whether they are registered in an exact coordinate system with similar scales. To evaluate this concern, a detailed geometric accuracy analysis is performed, as presented in Section 3.4.2, and the results used for minor rescaling of UAV-based point cloud based on the TLS data set. Moreover, considering the TLS data set as the benchmark, the rescaled UAV-based data set is also co-registered to the TLS data set to make both point clouds ready and prepare for a reliable relative quality evaluation. Handling these point clouds containing such a massive amount of data is only possible by segregating the data sets into smaller objects/parts before feeding them into the computer system and software for further analysis. Therefore, two cross-sections passing through the bridge spans, shown in Fig. 3-4, were used to segregate the middle part of the bridge with its components as the intended surveying objects. This part contains concrete piers, capping concrete beam, parts of bottom and top timber chords, timber deck and diagonals, and wrought iron cylinder rods. As shown in Fig. 3-4(b), four sides of each concrete pier, two sides of the capping beam, parts of the iron cylinder rods, parts of bridge deck and trusses are considered to be analysed using the proposed methodology.

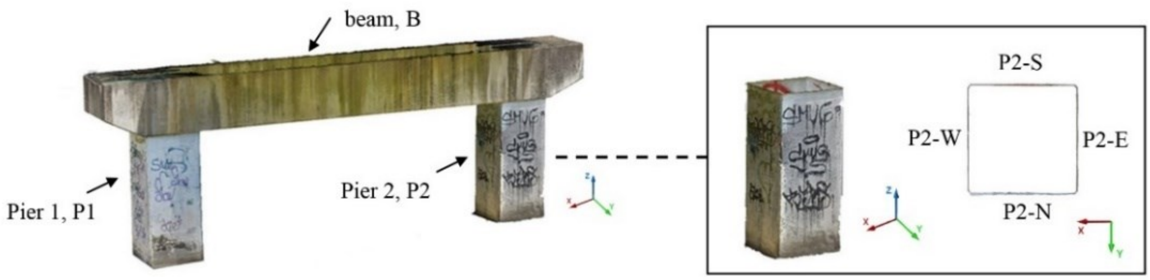


(a)

Figure 3-4 Bridge components and the intended surveying objects; (a) Bridge top view and cross-section.



(b)



(c)

Figure 3-4 Bridge components and the intended surveying objects; (b) Selected components, (c) Intended surveying objects and parameters.

3.4.1. General Approaches

3.4.1.1. Points Distribution

Based on the aforementioned methodology, the distribution of points generated via both UAV photogrammetry and TLS is evaluated and compared by calculating the density of the points per area on the selected object's surfaces after applying statistical outlier removal algorithm in CloudCompare software (Girardeau-Montaut, 2006, Karami et al., 2021). Table 3-1 presents the result of this evaluation considering the surfaces of bridge piers and beam, shown in Fig. 3-4(c), as the intended surveying objects.

Table 3-1 Evaluation of points distribution and density

Plane	Selected area (m^2)	UAV-based photogrammetry		TLS	
		Number of points	Density (P/cm^2)	Number of points	Density (P/cm^2)
P1-N	2.12	504013	24	921011	43
P1-W	2.11	504902	24	606975	29
P1-S	2.00	104235	5	1056905	53
P1-E	1.99	374667	19	1014998	51
P2-N	2.03	482906	24	904120	45
P2-W	1.97	471907	24	730039	37
P2-S	2.04	336240	16	976529	48
P2-E	1.96	442194	23	575410	29
B-N	4.63	1153831	25	2334752	50
B-S	5.28	1123152	21	962805	18
Average	2.61	549805	21	1008355	39

According to Table 3-1, the average density of the point cloud generated via TLS is calculated as 39 points per square centimeter (P/cm^2) while this amount is roughly half of the density calculated for similar surfaces generated based on UAV photogrammetry. In some instances, such as planes P1-S and P2-S, the results demonstrate even more than 50% difference in terms of point cloud density which indicates a denser and more reliable point cloud using TLS with the aims of 3D model reconstruction and inspection.

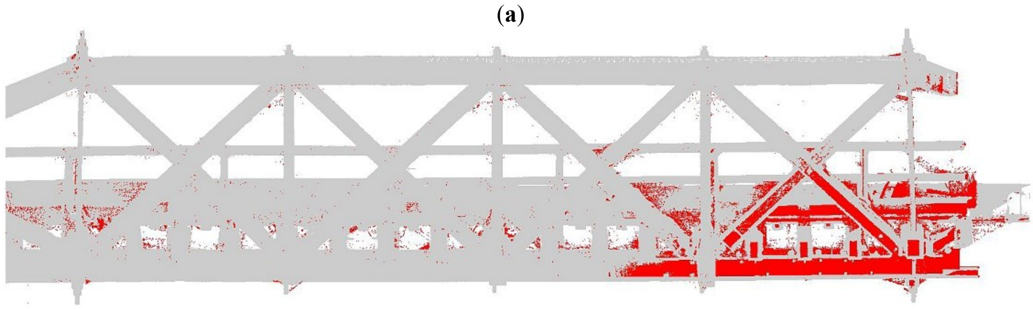
3.4.1.2. Outlier Noise

Considering the filtering method presented in Section 4.3.1 and Eq. 3-9, the TLS point cloud is aligned with the UAV data using the ICP algorithm (Besl and McKay, 1992), and the outlier noise level for TLS data point is calculated, shown in Table 3-2. This calculation is conducted for three different segregation of the bridge named part A, B, and C including parts of the timber truss and bridge deck, shown in Fig. 3-4(a). Fig. 3-5 presents the outlier noise points by red colour after conducting this evaluation for parts A and C. The result of this evaluation shows the average outlier noise level of 2.36% for TLS data points based on the referenced UAV data set. Although this amount of noise level is quite normal for a bridge size point cloud captured by TLS, the evaluations indicate less outlier noise for UAV data in the case of McKanes Falls Bridge inspection.

Table 3-2 The results of outlier noise evaluation

Reference objects (Part)	λ'(mm)	β'(mm)	α'(mm)	Number of points	Number of outlier points	Outlier noise (%)
A	0.50	7.90	16.30	226,257,806	5,328,371	2.35%
B	0.39	7.13	14.70	249,620,401	3,896,574	1.56%
C	2.00	20.00	42.00	156,609,279	4,991,137	3.18%
Average						2.36%

(**a**)



(**b**)

Figure 3-5 Outlier noise evaluation for; (a) Part A, (b) Part C

3.4.1.3. Visual Quality Assessment

During the initial check of the generated point clouds, some missing/incomplete data observed on the UAV data set. In order to further evaluate this issue, the generated TLS point cloud is revisited on the computer by an expert engineer using CloudCompare software. As shown in Figure 6, it is observed that some locations/areas of the bridge deck are not well reconstructed in the UAV data set while these areas are completely reconstructed in the TLS point cloud. In UAV-based photogrammetry and following reconstruction procedures, the missing/incomplete data issue is inevitably caused by poor overlapping of the images or extracting an insufficient number of features during the registration/matching process (Mousavi et al., 2021). However, in the case of laser scanning, the shadowing effect caused by beam obstruction can be the origin (Gärtner et al., 2009).

(a) (b)

Figure 3-6 Visual quality assessment; (a) UAV data versus, (b) Laser data

3.4.2. Specific Approaches

3.4.2.1. Surface Deviation Evaluation

As previously mentioned, measuring the spatial distribution of the generated points is recommended to be conducted based on surface deviation analysis methods. In this study, all sides of the bridge piers and two sides of the beam are considered to be analyzed based on the proposed methodology by defining the best-fitted plane and evaluating the spatial distribution of the points in both data sets using well-known error metrics such as STD, RMSE, etc. The result of this evaluation is presented in Table 3-3.

Table 3-3 Surface deviation analysis using the plane fitting method, Unit: mm

Plane	UAV based photogrammetry					TLS				
	STD	Mean distance	Max distance	RMSE	MAE	STD	Mean distance	Max distance	RMSE	MAE
P1-N	2.13	0.59	7.93	3.13	2.47	1.37	0.13	8.54	1.37	1.10
P1-W	1.67	0.33	7.86	1.67	1.08	1.16	0.07	8.73	1.16	10.00
P1-S	1.35	0.20	7.96	1.35	2.30	1.77	0.30	8.50	1.77	1.20
P1-E	2.60	0.40	7.92	2.60	2.02	1.92	0.20	8.40	1.92	1.60
P2-N	1.28	0.19	8.18	1.28	1.00	1.36	0.12	8.68	1.36	1.00
P2-W	1.50	0.10	8.08	1.50	1.00	1.55	0.15	8.40	1.55	1.20
P2-S	2.32	0.30	8.06	2.30	1.70	1.31	0.10	8.80	1.31	1.00
P2-E	1.96	0.20	8.07	1.96	1.60	1.94	0.10	8.80	1.94	1.60
B-N	1.97	0.10	14.10	1.90	1.47	2.11	0.13	17.00	2.13	1.95
B-S	1.90	0.10	14.34	1.90	1.49	1.67	0.41	20.77	1.67	1.30
Average	1.80	0.25	9.25	1.96	1.61	1.62	0.17	10.66	1.62	1.29

As shown in Table 3-3, The average standard deviation (STD) and Root Mean Square Error (RMSE) for UAV data are 1.80 mm and 1.96 mm, respectively. These amounts are calculated as 1.62 mm for the TLS data set. All of which indicates an almost similar level of noise for both data sets. Individual comparisons also indicate greater performance using TLS in terms of generating precise 3D models.

In another effort, this evaluation is extended to measure the reliability of using these two surveying methods in generating small-size components. In this regard, five cylinder rods (Cyl.), shown in Fig. 3-4(b), are considered to be evaluated based on the surface deviation analysis by fitting the best cylinder surface to the object's points. Then, calculating the spatial distribution of the points to these surfaces using well-known metric errors such as STD, RMSE and MAE. The result of this evaluation is presented in Table 3-4.

Table 3-4 Surface deviation analysis using the cylinder fitting method, Unit: mm

Plane	UAV based photogrammetry					TLS				
	STD	Mean distance	Max distance	RMSE	MAE	STD	Mean distance	Max distance	RMSE	MAE
Cyl. 1	3.60	1.50	3.00	4.00	2.00	2.70	0.60	5.40	2.80	2.20
Cyl. 2	3.90	1.40	5.00	5.50	4.00	3.50	0.29	5.10	3.53	2.60
Cyl. 3	3.90	2.55	5.10	4.70	3.00	4.40	0.10	5.22	3.56	2.40
Cyl. 4	3.45	1.20	4.00	3.60	0.26	3.00	0.12	4.80	3.30	2.40
Cyl. 5	5.00	0.80	4.80	5.40	4.00	3.20	2.30	4.90	4.00	3.20
Average	4.00	1.49	4.00	4.60	2.60	3.36	0.68	5.10	3.40	2.60

According to Table 3-4, the average results of STD, RMSE for the UAV data set shows values greater than 4 mm while these amounts are calculated less than 3.4 mm for TLS data points. However, the maximum distance obtained for the TLS data set shows a millimeter larger value than the UAV data points. This indicates a higher noise level for TLS data while having greater performance in terms of geometric accuracy subjected to 3D model reconstruction of the small-sized object.

3.4.2.2. Geometric Accuracy Evaluation

Adopting the method presented by Koutsoudis et al. (2014), the geometric accuracy of both point clouds were evaluated and compared using the point-to-point comparison referring to measure the relative distances between specific points in each data set. This method is also extended to be more reliable by measuring the relative distances between several fitted planes. In this study, considering the intended surveying object presented in Fig. 3-4 (c), the average relative distances between the best-fitted planes of the bridge piers are measured by selecting several corresponding points on their facing planes. Then, the results are compared with as-is measurements captured by traditional survey equipment. The results of this comparison, shown in Table 3-5, are later used for data preparation and re-scaling of the raw point clouds. As presented in Table 3-5, this evaluation shows greater scaling errors for the UAV data set than TLS based scaling errors in comparison to the reference as-is measurements.

Table 3-5 Geometry accuracy and scaling error evaluation

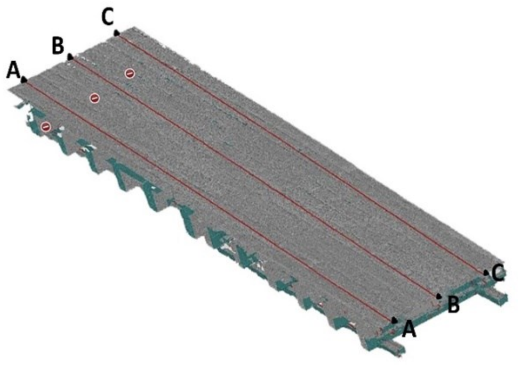
	UAV (mm)	TLS (mm)	As-is (mm)	UAV scaling error (mm)	TLS scaling error (mm)
P1-N to P1-S	941.7	910.2	908.1	33.6	2.1
P1-W to P1-E	944.1	910.5	907.9	36.2	2.6
P2-N to P2-S	942.5	911.2	909.0	33.5	2.2
P2-W to P2-E	939.8	911.5	910.1	29.7	1.4

According to the acceptable agreement between the geometric accuracy of the TLS data and as-is measurements, presented in Table 3-5, the TLS data set was served to be the reference data in the preparation phase and UAV data was rescaled and co-registered based on TLS data. Successful completion of this phase was further verified by conducting the proposed geometric accuracy evaluation and calculating the mean distance, standard error and uncertainty of the measurements for both point clouds in more than 10 iterations. The result of this verification, shown in Table 3-6, provides the standard error up to 0.01 mm difference and uncertainty of 0.016% in measurements from the TLS data set.

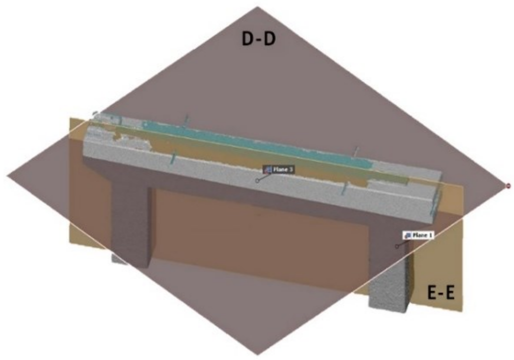
Table 3-6 Verification and geometry accuracy evaluation (Unit: mm)

Number of iterations	P1-E to P2-W		P1-W to P2-E	
	UAV	TLS	UAV	TLS
1	5479.1	5479.5	7300.0	7298.9
2	5472.1	5471.0	7301.0	7293.6
3	5478.3	5479.2	7299.9	7298.6
4	5479.0	5478.7	7301.5	7301.5
5	5474.7	5476.4	7299.6	7300.5
6	5474.5	5474.2	7301.0	7298.4
7	5472.6	5473.3	7297.3	7302.0
8	5471.2	5472.4	7293.4	7301.1
9	5472.7	5472.5	7300.9	7302.3
10	5475.6	5475.4	7309.4	7302.6
11	5472.8	5472.0	7301.4	7309.0
Average	5474.8	5474.9	7300.5	7300.7
STD	3	2.9	3.8	3.7
Standard error	0.9	0.89	1.14	1.13
MAE	51	51	48	50
Uncertainty in measurement	5470±4	5470±3.5	7300±7	7300±7
Uncertainty (%)	0.016	0.016	0.016	0.016

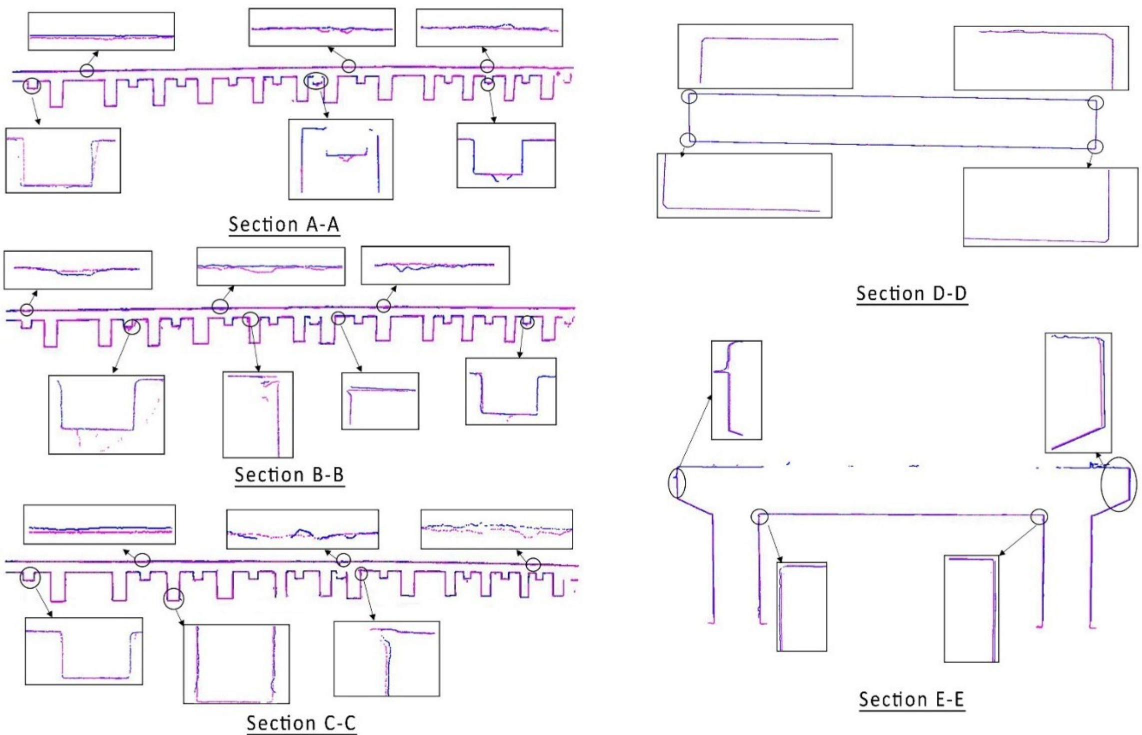
In another effort, the segmented bridge deck and piers, shown in Fig. 3-4(b), are considered to be inspected using the profiling method. In this regard, both point clouds were converted into polygon meshes (triangle mesh models) using GOM Inspect computer software (GOM Gmbh Company, 2020) considering similar settings and parameters. Following this research, several cross-sectional profiles of the bridge deck and piers, shown in Fig. 3-7(a, b), were extracted and evaluated. In Fig. 3-7(c), red lines present the TLS-based cross-sectional profile while the blue lines show linear paths of UAV-based point clouds.



(a)



(b)



(C)

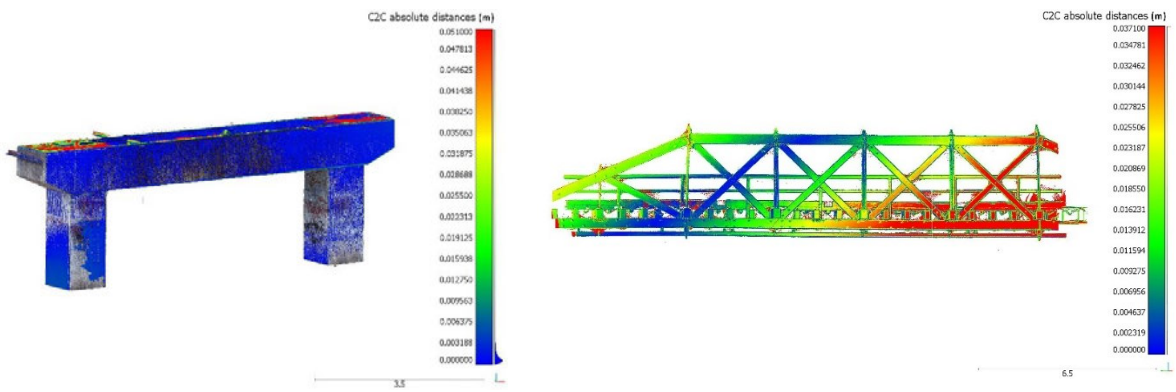
Figure 3-7 The inspected cross-sectional profiles of the bridge; (a) Bridge deck, (b) Piers, (c) Cross-sectional profiles and details, blue lines: UAV data, red lines: TLS.

The result of the profiling comparison, presented in Table 3-7, shows the maximum and average distances, STD and RMSE between the generated cross-sectional profiles in both point clouds. Considering deck cross-sectional profiles, the average distance between two point clouds is less than 7.27 mm, however, this amount is 0.82 mm on section D-D and 10.17 mm on section E-E for the bridge pier cross-sectional profiles. Moreover, the STD and RMSE are less than 6.97 mm and 7.53 mm, respectively. All of which indicates an acceptable agreement between the generated point clouds, however, some minor defects might occur due to self-shadowing or lack of beam reflection, reflection loss, in laser scanning or matching issues in UAV photogrammetry.

Table 3-7 Profiling comparison (Unit: mm)

Cross-sectional profiles	Max distance	Average distance	STD	RMSE
Sec A-A	15.44	3.11	4.10	3.61
Sec B-B	14.21	3.29	3.94	3.62
Sec C-C	19.79	7.27	6.97	7.13
Sec D-D	6.23	0.82	0.48	0.65
Sec E-E	17.43	10.17	4.89	7.53

The last evaluation involves the analysis of Cloud-to-Cloud (C2C) distances based on the local modelling strategy for two different parts of the bridge using various algorithms of LSF, triangulation, quadric surface function and nearest neighbour. The results of this evaluation are presented in Fig. 3-8 and Table 3-8. In order to further clarify the results, the deviation analysis is presented based on color scales with distance values in meters from blue to red. Points with blue colors have the closest distance, however, the points with red colors are located away in both point clouds.



(a) (b)
Figure 3-8 C2C distance comparison for; (a) pier, (b) part C

According to Table 3-8, the comparison of bridge piers point clouds shows the average distances less than 4.5 mm using all local modelling methods, however, this amount is less than

8.5 mm for part C, which means lower precision in point clouds' coordination/matching considerably due to structural complexity of the part C as the intended surveying object. Moreover, the resulted STD values have differences with average distances values calculated, showing the different level of noises in generated point clouds.

Table 3-8 C2C distance computations

Local modelling method	Number of neighboring points	Pier		Part C	
		Average Distance (mm)	STD (mm)	Average Distance (mm)	STD (mm)
Least square plane	6	2.08	3.83	5.83	10.03
	12	2.41	4.20	6.61	10.86
Triangulation	6	2.97	9.51	8.13	15.54
	12	2.91	9.39	8.07	15.52
Quadric function	6	2.18	4.10	6.16	10.99
	12	2.45	4.41	6.80	11.56
Nearest neighbor	-	3.08	9.54	8.24	15.54

3.5. Discussion on this chapter

The proposed methodology of this research study contains two series of general and specific approaches to evaluate the consistency, quality, and precision of the generated bridge size point clouds. This methodology is further verified and evidenced via comparisons of two available bridge point clouds generated/scanned from a bridge named McKanes Falls Bridge using both UAV and TLS.

In the case of McKanes Falls Bridge evaluation, the results of general approaches indicated denser TLS based point cloud. Denser point clouds generally possess a higher number of points representing objects' surface thereby improving the level of accuracy for precise damage identifications and Level of Detail (LoD) in terms of as-is/as-built 3D model reconstructions. Moreover, the result of visual quality assessment showed some missing/incomplete data in UAV derived point cloud which can be caused by poor overlapping of the images captured or defining an insufficient number of features in matching process. However, the outlier noise evaluations demonstrated less outlier noise for UAV based point cloud.

The results of specific approaches indicated an almost similar level of noise for both TLS and UAV based data points, however, individual comparisons and other factors showed greater performance of using TLS in terms of detailed 3D model reconstruction. The result of geometric accuracy evaluations showed scaling errors in millimetre for TLS, however, UAV based data point exhibited centimetre level of agreement with as-is measurements. In terms of UAV photogrammetry, scaling errors may be a result of the inaccurate definition of Ground Control Points (GPCs) or some issues related to vehicle settings and the post-processing procedures. Thus, surveying aspects of a bridge inspection such as selecting a suitable surveying plan, data acquisition and post-processing techniques can affect a qualitative point cloud generation which deserves future investigations. After serving TLS data point as the reference data and rescaling the UAV data point, the result of profiling and cloud-to-cloud comparisons showed acceptable agreement with minor defects between both point clouds.

In overall, the results of McKanes Falls Bridge case study proved the capabilities of the proposed methodology in data quality evaluation of such voluminous point clouds. It is clear that both UAV based photogrammetry and TLS have their own advantages and drawbacks. Compared to the traditional inspection method, UAV-based photogrammetry possesses clear advantages regarding its flexibility in the level of geometric accuracy, accessibility to high altitude areas, inspection safety, cost-effectiveness, and reasonable inspection time. However, TLS also offers various levels of point density with range based geometric accuracy suitable for detailed inspections while taking longer surveying and post-processing times. Therefore, selecting the suitable bridge inspection method and technology may rely on other considerations such as intended surveying object, available budget, the required Level of Detail (LoD), site accessibility and project significance.

3.6. Summary and conclusions

With respect to bridge inspection and monitoring, this chapter introduced a comprehensive methodology for having a reliable quality analysis of digital point clouds generated via various techniques such as imagery acquisition and laser scanning subjected to the implantation of a detailed 3D reconstruction model. In this regard, a range of general and specific data evaluation approaches was proposed to evaluate and compare such voluminous point clouds in terms of points distribution, outlier level of noise, data completeness, surface deviation and geometric accuracy evaluation. The proposed methodology and approaches were further verified and proved in evaluating and comparing two available bridge point clouds captured/scanned via UAV photogrammetry and Terrestrial Laser Scanning (TLS) from a heritage bridge named McKanes Falls Bridge located in NSW, Australia.

The comparative result of this case study exhibited the capability and applicability of the proposed methodology and evaluation approaches which lead to a reliable and acceptable/fair data quality evaluation and comparison. In the case of McKanes Falls Bridge inspection, the results of the proposed methodology and approaches showed a higher level of points density, more acceptable agreement with as-is measurements, normal levels of outlier and general noise using TLS. However, considering similar surveying objects and evaluations, the results exhibited some missing data, greater scaling errors with lower geometric accuracy for UAV based point cloud. All of which indicates that TLS can offer significant advantages in level of geometric accuracy while having a high level of point density which are important considerations in terms of precise 3D model reconstruction for detailed quality inspections of the bridges. However, concerns remain including the implementation time, high equipment cost and limited/restricted access of TLS, which all can be compensated using UAV-based photogrammetry techniques.

According to the presented study, the future research can be focused on assessment of the surveying aspects of bridge inspections such as data acquisition/collection, surveying plans and post-processing procedures which can affect qualitative point clouds generation.

Chapter 4

(BrIM Development)

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4.1. Introduction

Bridge infrastructures are among the essential components of the road/transport network the world over that require regular inspection and condition assessment to remain durable and healthy while maintaining an acceptable level of safety and serviceability during their lifetime. Over the years, bridges of all types have had to support increasingly greater loads, at greater frequencies, causing these expensive and vital infrastructures to wear out at an ever increasing rate (Shojaeddin, 2019, Wan et al., 2019).

The collapse of Taiwan's Nanfang'ao bridge in 2019 (Horgan, 2019) and Italy's Morandi bridge collapse in 2018 (Calvi et al., 2019) are two recent examples of disasters caused by a lack of proper bridge monitoring and management. Therefore, the importance of monitoring, documenting, and managing the state of bridge health, cannot be overstated. A common, yet vital, part of bridge monitoring is the inspection of bridges by visual means (Puž et al., 2012, Moore et al., 2001, Dorafshan and Maguire, 2018). These attributes of visual bridge inspection are reinforced by inspection regimes established by transportation authorities' (TfNSW, 2007), wherein it is explained that initial detection of defects in concrete bridges is usually through visual inspection; which is a technique that also has the capability of detecting many damages in steel and timber bridges (Rashidi et al., 2021, Rashidi et al., 2017, Javidan and Kim, 2021, Gorji Azandariani et al., 2021). Despite its prevalence and versatility, visual inspection involves an element of subjectivity, is influenced by the experience of the inspectors involved. This procedure is labor-intensive, is not traceable, and may necessitate special equipment to enable access to places otherwise out of reach (Waheed et al., 2013, Sabrie, 2010, Azim and Gül, 2020, Pourzeynali et al., 2021, Yu et al., 2022, O'Brien et al., 2015). The prevalence of visual inspection is not surprising, given that humans are highly visual creatures (Patch, 2015). The human quality establishes a need to link electronic written bridge inspection and maintenance records with a digital three-dimensional (3D) model of the subject bridge so that the records can have their storage organized. In this regard, the recorded information can be accessed via an ergonomic navigation medium, as opposed to paper records maintained in a file cabinet drawer. In doing so, bridge inspection records can be more meaningful to, and be better understood, by bridge maintenance team, which, in turn, can permit greater collaboration and teamwork between the members (Nicolle and Cruz, 2011, Chan et al., 2016, McGuire et al., 2016a).

Whilst a bridge may be modelled in 3D during its design period, the built structure may diverge from the details within a design model, and, once built, a bridge's condition constantly changes over time. This makes it necessary for the geometry of a bridge to be recorded at a nominated frequency in order for the possible realization of a 3D model that better reflects the real bridge's as-is condition (Barazzetti, 2016, Brilakis et al., 2010). Amassing the information required to produce a 3D model of a bridge can be a time-consuming task, especially if data collection is performed as a visual inspection clambering over components while using measuring staffs, tapes, plumb bobs, string lines, and callipers. However, advancements in technology present possible solutions to the problem of efficiently measuring the extensive geometry within bridges. Specifically, the relatively new technology of Terrestrial Laser Scanning (TLS) has developed a reputation for rapid collection of spatial information remotely (Rashidi et al., 2020b, Gyetvai et al., 2018, Lubowiecka et al., 2009). TLS is a ground-based system, typically operated from a stationary vantage point, such as atop a tripod, and makes use of lasers to record the shapes of objects' surfaces within a field of view (Wilford, 2020). TLS is now used in many engineering applications, including bridge inspection, assessment and management (Spring, 2020, Tang et al., 2007, Miśkiewicz et al., 2021, Artese and Zinno, 2020).

In the field of bridge inspection and assessment, Tang et al. (2007) were among the first researchers who suggested the application of TLS in collecting bridge geometric features such as vertical clearance measurements as the requirement of the National Bridge Inventory (NBI) guideline proposed by the U.S. Department of transportation. In this study, the advantages of utilizing TLS in collecting accurate data were compared to traditional ways of manual data collection. Another research study conducted by Chen (2012) described how TLS can be used to ascertain minimum clearance measurements, detect damage, confirm and compare post-event geometry with pre-event geometry. Moreover, they provided an example where TLS has served as an alternative means of evaluating static load deflections of a bridge which could not have reasonably had strain gauges attached to its underside without shutting down a major thoroughfare. Stull and Earls (2009) used collected TLS information to estimate the capacity of a damaged bridge structure by extracting the finite element model. Another effort by Miśkiewicz et al. (2021) described a thorough interdisciplinary bridge assessment using the combination of TLS technology, Ground Penetration Radar (GPR), and Finite Element (FE) computation to evaluate the factors that contribute to the incidence of premature pavement cracks. In a similar strategy, Pérez et al. (2018) also used the combination of TLS and GPR for evaluating the integrity of a Roman Bridge in Spain. Other bridge research studies by Artese and Zinno (2020), Arbi and Ide (2015), Gawronek et al. (2019), and Mill et al. (2015), cover the use of TLS in projects involving bridge assessment, monitoring, and updating of bridge information to reflect the presence of additions, required maintenance, and evaluating suitable locations for new equipment under a bridge. They all stated that by using TLS in bridge inspection, dependence on access equipment such as under bridge units and scaffoldings, which can impact on the flow of traffic, is greatly reduced. In terms of quality and accuracy of TLS's data, a recent research study conducted by Mohammadi et al. (2021c) evaluate the quality of two digital bridge point clouds captured via TLS and another technology of Unmanned Area Vehicle (UAV) photogrammetry. The result of this research indicated more accurate and denser data using TLS technology. It is worth noting the denser datasets generally have a greater number of data presenting the surface of the object that could positively affect the 3D model reconstructions and surface condition assessments. Similar statements have been presented in research studies by Kwiatkowski et al. (2020a), Gawronek and Makuch (2019).

In the field of bridge management, Chan et al. (2016) explained the essential need of using Bridge Management System (BMS) or Bridge Information System (BIS) to collate various types of bridge information such as visual inspection data, test findings, modeling results, repair and rehabilitation activities. However, the limitation with BMS and BIS was the visualization of the collected data, thereby engineers could readily misinterpret the bridge health condition thus managed. Over the last decade, application of Bridge Information Model (BrIM) as the specific form of Building Information Modelling (BIM) in the context of bridge engineering, has provided faster solutions in management processes. This shared platform containing a 3D Computer-Aided Design (CAD) model connected with non-geometric information, including, but not limited to, inspection reports, descriptions of maintenance actions, the material used, etc. As noted by Chan et al. (2016), BrIM can allow better visualizations, and therefore understanding of data pertaining to a bridge, through the integration of bridge data with a 3D model of the same bridge. Moreover, the combination of 3D laser scanning with BrIM can result in a better means of both recording information for bridge inspection, and housing this information for future references. BrIM development using laser scanner data was initiated as a concept for asset management purposes in studies conducted by Tang et al. (2007, 2010, 2012a, 2012b). In recent years, the clear advantages of creating TLS-derived BrIMs has meaningfully improved the reliability of the generated management models. In this regard, a case study conducted by Kasireddy and Akinci (2015) discussed the valuable benefits of using TLS technology in BrIM development comparing to manual 3D CAD model creations using existing drawings, and inspection reports. In this research, the misalignment between the geometry of the bridges as they are, and their respective drawings, were attributed to the lack of preparing new/updated drawings. The updated drawings could depict alterations at each instance where a bridge's geometry has been altered from that shown in the original drawings. However, by necessity, preparation of these updated drawings and 3D CAD models, as the core of the BrIM, would have been a time-consuming manual process even in computer days. Currently, various methods of data processing and reverse engineering employ TLS data points to create 3D CAD models that can accurately represent the geometry and physical properties of the real-world structure. Studies dealing with automation in reconstruction of geometrical CAD models can be found in Hinks et al. (2013), Bitelli et al. (2016), Castellazzi et al. (2017), Conde-Carnero et al. (2016), and Mehranfar et al. (2021). In a common approach, researchers tend to make use of mesh for representations of the objects' surface or classifying the scanned object into different components. Although these processes are known to be efficient for geometrical modelling and visualization of small size components, they may remain inefficient, time-consuming, and require a high level of computing demand for reconstruction of a bridge-sized 3D CAD model with intricate details.

In overall, with the huge bridge inventory worldwide, condition assessment and management of these bridges have become especially important and challenging. Although various bridge management methods have been implemented by bridge owners, a newer method has been developed over the last decade in the form of the BrIM, containing the 3D CAD model and additional non-geometric information. Given the time, and effort involved in data collection and 3D CAD model creation, as the requirement of BrIM, there is a need for an efficient means of recording the extensive geometry and condition of the bridges. The state-of-the-art technology of TLS has already developed a reputation as a tool capable of rapid and precise collection of spatial information. However, the adoption of this technology in the cases of bridge engineering, and in terms of asset management has not been equally as rapid. Therefore, this chapter of this research study aims to make use of TLS technology and provide a comprehensive and practical methodology as a pathway for engineers to develop a TLS-derived BrIM. Following this study, the procedure for generating a quantitative point cloud using TLS is elaborated, and a novel sliced-based approach for bridge geometric 3D CAD model reconstruction, and a workflow for non-geometric data connection is presented. Finally, the reliability and soundness of the proposed methodology is proved in the form of a real bridge case study by evaluating the quality of the captured point cloud and the extracted 3D CAD model, and then illustrating the outcome as a BrIM. The followings are the main objectives of this chapter of study:

- Provide a practical methodology for generating a TLS-derived BrIM.
- Elaborate the process to generate a quantitative bridge point cloud using TLS.
- Provide a novel slicing-based method to extract a precise geometric 3D CAD model from the captured bridge point cloud.
- Prove the soundness of the proposed methods in form of a real bridge case study and validating the outcomes by comparing the quality of TLS data, CAD model versus the as-designed CAD drawings, and illustrating the outcome as a BrIM.

4.2. TLS-derived BrIM Methodology

As outlined in the literature study presented, the successful application of BIM in the field of bridge engineering, commonly known as BrIM, has made this platform a right alternative for paper-based and manual asset management processes. BrIM is a collaborative, digital approach that involves the creation of a 3D model containing detailed information about the bridge's geometry, materials, and functional requirements, as well as information related to the construction process and maintenance. BrIM, as a data-driven digital twin, not only allows better visualization and an enhanced understanding of the bridge condition but also benefits bridge managers and assessors to make more reliable decisions either in bridge assessment or management. At its core, BrIM consists of the bridge 3D CAD model connected with non-geometrical information such as bridge location, its identification number, design revisions, inspection reports, number of bridge components and their condition, description of acts of maintenance, the material used, etc. The combination of TLS with BrIM not only can speed up the creation of bridge 3D CAD models, but also can result in a better means of both recording well-detailed information from bridge inspection, as well as a source of information for condition state and maintenance history. During the asset management phase, TLS data can also be used for detecting bridge deterioration throughout the structure’s service life, and this information can be used to update the BrIM. Therefore, TLS-derived BrIM in long term, improves productivity of bridge inspection and maintenance programs.

This section elaborates on all the necessary steps of a reliable bridge survey using TLS and the proposed method of extracting a well-detailed 3D CAD model from the registered point clouds as the BrIM core model. In particular, all the requirements of phases from bridge survey, post-processing, 3D CAD model creation to final data connection into the 3D solid model are described. The proposed workflow is presented in Fig. 4-1. This workflow can be useful for bridge surveyors concerning a quantitative TLS survey as well as a well-detailed 3D CAD model extraction and BrIM development from the generated point cloud.

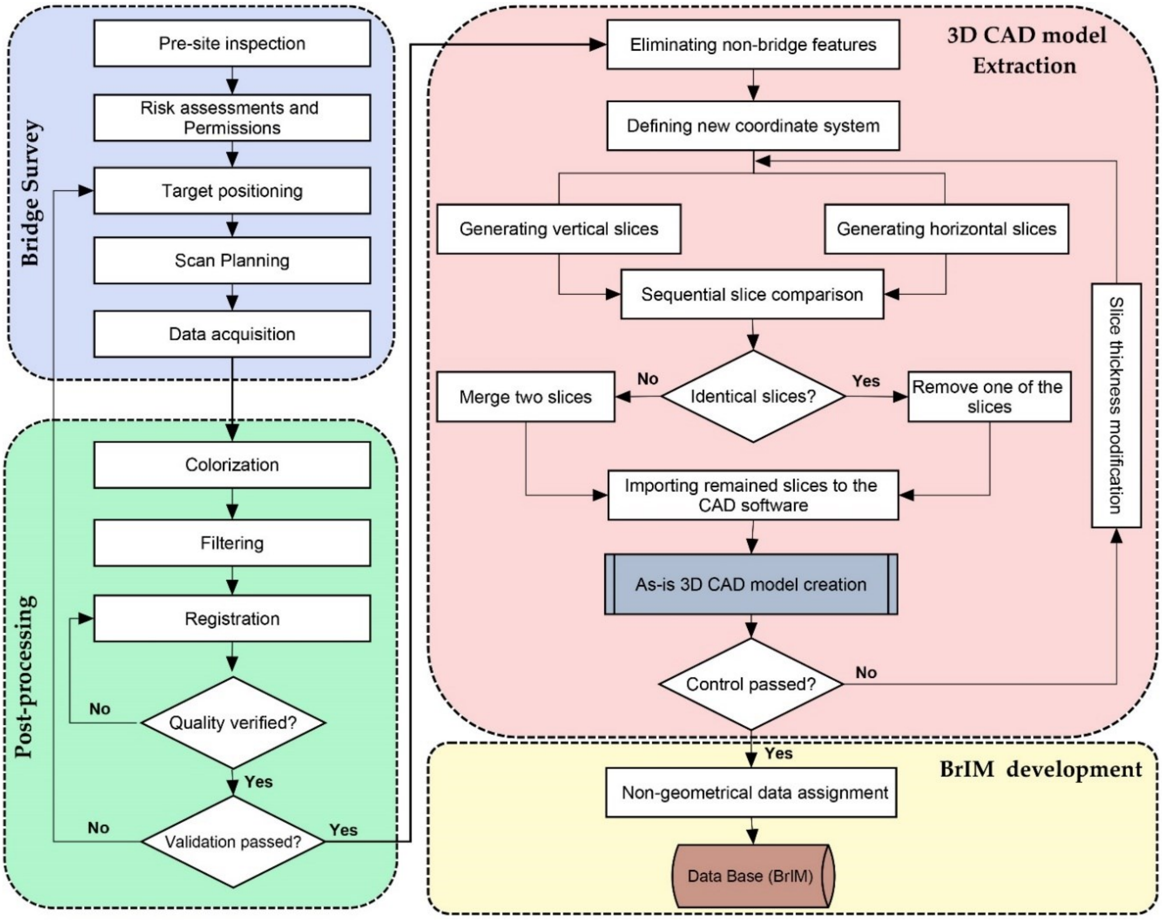


Figure 4-1 TLS-derived BrIM methodology workflow.

4.2.1. TLS based bridge survey and post-processing

The Bridge survey phase contains pre-site inspections, risk assessment and permissions steps that require an expert engineer's vision to evaluate the topological location of the object/structure, and assess the logistical requirements while evaluating the vulnerable risks involved for a surveyor, or arrangements for the necessary permissions. Selecting suitable scan positions, and target locations, is particularly relevant for bridges, where the shapes of such structures may cause self-shadowing, or components blocking the view of other components, is often encountered from any one viewpoint (Truong-Hong and Laefer, 2019). When determining suitable scan positions consideration also needs to be made to the distance between the involved scanner(s) and the target surface(s) to be scanned in multiple scans, as well as the angle of the object surface(s) relative to the scanner(s). In this respect, for all else being equal, both the closer an object surface is to an active laser scanner, and the closer that an object surface is to being viewed perpendicularly by an active laser scanner, the greater the number of points on that surface that would be observed by the scanner (Wilford, 2020). Capturing a greater number of points is an important consideration for effective recording of the object surface subjected to implementation of 3D model reconstruction (Heidari Mozaffar and Varshosaz, 2016).

The collection of on-site data is an important stage concerning the quality and quantity of data-point clouds and their subsequent usefulness for bridge engineering applications (Song et al., 2014). This step is important as scan positions, and their number, selected without a prepared strategy plan could result in a captured data set of poorer quality and detail than that required (Rashidi et al., 2020b, Truong-Hong and Laefer, 2019). Therefore, in order to minimize the amount of time spent on-site (and in data post-processing), and at the same time, maximize the quality of data collected in the time that is spent on-site, a scan plan should be devised. Considering the need for scanning, an evaluation can be made to identify the amounts of detail to be captured when scanning, and how this can be achieved for the given complexity of surface details and intricacy of features of a bridge planned to undergo scanning (Mahmood et al., 2020, Biswas et al., 2015, Jia and Lichti, 2019).

Scan quality and resolution settings of a laser scanner are two parameters that need to be considered before acquiring point cloud data. These two parameters need to be adjusted by the operator who must take into consideration the size of the smallest object which would need to be discernible in the amassed point cloud. Negligence in selecting appropriate values for these parameters can yield low-quality data, could negatively affect the scanning time, and hamper post-processing of the point cloud data (Rebolj et al., 2017, Dai et al., 2013). The data quality setting within a TLS has a great impact on both the prevalence of noise and data acquisition rate, which affects the total scanning time, and can accentuate the time spent collecting redundant data. Captured point clouds generally contain noises that refer to the deviation of the recorded position of a point in a point cloud from the actual position of the same point; the position which would have been recorded if laser scanning was a perfect process (Genechten, 2008). Although normal noise is defined as usual redundant data with modest error, outlier noise can be defined as a wider notion that encompasses discordant data with significant error. The point cloud's normal noise can be assessed using the Standard Deviation (STD) analysis and the well-known STD formula described in Eqs. (3-4) and (3-5), more discussed in Chapter 3. The captured TLS data registration is not always perfect, and differences in the coordinate values of common/target points within mutually registered point clouds can negatively affect the quality of the point cloud. Other aspects of laser unit calibration, lack of surveying targets and choosing unstable scan locations might lead to low-quality and noisy point clouds. Therefore, the registered point cloud also needs to become optimized in a procedure named data filtering. The quality of the registered/optimized point cloud can be evaluated by employing some quality analysis methods using well-known error metrics such as Standard Deviation (STD), STD Error, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) presented in Eqs. (3-6), (3-7) and (3-8), respectively (Mohammadi et al., 2021c). These equations and methods are also discussed in Section 3.3 in more details.

4.2.2. Geometric 3D CAD model extraction

After point cloud registration and quality evaluation processes discussed, the next following step consists of creating a suitable geometrical 3D CAD model of the captured structure with aims of developing a BrIM. This step may be the most challenging task since the generated 3D CAD model will serve as the foundation for bridge inventory data connections to be a reference for future works and bridge management plans. In this respect, bridge structural shapes often contain complex architectural components that make difficulties for this task to be greatly performed.

In recent years, variety of data processing and reverse engineering methodologies tend to make use of TLS based point cloud and mesh generation for the representation of the object's surface (Truong-Hong and Laefer, 2019, Rashidi et al., 2020b). Although this process is well-known for its efficiency in geometrical model reconstruction and visualization of small-scale components, it may be inefficient, time-consuming, and require a high level of computer demand in developing a bridge-sized 3D mesh with detailed features. Moreover, the other concern/limitation of this method is related to its nature and use of surface-based representation for a structure. However, in many circumstances, a complex structure such as a bridge needs to be converted into a solid model using volumetric representations (Lubowiecka et al., 2009). In a common approach, researchers attempted to overcome this limitation by classifying the scanned bridges into their individual main elements such as a pier, deck, girder, and so on and then applying mesh-based algorithms or creating extrusions utilizing cross-sections of the mesh model to achieve a reliable approximation of the best fitted primitive for their volumetric presentation (Mehranfar et al., 2021, Rashidi et al., 2020b, Conde-Carnero et al., 2016, Hinks et al., 2013, Bitelli et al., 2016, Castellazzi et al., 2017). Although this approach has the advantage of producing useful 3D CAD models without requiring substantial computing demand, it might lead to errors and discrepancies if the components do not conform to their idealized shape.

To overcome the challenges involved, the slicing approach presented in this research study serves a different and practical workflow reducing the time and effort involved for a bridge size 3D CAD model extraction. The proposed method consists of dividing the bridge into different slices/segments extracted from the optimized point cloud after applying post-processing filtration such as noise reduction and removing non-bridge features such as surrounding thoroughfares, terrains, and vegetations. These slices contain similar information as the initial bridge point cloud that the points of a slice are positioned between two planar cross-sectional surfaces that intersects the objected bridge in a certain direction with a specific relative distance (slice thickness). This approach is basically a point-based method combined with an automated slicing algorithm that avoids creating a surface mesh model for the whole bridge. The proposed approach offers several advantages over the mesh-based methods, such as the ability to work directly with the point cloud, data volume reduction as a result of slicing the point cloud, eliminating mistakes caused by poor smoothing and sharp edge features.

Following this approach, the sliced bridge point cloud can then be imported into CAD software for 3D solid modeling employing general plane fitting and extrusion techniques while considering the constraints imposed by the sliced point clouds. The creation of 3D models is a straightforward operation, and auxiliary planes fitted to the point cloud can serve as a valuable guide for sketching the appropriate representations. The workflow of the described methodology is presented in Fig. 4-1, 3D CAD model extraction part. Although the proposed approach sometimes may require specialized skill operators on the point cloud processing, this approach can lead to an accurate 3D geometric model in a timely manner that cannot be achieved by conventional methods presented. The outcome of this approach as a 3D CAD model can then be utilized directly for various aspects of structural assessments such as Finite Element Model (FEM) development, and asset management purposes in BrIM creations. In the following section, the process of point cloud slice-based approach is described.

4.2.2.1. Point cloud slice-based approach

Throughout this approach, the slice direction and thickness play an important role in effective feature extraction and the resultant model. Therefore, regardless of the existing Coordinate System (CS) of the captured bridge data, a new/local CS needs to be established for the optimized point cloud after filtering and eliminating non-bridge features from the raw data. The new CS needs to have an x-direction parallel to the bridge direction, a y-direction running along the width, and a z-direction perpendicular to the xy plane. Moreover, considering $P = \{P_1, P_2, P_3, \dots, P_i\}$ as the whole point cloud dataset containing i individual points, which $P_i = (x_i, y_i, z_i)$ and is defined based on the new coordinate system, the total number of vertical slices, n, can be calculated using Eq. (4-1). Considering j as the number of vertical slices, V_{jx} is the specific vertical slice along the x-direction, presented in Eq. (4-2).

$$n = \frac{Max\ (x_i \in P) - Min(x_i \in P)}{\delta_x} \tag{4-1}$$

$$V_x = \ \{V_{jx}: j = 1, 2, 3, \dots, n\} \tag{4-2}$$

where δ_x denotes slicing thickness along the x-direction. Slicing thickness can be calculated based on the minimum length of the bridge components, level of required detail, etc. that is not the main concern of this study. It is worth noting that the points of a very thick slice may not provide useful information since various features may become entangled, and vice versa, a very thin slice may not provide sufficient details for efficient feature extraction. Therefore, the proposed automatic algorithm of this research is developed based on a cloud-to-cloud comparison. In this step, the cloud-to-cloud comparison is performed between the sequential point cloud slices, and then slices with a substantially comparable RMSE value are eliminated otherwise merged/connected to form a larger sliced point cloud. In a similar strategy, horizontal slices also need to be generated considering a slice thickness along the z-direction, and then slices have to be compared and eliminated using cloud-to-cloud comparison and RMSE values. The remained slices of the point cloud will be imported as input into CAD software for 3D solid model extractions. Fig. 4-2 depicts the pseudocode and the parameters defined for the slice-based method.

Data: P = $\{P_1 . P_2 . P_3 \ldots P_i\}$ TLS point cloud, **Data:** δ_x = slicing thickness along the x-direction
Data: δ_z = slicing thickness along the z-direction, **Data:** T_x = C2C RMSE threshold along the x-direction
Data: T_z = C2C RMSE threshold along the z-direction, **Result:** A = slices returned

n =compute number of vertical slices (P, δ_x), m =compute number of horizontal slices (P, δ_y)
for $n_j \epsilon\ n$ **do**
    V_{jx} generate vertical slices (P, n_j)
end
for $m_k \epsilon\ m$ **do**
    V_{kz} generate horizontal slices (P, m_k)
end
for $V_{jx} \epsilon\ V_x$ **do**
    if C2C-distance ($V_{(j-1)x} . V_{jx}$) > T_x
        then Add V_{jx} to A
    else
        Merge ($V_{(j-1)x} . V_{jx}$) into one slice
    end
end
for $V_{kz} \epsilon\ V_z$ **do**
    if C2C-distance ($V_{(k-1)z} . V_{kz}$) > T_z
        then Add V_{kz} to A
    else
        Merge ($V_{(k-1)z} . V_{kz}$) into one slice
    end
end
Return A

Figure 4-2 Pseudocode of the sliced-based method.

4.2.3. BrIM development

As previously stated, connecting the BrIM with laser scanning information for a quick and intelligent survey not only can be an innovative approach for effective inspection but also can be used as valuable source information for management consideration. In this step, the as-is 3D CAD model forms the core of the BrIM, and different non-geometrical information such as components' condition state, their specific properties, ages, enacted maintenances, designed revisions can be collected by an expert engineer and assigned to each component of the 3D model to create a database as an information model for bridge management purposes in development of a BrIM-oriented BMS. This system provides considerable benefits not only in the transmission of digital information data to users such as asset managers, but also in the assimilation of semantic information that supports decision making and strategic planning. The conceptual framework of the proposed method is provided in Fig. 4-3. This framework shows the constituents required to form an effective bridge management system using the reliable input of TLS data.

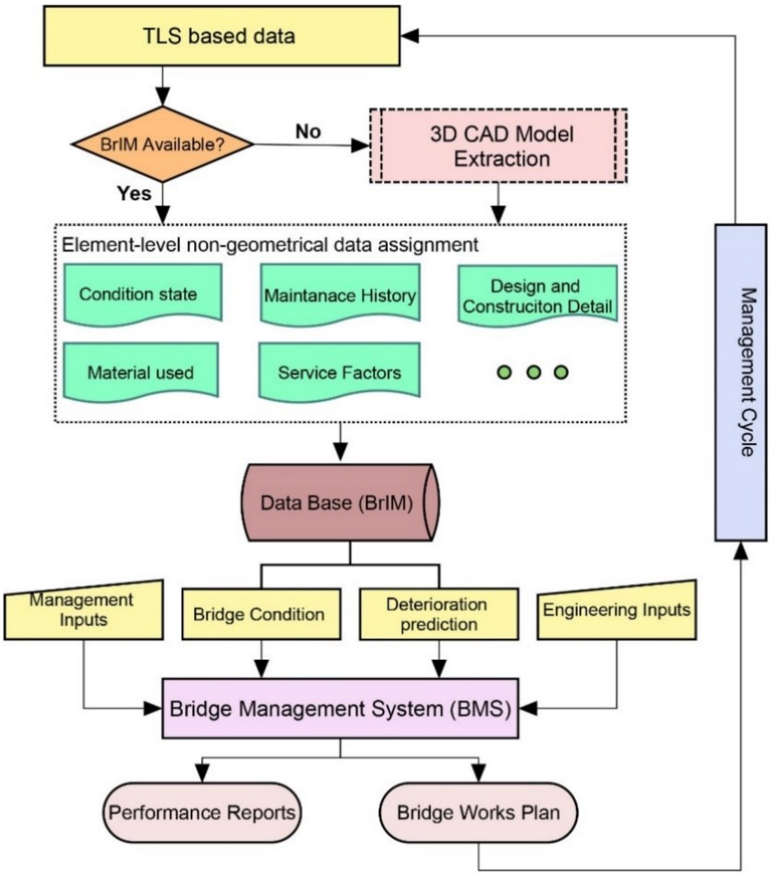


Figure 4-3 Conceptual framework for data integration and BrIM development.

As illustrated in the framework, non-geometrical data can be assigned into the as-is 3D model, specifically for each element, and used to create a BrIM database. Note that these data are known as static information that needs to be stored by an expert engineer based on existing reports, and records such as TLS based inspections and non-destructive tests. In some circumstances, some data such as the condition state of bridge components need to be interpreted by the expert engineer using the element level bridge inspection procedure, which necessitates a qualitative expression via a grading system based on local standards (TfNSW, 2007). Furthermore, the data required for BrIM can be gathered real-time and interpreted through the use of remote sensors and Artificial Intelligence (AI), also known as dynamic information. All these data can then be utilized for a variety of purposes, including bridge condition assessment and deterioration predictions in a BMS to identify the issues of high critically by interpreting the information, and assigning related bridge works orders that need to be performed during bridge lifetime. Similar to other management systems, this system is also defined as a cyclic process and need consequent update during bridge performance. Therefore, it is necessary to develop, and associate updated data at a nominated frequency so that the BrIM reflects the as-is condition of its physical twin. Therein, the application of TLS, proposed in this methodology, can be used as a valuable technology for rapid and precise data collection of bridge information used for detailed structural inspection, monitoring, and management.

4.3. Bridge Case Study

In order to better understand the application of TLS in 3D CAD model development and investigate the valuable benefits of the proposed methodology and challenges involved, a real field study was carried out to collect the point cloud of a bridge named Western Sydney University Bridge (commonly known as Werrington Bridge), over the Great Western Highway, located in Werrington city, New South Wales, Australia, Fig. 4-4. The Werrington Bridge is a cable-stayed bridge with an A-frame pylon consists of two legs, both composed of steel plates butt welded together along their long edges to form lengths of built-up Rectangular Hollow Sections (RHS), which in turn form the pylon's height above ground. Drawings of the bridge dated 1990 and 1991, from around the time when the bridge was constructed (Western Sydney Unievrsity, 2014), indicate that the concrete deck is steel reinforced and forms a composite structure with the underlying steel frame via shear studs (shown in the drawings) and BONDEK steel sheeting. Along each side of the composite deck are concrete kerbs topped with steel railings. The composite deck is supported by three lines of four bearings (one line at each concrete abutment, and one line at the pylon's beam) and a set of eight stay cables, which are in fact round bars, anchored to the upper end of the pylon. The pylon is stabilized against toppling into the bridge's main span by another set of eight stay cables anchored into a concrete block within the southern end of the bridge. The research study is defined as part of an asset management project for developing a well-detailed BrIM consist of an as-is 3D CAD model connected with some non-geometrical information to be used for health monitoring and asset management purposes.

4.3.1. Site survey and data acquisition

The site survey was carried out after initial investigations considering important factors previously mentioned in Section 2.1 and safety risks involved. In order to avoid making multiple site visits, the site survey was also confirmed via available photographs, specifically satellite images of bridge and its surrounding using Google Street View photographs taken from the vicinity of the bridge. Finally, the scan plan of Fig. 4-5 which shows 40 stations on and around the Werrington Bridge was developed to enable the TLS to gather sufficient data without the need to either set foot on the highway below the bridge based on safety requirement or introduce specialized access equipment. During this procedure, scan stations were placed at

(a)

(b)

Figure 4-4 Werrington Bridge: (a) Bridge satellite view, (b) Bridge status in 2021.

regular intervals, where possible, in order to have at least one primary connection with other scan stations having several views/points in common. Moreover, redundant connections which relate to additional instances of networks, were considered in the suggested scan plan in order to assure scan station connections and facilitate registration procedures. As shown in Fig. 4-5, 28 of the proposed scan stations were at the level of bridge's deck to approach the roads, and adjacent grassed areas. However, with a view to scanning the underside of the bridge's deck, 12 scan stations on the scan plan were spread out on the grassed areas below the level of the bridge's deck.

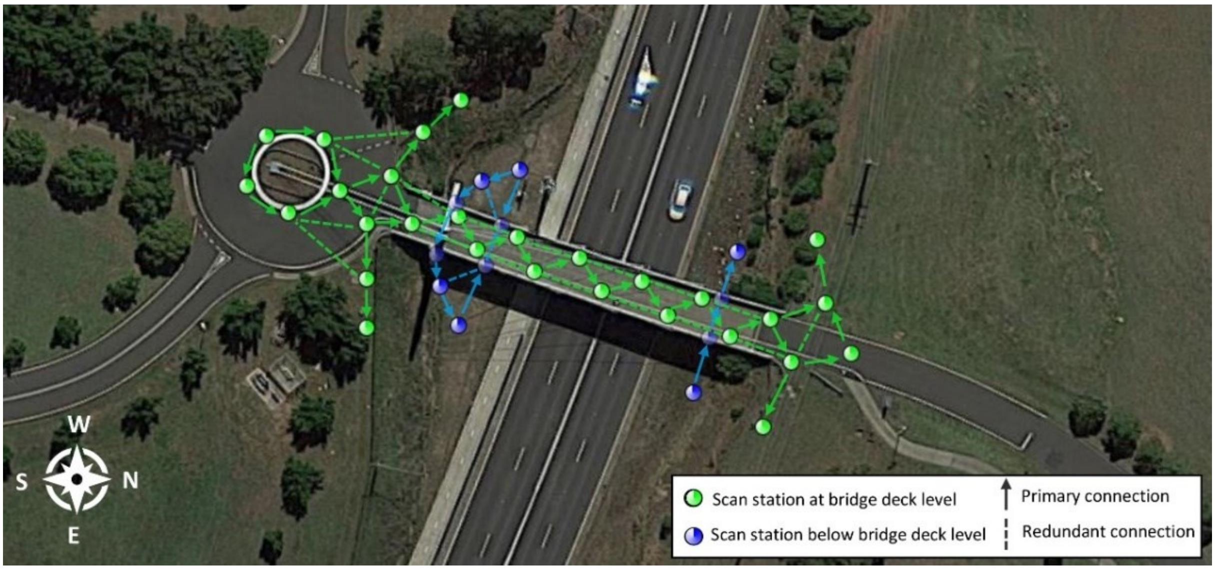


Figure 4-5 Werrington bridge scan plan.

Following this process, suitable locations of the target placements were identified. Consideration was made towards placing the targets at locations at which they would be as conspicuous as possible, while at the same time, attention was given to the need to attach the targets to objects which ideally would not move. However, small movements of the bridge during its operation was unavoidable. As the registration precision of multiple scans is affected by both the number of targets and their distribution in the overlapping region (Yang et al., 2020b), on the scan day, a total of 29 targets were strategically placed on and around the Werrington Bridge to facilitate point cloud registration. Five targets were of the spherical type (a purpose-made sphere with a special coating), and 24 were of the planar type (a high-contrast black and white pattern on laminated A4 paper), with a minimum distribution of three common targets in each scan.

The Werrington bridge was scanned utilizing the Z+F IMAGER 5016 terrestrial laser scanner, shown in Fig. 4-6. This laser unit offers great versatility of features including fast rating data acquisition (about one million data points per second), range resolution of 0.1 mm and average range noise of 0.25 mm RMS for the laser system, various scanning resolutions (up to 0.8 mm at the subject distance of 10 m), long-range scanning (up to 360 meters away from the scan unit), a wide field of view 360º×320º along with an integrated High Dynamic Range (HDR) panorama camera (80 Megapixel) allows the capture of colour information. This laser unit is also equipped with an integrated positioning system, that optimizes post-processing operations and enables on-site registrations in real-time (Zoller + Fröhlich GmbH, 2021).

Scans were carried out from 40 scan stations including multiple positions of the bridge deck, bridge sides and bridge underneath in line with the scan plan presented in Fig. 4-5, considering close range positions with an offset not more than 20 meters to the nearest part of the bridge. Given the limited timeline regarding the arrangements for bridge traffic control, it was decided to employ a scan resolution of 6.3 mm at 10 m, and a normal scan quality setting to complete the task in a timely manner. During this process, the panorama photographs were also set to be captured by the laser scanner's in-built camera.

Figure 4-6 Laser scanning of Werrington bridge.

4.4. Results

In this section, in order to further investigate the application of the proposed methodology, the whole process, from bridge point cloud generation to BrIM creation of the Werrington Bridge, is described.

4.4.1. Werrington bridge point cloud generation

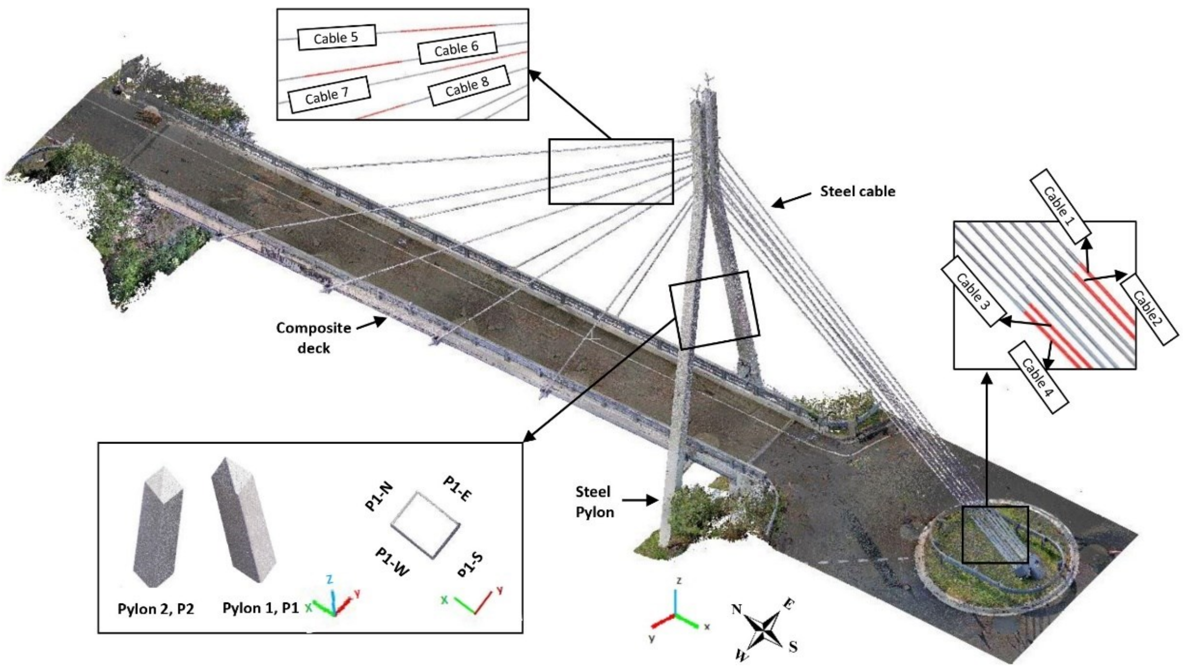
The TLS data captured from each scan position on and around the Werrington Bridge has undergone relative registration to form one large point cloud encompassing much of the structure, as shown in Fig. 4-7. The outcome of the Werrington Bridge point cloud developed from TLS data contains more than 525 million discrete points, as well as color information obtained via the TLS's in-built camera, and required around 15 gigabytes of computer storage space.

Figure 4-7 Generated point cloud of Werrington bridge.

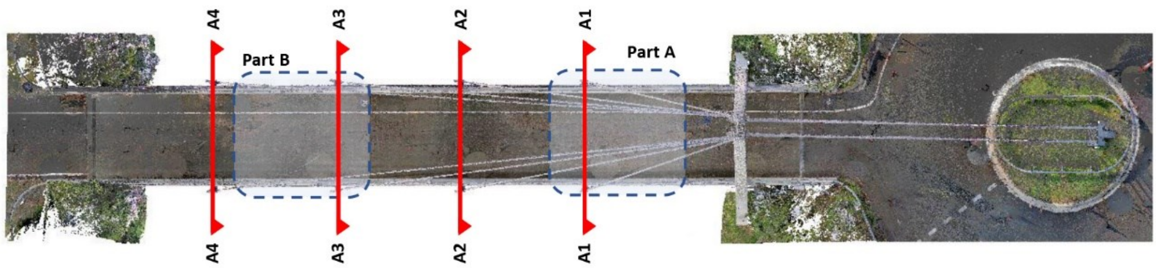
The process of filtering and registration/merging of all 40 scan stations' point clouds was conducted using Z+F Laser Control V9 software (Zoller + Fröhlich GmbH, 2019), considering non-destructive general filters such as intensity filter, mixed- and single-pixel filters and manual noise reduction to remove undesirable noises. The challenging part of the registration process was in locating/matching common points between scans taken at the level of the bridge deck, and the scans taken below the bridge deck. In this regard, automatic scan alignment/cloud-to-cloud technique, referring to use of Iterative Closest Point (ICP) algorithm (Besl and McKay, 1992), and artificial targets, referring to select some specific common points as the target, were utilized to improve the level of registration and reduce the standard deviation of the cloud-to-cloud calculations. Overall, the average standard deviation between scan stations' point clouds was calculated as 4.9 mm after the registration.

4.4.2. Quality evaluation of the generated point cloud

According to the literature presented, the state-of-the-art emerging technology of laser scanning provides advantages in terms of rapid, precise, and voluminous data collection. However, several common concerns/errors, discussed in Section 4.2.1, may have a significant impact on the quality of the acquired data point and, in some cases, result in erroneous 3D models and incorrect interpretations compare to the as-is conditions. The methodology presented in Section 4.2 of this chapter of the research study is a comprehensive pathway for engineers not only to consider all parameters involved in a bridge survey but also to achieve a qualitative point cloud. Therefore, as an illustration of the procedures provided, the quality of the Werrington bridge point cloud captured via TLS was evaluated and compared using the most common quality evaluation methods including surface deviation analysis, point distribution, and geometrical accuracy evaluations adopted from the VDI/VDE 2643 guideline (Mohammadi et al., 2021c, Verein Deutscher Ingenieure and Verband Der Elektrotechnik, 2008, Mousavi et al., 2018). In this regard, different components/objects of the bridge including eight cables, two pylons, and four cross-sections passing through the bridge span, shown in Fig. 4-8, were selected to be analysed using these methods.



(a)



(b)

Figure 4-8 Intended surveying objects and bridge components: (**a**) Selected bridge components and parameters, (**b**) Bridge top view and cross-sections.

4.4.2.1. Surface deviation analysis

In theory, the captured texture of a smooth-surfaced object is expected to be retrieved in only one layer of points without thickness, however, in reality the surface is normally formed based on points with deviations from the expected flat ideal shape. In surface metrology, the amount of this analysis is generally used for quality assessment of the generated point cloud, subjected to the creation of a 3D solid model (Mohammadi et al., 2021c). In this analysis, the spatial distributions of the objects' points are measured with respect to their best fitted primitive such a flat plane, known as plane fitting technique, or a cylinder, known as cylinder fitting technique.In this research study, different sides of the steel pylons, shown in Fig. 4-8a, are considered to be analysed using plane fitting technique by defining the best-fitted plane and calculating the spatial distribution of the points using error metrics. As shown in Table 4-1, plane fitting analysis indicated an average standard deviation (STD) of 3.883 mm and Root Mean Square Error (RMSE) of 2.687 mm for the optimized point cloud data. Moreover, the amount of Mean Absolute Error (MAE) was calculated as 2.731 mm. Overall, the findings revealed millimetre noise level for the acquired point cloud, indicating that the dataset retains reliable model when subjected to 3D surface representation.

Table 4-1 Surface deviation analysis, plane fitting analysis. Unit: mm.

Plane	STD	Mean absolute error	Max absolute error	RMSE
P1-S	1.779	1.059	12.300	1.453
P1-N	2.452	1.889	8.800	1.560
P1-E	1.765	1.212	14.700	1.283
P1-W	3.040	2.749	6.060	1.212
P2-S	2.356	1.793	7.378	1.529
P2-N	2.478	1.323	18.900	2.096
P2-W	6.815	4.047	44.620	5.483
Average	**3.883**	**2.731**	**15.381**	**2.687**

In a similar strategy, the cylinder fitting technique was also utilized to assess the quality of the TLS survey in generating the small-size components such as a bridge cable. In this regard, the bridge's eight cables, as illustrated in Fig. 4-8a, were considered to be analysed by matching the best-fitted cylinder, and then computing the spatial distribution of the point using different error metrics. Moreover, in order to analyse the TLS measurement error, the diameter of the best-fitted cylinders was compared to the as-designed dimensions available. The results of this analysis are presented in Table 4-2.

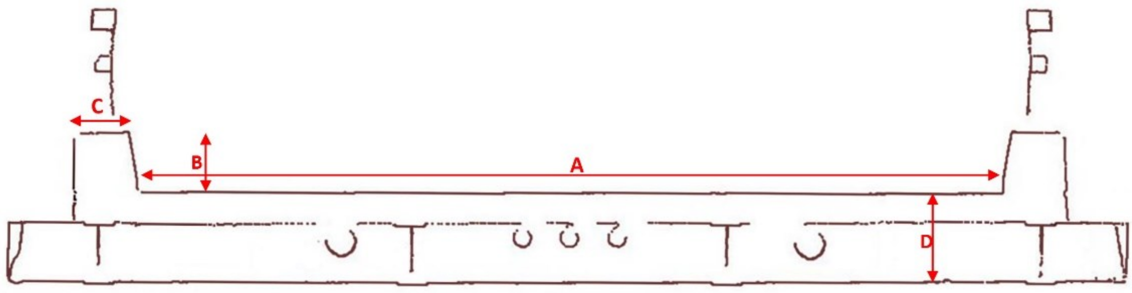
Table 4-2 Surface deviation analysis, cylinder fitting analysis. Unit: mm.

Cylinder	TLS				As-designed diameter	Measurement absolute error
	STD	Mean absolute error	Max absolute error	Diameter		
Cable 1	1.401	0.912	14.791	62.822	60.300	2.522
Cable 2	1.473	4.231	12.134	62.614	60.300	2.314
Cable 3	1.102	2.021	13.231	62.167	60.300	1.867
Cable 4	1.321	0.601	15.221	62.212	60.300	1.912
Cable 5	4.745	2.935	25.753	52.628	48.300	4.328
Cable 6	4.291	2.922	23.424	52.061	48.300	3.761
Cable 7	4.881	3.334	27.521	52.879	48.300	4.579
Cable 8	4.692	2.981	29.332	47.218	48.300	1.082
Average	**2.988**	**2.492**	**20.175**	-	-	**2.795**

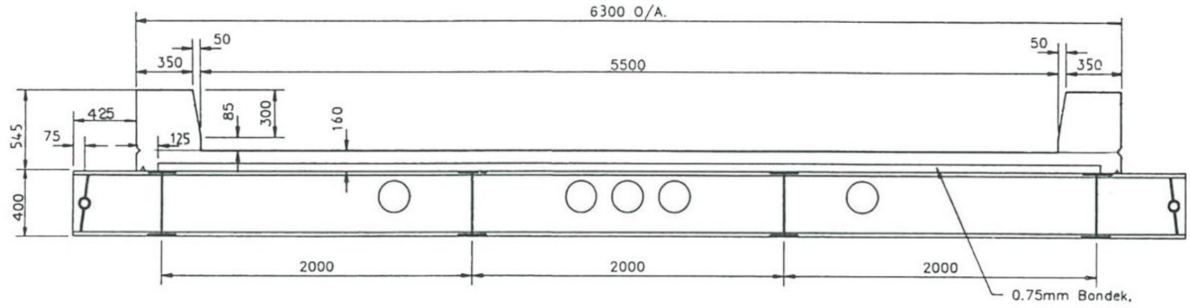
The results of cylinder fitting, shown in Table 4-2, demonstrated an average STD of 2.988 mm and MAE of 2.492 mm, both in millimetre values, indicating that TLS data can perform well in millimetre-level 3D model reconstruction. However, concerns remained about the maximum absolute error values showing the level of outlier noise, which is remained greater while collecting objects at high altitudes and far away from the laser unit.

4.4.2.2. Relative geometric accuracy evaluation

Employing the profiling method described by Mohammadi et al. (2021c), the relevant geometric accuracy of the generated point cloud was evaluated and compared for several parameters (lengths) shown in Fig. 4-9 with the collected as-is measurements and available as-designed drawings. Using this method, the lengths/distances were calculated after converting four cross-sections of the bridge point cloud, shown in Fig. 4-8b, into polygon meshes (triangular mesh models) and conducting distance measurement using GOM Inspect computer software (GOM Gmbh Company, 2020). The results of this evaluation over the proposed cross-sectional profiles of the bridge are presented in Table 4-3 and Table 4-4.



(a)



(b)

Figure 4-9 Geometrical parameters for distance measurement: (**a**) extracted cross-sectional profile of the bridge, (**b**) As-designed CAD drawing, Unit: mm.

Table 4-3 TLS error evaluation versus as-is measurements, Unit: mm.

Cross-sectional profiles	**TLS based measurements**			**As-is measurements**			**Measurement absolute error**		
	A	**B**	**C**	**A**	**B**	**C**	**A**	**B**	**C**
Sec A1-A1	5507	386	355	5498	388	352	9	2	3
Sec A2-A2	5504	387	352	5496	389	348	8	2	4
Sec A3-A3	5503	387	357	5493	388	353	10	1	4
Sec A4-A4	5492	388	343	5486	391	346	6	3	3
Average	**5501**	**387**	**352**	**5493**	**389**	**349**	**8**	**2**	**3**

According to the results presented in Table 4-3, the average absolute error across the four separate cross-sectional profiles compared to the as-is measurement was determined to be less than 8 mm. This error was also calculated to be less than 5 mm, shown in Table 4-4, compared to as-designed drawings/dimensions. All of which demonstrates a millimetre-level geometrical relative accuracy for the TLS-based Werrington bridge point cloud.

Table 4-4 TLS error evaluation versus as-designed dimensions, Unit: mm.

Cross-sectional profiles	TLS based measurements				As-designed dimensions				Measurement absolute error			
	A	B	C	D	A	B	C	D	A	B	C	D
Sec A1-A1	5507	386	355	566	5500	385	350	560	7	1	5	6
Sec A2-A2	5504	387	352	568	5500	385	350	560	4	2	2	8
Sec A3-A3	5503	387	357	566	5500	385	350	560	3	2	7	6
Sec A4-A4	5492	388	343	559	5500	385	350	560	8	3	7	1
Average	**5501**	**387**	**352**	**565**	-	-	-	-	**5**	**2**	**5**	**5**

4.4.3. Werrington Bridge 3D CAD Model Extraction

Using the sliced-based approach presented in Section 4.2.2, the bridge point cloud was divided into several horizontal and vertical point cloud slices before being imported into the CAD software. The schematic of this process is shown in Fig. 4-10. After this step, Tekla structures software (Trimble Solutions Corporation, 2021) was utilized as the CAD software. This software not only allows the importation of the point cloud files but also provides powerful functionality for 3D CAD modelling. Recent versions of this software have incorporated useable point cloud functionalities, allowing users to adjust the position and scale of the point cloud, modify the point cloud's density, and colorize the points based on the predefined classification categories. After importing the point cloud slices, the 3D model creation was a straightforward process by fitting the auxiliary lines to the point cloud in different 2D views and simply drawing the desired representations, and then extruding the drawings or specified elements while considering the constraints imposed by the sliced point clouds. Following this process, the generated 3D model was also upgraded to a higher Level of Detail (LoD) in constructive modelling, using predesigned details, components, and connections available in this software. Fig. 4-11 depicts a view of the 3D CAD model generated using this technique as well as 3D model's acceptable agreement with its physical counterpart in a photograph taken from the bridge site.

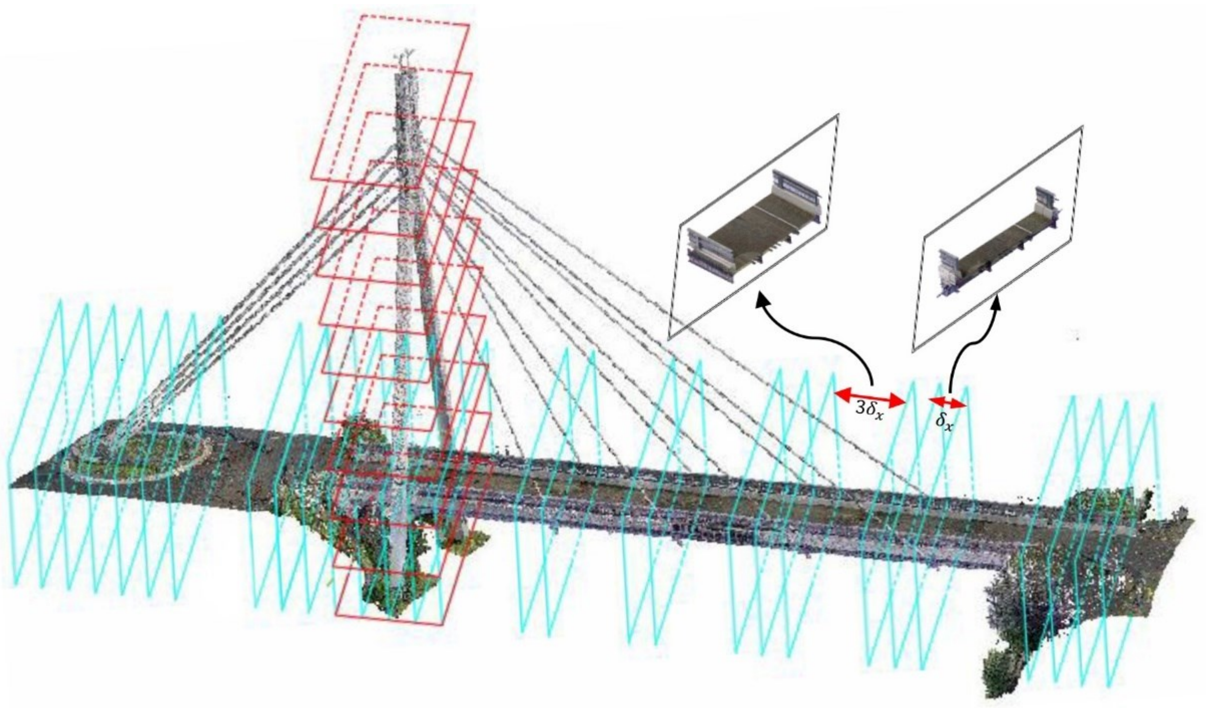


Figure 4-10 Horizontal and vertical point cloud slicing and merging process.

Figure 4-11 Werrington Bridge 3D CAD model**,** agreement with the real bridge.

To further validate the reliability of the sliced-based approach, two parts of the Werrington bridge, depicted in Fig. 4-8, are inspected, and analysed by calculating the deviation of the created 3D CAD model from the conventional mesh-based 3D CAD model and the TLS based point cloud. The comparison results of this analysis are reported in Table 5. Additionally, a cross-sectional profile of the part A was extracted and analysed from both the sliced-based model and the mesh-based model, as shown in Fig. 4-12.

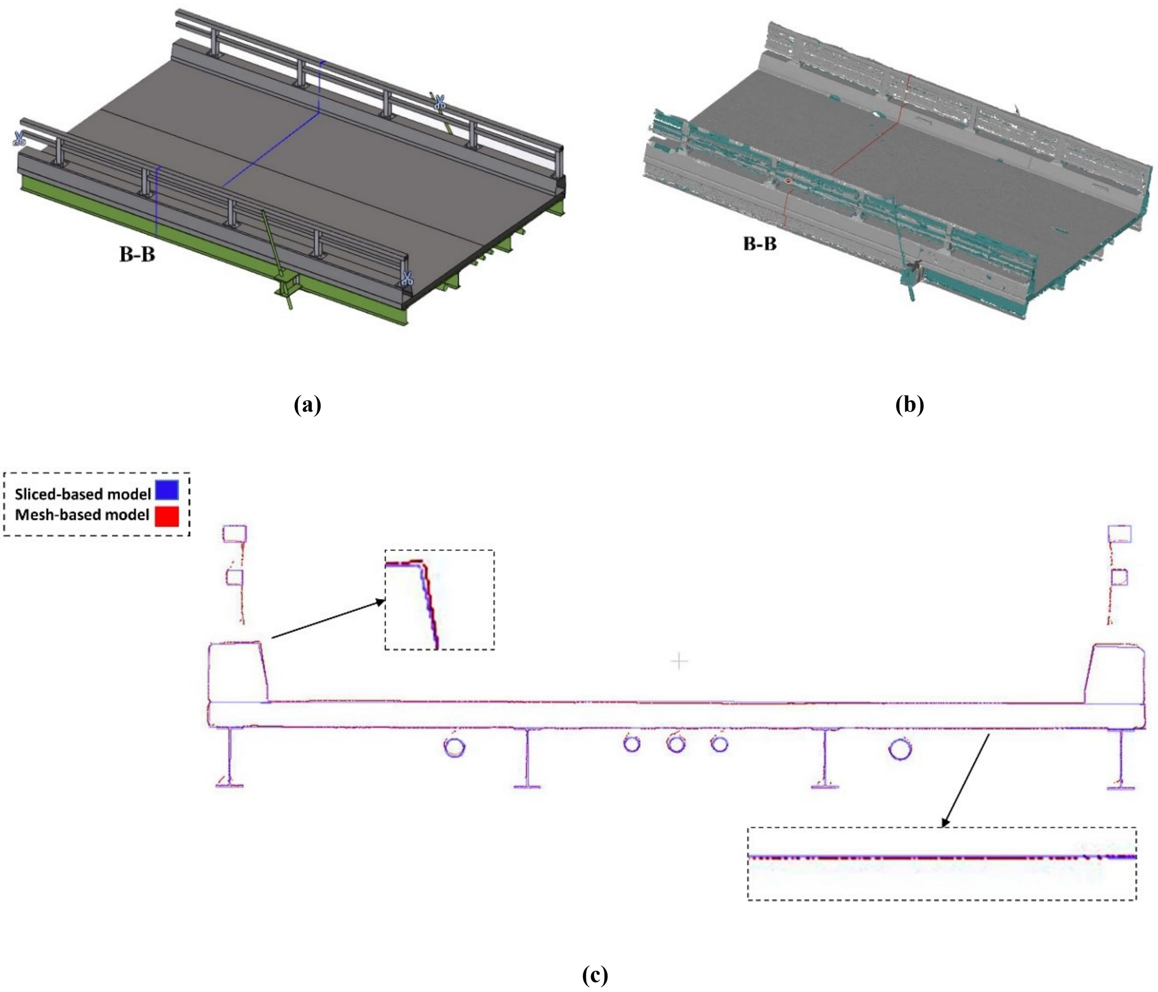


Figure 4-12 Inspection of part A; (**a**) Sliced-based CAD model, (**b**) Mesh-based CAD model, (**c**) B-B cross-sectional profile.

Table 4-5 Deviations analysis between the slice-based vs mesh-based CAD models and point cloud, Unit: mm.

Sliced-based CAD Model	Mesh-based CAD Model				TLS-based point cloud			
	STD	**Mean**	**RMSE**	**MAE**	**STD**	**Mean**	**RMSE**	**MAE**
Part A	4.11	3.90	5.23	2.17	3.40	4.51	4.57	3.32
Part B	5.12	5.72	6.26	4.44	5.12	5.78	6.22	4.58
Average	4.62	4.81	5.75	3.31	4.26	5.15	5.40	3.95

As presented in Table 5, the average STD and RMSE of the sliced-based CAD model versus the mesh-based CAD model are 4.62 mm and 5.75 mm, respectively. These values are calculated as 4.26 mm and 5.42 mm versus the point cloud data. All of which indicates an acceptable agreement between the models created based on the proposed algorithm and the conventional mesh-based method and point cloud. However, the creation of mesh-based models took significantly more time, which can be varied according to the level of detail required, computer and software configurations, as well as the operator involved.

In another effort, considering the group of bridge girders as the reference elements, the deviation of the generated 3D CAD model and the point cloud was evaluated and compared. This evaluation shows the distance less than 5.00 mm between the majority of the girder elements drawn and the point cloud, indicating that the two datasets are in an acceptable agreement. The result of this evaluation is shown in Fig. 4-13. It is worth mentioning that the deviation analysis may also be utilized as a clash detection process to find areas where elements from the constructed 3D model could not perfectly overlap the acquired point cloud.

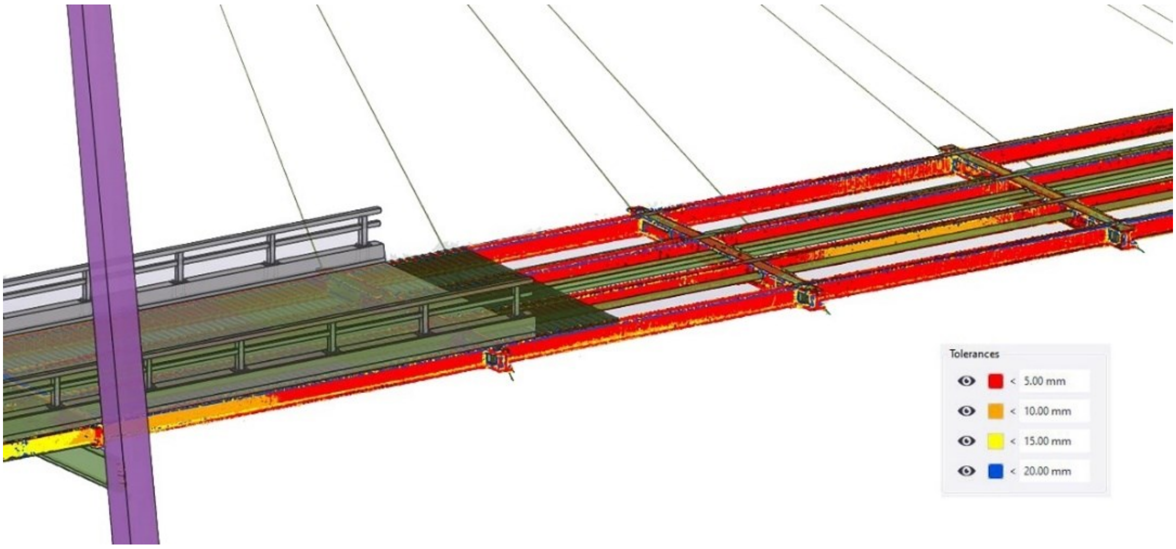


Figure 4-13 Deviation of 3D CAD model versus point cloud.

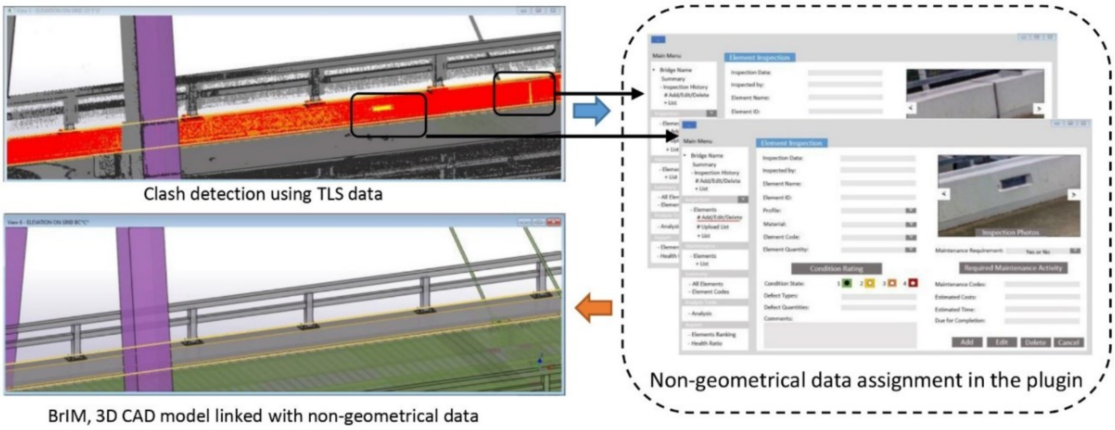
4.4.4. Werrington bridge BrIM and designed plugin

In this step, the generated 3D CAD model of the Werrington bridge forms as the core of the BrIM, and various non-geometrical data were assigned to each component of the bridge using Tekla structures' Application Programming Interface (API) (Trimble Solutions Corporation, 2021). Tekla Open API is an interface that allows software developers to create plugins that can interact with the 3D model generated. Based on this, a plugin was designed to communicate with the 3D CAD model, assigning various non-geometrical information to each component of the bridge. This plugin allows users (expert engineers, inspectors, etc.) to create and assign element-level reports, records, and documentations to each component of the bridge.

As a benefit of TLS-derived BrIM, the acquired TLS data, which serves as the database's precise geometrical record, can subsequently be utilized for bridge inspection and detection of damages/defects that occur over the bridge's lifespan in different time intervals. In this regard, clash detection analysis and progress tracking algorithms (Koch and Firmenich, 2011), which discover changes/conflicts between two models, are essential additions, allowing asset managers to conduct thorough inspections of bridge assets over time. This useful information may potentially be utilized as a reliable source of data for effective/successful bridge monitoring, assessment, management which contribute in making decisions while providing a suitable starting point for development of a BMS.

In the case of Werrington Bridge BrIM, the designed plugin was utilized for assigning various reports, and records to each individual bridge element. In this regard, component-level information such as the element's details, material, maintenance history, and some interpretations of the element's condition state were gathered and assigned to create a reliable BrIM. Moreover, TLS data was used for clash detection in order to identify discrepancies between the ideal 3D CAD model and the captured point cloud. Fig. 4-14a depicts the effective detection of clashes and the importation of this information into the BrIM. This information can then be utilized for damage identification and interpretation of the element-based condition states. As a tangible example, Fig. 4-14b demonstrated the schematic of Werrington Bridge BrIM with interpreted condition state of each element.

As part of this, components in critical condition (with defects detected as affecting the structural integrity and serviceability) are indicated in red, while elements in "as new" condition are highlighted in gray. As previously stated, this information is the outcome of an expert engineer's interpretation based on the local grading system with four standardized condition states descriptions which condition state 1 denotes "new" or "good" element condition, whereas condition states 2, 3, and 4 indicate minor, moderate, and severe defects, respectively (TfNSW, 2007). As demonstrated, through the developed BrIM, the severity and locality of the defects, as well as other non-geometrical information, can be readily transferred to asset managers for management purposes and future maintenance planning. The successful implementation of this plugin at an early stage has opened the door to the development of a comprehensive BMS in future research studies.



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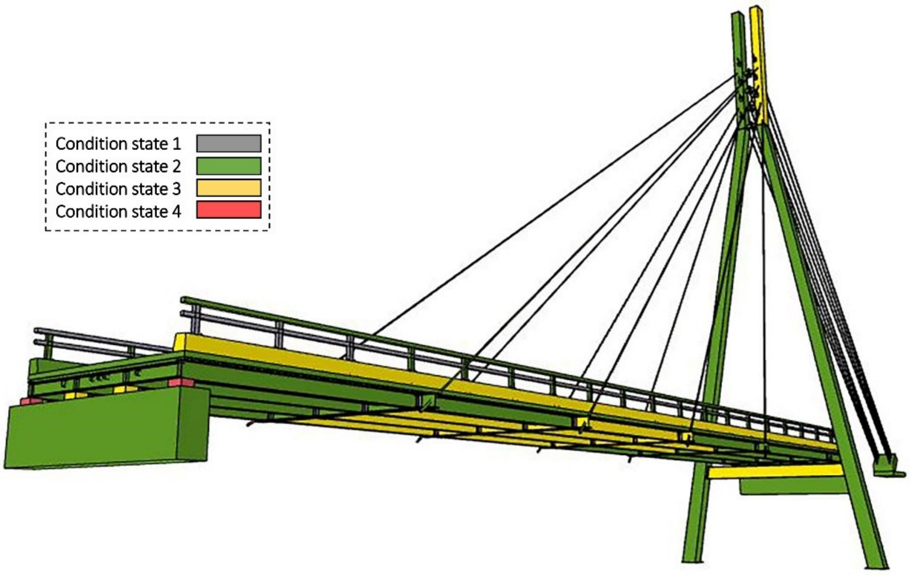


(b)

Figure 4-14 Inspection data assignment and condition state report; **(a)** Clash detection and data assignment, **(b)** Element-level condition state report.

4.5. Discussion and future directions

This study established a practical methodology for developing a TLS-derived BrIM that contains a 3D CAD model and the ability to connect non-geometrical information to each component of the bridge structure with the aim of bridge monitoring and asset management. Given the time and effort required to gather manual measurements and update information, the significant use of TLS application, described in this research study, introduces an efficient and precise method for data collection and 3D CAD model generation.

In order to further evaluate the soundness of the proposed method provided in this research study, the process of bridge surveying, 3D CAD model creation and BrIM development of a real bridge case study was thoroughly discussed. In relation to the bridge surveying phase, important factors of a proper bridge surveying plan and the essential activities using TLS were reviewed. In the case of the Werrington bridge case study, the TLS application shows an acceptable data acquisition time, although this operation would take a couple of weeks utilizing manual approaches. In another effort, the quality of the generated bridge point cloud was evaluated and compared employing several quality analysis methods. The result of surface deviation analysis indicated millimetre-level of noise which led to a reliable surface representation and 3D model reconstruction. Moreover, the result of geometric accuracy evaluation indicated the average TLS measurement error of less than 5 mm. However, concerns remained regarding the outlier noise for components located at high altitudes, far away from the scan unit. In the next following step, the generated point cloud was converted to a 3D CAD model using the slicing approach presented. The result of deviation analysis proved the soundness of the proposed approach with a majority of deviations being less than 5 mm between the generated 3D CAD model, conventional mesh-based model, and the point cloud. However, the process of transforming TLS data into mesh model takes significantly more time than the proposed method. This time can also vary according to the level of detail required, available computer hardware, available processing/modelling software and their inter-compatibility, as well as the operator involved.

Finally, the constructed 3D CAD model of the bridge forms as the core of the BrIM and non-geometrical data assigned to each component of the model for future asset management planning. Future research is also recommended for the development of bridge management systems (BMSs) including Artificial Intelligence (AI) (Yu et al., 2021, Liu et al., 2021), decision support system (Rashidi et al., 2016b), and the Internet of Thing (IoT) (Zinno et al., 2019) not only to collect real-time information but also to evaluate and prioritize the tasks. Therein, asset managers may benefit from real-time decisions, recommending strategic plans, and distributing tasks to other sub-team members. Over the last decade, the new technology of laser scanning has developed a reputation in precise and rapid data collection, making this emerging technology perfectly suited for creating and updating information models such as BrIMs, presented in this research study. However, the research is lacking in automated and dynamic methodologies, as well as AI interpretations for real-time health monitoring and updating the BrIMs (McGuire et al., 2016b).

4.6. Summary and conclusions

With respect to bridge inspection and management, this study proposed a methodology not only to generate a well-detailed and precise source of information using Terrestrial Laser Scanning (TLS) for bridge inspection but also to develop a TLS-derived Bridge Information Model (BrIM) containing a 3D CAD model associated with an element based non-geometrical data. The proposed BrIM database can be utilized as a valuable source of information for a variety of purposes including bridge asset management and also structural assessment. With the ability to capture and store large amounts of data, including detailed geometric and material information, as well as collecting remote sensor's data, the BrIM database can serve as a valuable tool for engineers and asset managers in conducting real-time structural assessments. The proposed TLS-derived BrIM in this research study, not only can be beneficial for asset managers and bridge engineers in potential time saving through overcoming the necessity to frequently revisit a bridge in person but also can ease the document management through substitution of digital models over hard formats. Moreover, linking additional information such as bridge reports, or any other bridge inspection data, with digital replication of a bridge will lead to a better understanding, and smoother communication of such data being exchanged between the relevant personnel.

An attempt to fulfil these objectives was made by performing a real bridge case study via laser scanning a cable-stayed bridge named Werrington Bridge, located in Western New South Wales (NSW), Australia. Following this case study, the process to develop a 3D point cloud using TLS is elaborated, the quality of the acquired data is evaluated and compared, and the soundness of the proposed methodology in generating a TLS-derived BrIM is proved. In the case of Werrington Bridge, the comparative results between the TLS-based point cloud and the as-designed CAD models showed millimetre-level error in geometric accuracy evaluations. Moreover, the deviation analysis showed acceptable agreement between the generated 3D CAD model and the captured point cloud. The constructed 3D model of the Werrington Bridge was used as the core of its BrIM and different non-geometric data were perfectly assigned for future references.

Nonetheless, concerns remained for future research studies regarding the automatic methods for real-time BrIM updating algorithms using Artificial Intelligence (AI). Moreover, introducing a decision support system to further evaluate the collected information and support asset managers in their judgments is critical.

Chapter 5

(BrIM-oriented BMS integrated with DSS)

** The content of this chapter has been submitted as a paper titled "Integration of TLS-Derived Bridge Information Modeling (BrIM) with a Decision Support System (DSS) for Digital Twinning and Asset Management of Bridge Infrastructures", Computers in Industry Journal, 2023, Vol. 147, 103881; https://doi.org/10.1016/j.compind.2023.103881, Q1 journal with IF. 11.24 in 2023 **

5.1. Introduction

Bridge infrastructures are among the vital component of the built environment and road network. Over time, during bridge operation and exposure to the environment and service loads, the health of infrastructure deteriorates. If the process of deterioration is not controlled or managed, a situation can arise where the infrastructure ceases to serve its purpose or becomes obsolete. In this case, the bridge infrastructure may be decommissioned, repurposed/degraded, or replaced with a new infrastructure. Therefore, negligence in proper maintenance and management or delayed action, particularly for bridge infrastructure, may result in high future expenditures, degraded assets, and, in the worst-case scenario, lead to catastrophes such as the Morandi bridge (Calvi et al., 2019) and Taiwan's Nanfang'ao bridge (Horgan, 2019) collapses. As the number, and age of these infrastructures increase, so does the need to monitor the health, management, and maintenance of these important structures. Just as bridges are an integral part of society, it is important that new technology is given consideration towards improving the way in which these infrastructures become inspected, managed, and maintained (Elfgren et al., 2007).

For many years, bridge management approaches and condition assessments have been based on long-established manual paperwork and information retained from on-site inspectors and engineers (Rashidi et al., 2020b). These approaches have been primarily paper-based and significantly limit the ability to be readily transferred to asset managers or be referred after a few years. However, the development of Building Information Modeling (BIM) in recent years, has led to a transformation in the digitalization of structural assets and their information in form of a digital twin, which in the field of bridge engineering pertains to the Bridge Information Modeling (BrIM) (Kaewunruen et al., 2020, Perno et al., 2022, Semeraro et al., 2021). Chan et al. (2016) were among the researchers who emphasized that it is currently essential for bridge owners to make use of BrIM as a database to store various sources and types of information such as bridge drawings, inspection records, rehabilitation activities, condition state of elements, records of remote sensors, and history of decisions with a timestamp and reference. In general, BrIM is a shared database/platform, that often consists of the bridge geometrical 3D Computer-Aided Design (CAD) models, as digital representation of the physical characteristic of the bridge asset, as well as non-geometrical information as digital documentation such as visual inspection reports, damage locations and maintenance histories, remote sensors' records, diagnostic test results, element's material, and other specifications (Mohammadi et al., 2022, Wenner et al., 2021). With a BrIM, this information can then be widely shared/disseminated amongst the stakeholders involved, assisting bridge manager, and assessors, as a reference for their future decisions. Despite the fact that BrIM is an innovative method for storing varied information, two concerns remain in terms of: 1) creating an accurate digital representation and collecting remote and reliable information, 2) utilizing BrIM data for management purposes in a reliable Bridge Management System (BMS).

To address the first concern, BrIM development extracted from remote data collection was initiated as a reliable and qualitative concept in studies conducted by Lubowiecka et al. (2009), Tang and Akinci (2012a), and over time, this concept has seen exponential growth in its application, and scope (Sacks et al., 2018, Mohammadi et al., 2022). In general, determining changes in geometry, detection of defects, and the overall condition assessment of bridges were carried out through visual inspections, which were reinforced by inspection procedure manuals and guidelines developed by roads and traffic authorities (TfNSW, 2007). However, these inspections were prone to subjectivity, impacted by the experience and knowledge of the inspectors engaged, labour-intensive, time-consuming, and in most cases were not traceable (Riveiro and Lindenbergh, 2019). These inspections also require special tools and equipment, such as lifting units, scaffolding, or rope climbing, with its associated risks, to get access to areas that would otherwise be inaccessible. In recent years, in order to tackle this risk and ease the data capture process, emerging technologies such as Terrestrial Laser Scanning (TLS) and Unmanned Arial Vehicle (UAV) photogrammetry have been utilized, and have made a significant impact on remote data collection and qualitative inspection of the bridges (Dorafshan and Maguire, 2018, Mohammadi et al., 2021c, Mohammadi et al., 2021b). These technologies have eliminated the inefficiencies and risks of site inspections in favor of detailed office inspections based on high-quality data obtained. Although these technologies have the capability of remote data collection and inspection, each has strengths and weaknesses in terms of flexibility, geometrical accuracy, and data quality, which may need to be varied based on the requirements of a bridge project to the next (Mohammadi et al., 2021c). When compared to other technologies, TLS, being the ground-based and most prevalent form of laser scanning technology, delivers benefits through rapid and qualitative capture of an object's surface topography via the reflection of the emitted laser beams (Mohammadi et al., 2021c, Chen et al., 2019b). In the process of scanning, a TLS captures and stores three-dimensional (3D) data points, named point cloud. This file may subsequently be utilized for a variety of applications, after post-processing and optimization, including bridge inspection and assessment (Fuchs et al., 2004, Tang et al., 2007, Chen, 2012, Mizoguchi et al., 2013, Teza et al., 2009, Kim et al., 2015, Conde-Carnero et al., 2016), and Bridge Information Model (BrIM) development (Barazzetti, 2016, Xiong et al., 2013, Mohammadi et al., 2022).

In terms of bridge inspection, Fuchs et al. (2004) were among the key researchers who employed a laser-based instrument for bridge assessments of several highway bridges in the United States of America in 2004. In their research study, they employed the former technology of laser scanning to measure the deflections of bridge girders under static loading. In a similar strategy, Tang et al. (2007) employed this approach to expedite the collection of bridge geometrical information, such as vertical clearance, which was required for assessing bridge functional efficacy as specified by the National Bridge Inventory (NBI) program developed by American transportation authorities. In a research study, Mizoguchi et al. (2013) proposed a practical approach for using TLS data in quantifying surface damages such as mass loss and scaling. They utilized this approach to calculate the depth and area of damages caused by freeze–thaw cycles on an ancient concrete bridge. Similar methodologies were also explored for different damage detections in studies by Kim et al. (2015) and Teza et al. (2009) for structural elements' damage quantification, however, research remains fairly lacking a comprehensive methodology for estimating the overall condition state of the bridge structure using these valuable data.

In respect to bridge assessment, Conde-Carnero et al. (2016) utilized the acquired TLS-based point cloud to create a Finite Element (FE) model of a pedestrian bridge and assess its load-bearing capability following additional upgrades. In an interdisciplinary bridge assessment, Pérez et al. (2018) combined TLS technology for detailed geometrical identification and Ground Penetration Radar (GPR) to determine composition of fillers and structurally examine/analyze an ancient Roman bridge. Despite significant research efforts that resulted in empirical testing of more efficient models, most TLS-based bridge inspections were not utilized to develop a management system. In terms of BrIM development using TLS point cloud, known as TLS-derived BrIM, Tang et al. (2007), Hinks et al. (2013), Riveiro and Lindenbergh (2019), Mohammadi et al. (2022) proposed methodologies that have meaningfully improved the efficiency of automated data extraction, accelerated the creation of bridge 3D CAD models, and resulted in a better means of both recording detailed bridge information, as well as serving as a reliable source of information for future reference and decisions.

However, in response to the second concern, research remains relatively limited to the development of BrIMs, and current Bridge Management Systems (BMSs) as well as designed software rely on frameworks that lack an optimized management planning endorsed by a decision support system, which this process was originally vulnerable to subjectivity due to the varying experience and expertise of the engineers involved (Rashidi et al., 2016a, Li et al., 2021, Aflatooni et al., 2015). Although there are several BMSs available on the market, the majority of them are inventory asset management platforms with insufficient and subjective procedures, resulting in limited decision-making and asset management outputs.

Therefore, this research thesis provides a thorough methodology to not only use valuable benefits of having a detailed TLS-derived BrIM but also present an innovative BMS integrated with a multi-criteria Decision Support System (DSS), targeting a powerful bridge asset management system with more reliable bridge management decisions in remediation strategy planning using BrIM data. During this study, a redeveloped approach for calculating Priority Rating Condition Index (PRCI) of bridge elements is elaborated. This approach is then expanded to a DSS for optimizing major bridge maintenance plans within acceptable safety, functionality, and sustainability boundaries. This methodology is further implemented in a designed BMS plugin and validated using a real bridge case study, Werrington Bridge, a cable-stayed bridge in New South Wales, Australia.

5.2. Research Methodology

With the growth in the number of bridge inventory worldwide, bridge monitoring, condition assessment and management have become increasingly essential and challenging. Although many BMSs have been developed to date, the most recent update is the approach of BrIM-oriented BMS (Saback de Freitas Bello et al., 2022, Shim et al., 2019). This approach utilizes a bridge virtual representation includes lifetime and updated non-geometrical data, also known as the BrIM, that is linked to a management system, resulting in the digital transformation of structural assets to form a digital twin (Boyes and Watson, 2022). BrIM is often formed of a three-dimensional (3D) geometrical representation of the bridge linked to non-geometrical data such as maintenance records, monitoring data, and reports. As bridge condition constantly changes over time, it is necessary to update the BrIM to replicate the ‘as-is’ condition of its physical counterpart. Given the time and effort involved in updating the BrIM, amassing accurate and reliable information, can be a time-consuming task, especially if data collection is performed manually. Therein, this research study employs laser scanning as an efficient means of measuring the extensive geometry within the bridges as well as a reliable and accurate data for bridge condition assessment in a TLS-derived BrIM development. This information model is indeed a fundamental step in supplying proper inputs to any management system. Following this research, a collaborative management system is introduced to utilize the advantages of the TLS-derived BrIM and provide better services for bridge maintenance and management planning. This system introduces a concept of element-level Priority Rating Condition Index (PRCI) combined with a DSS to not only bring additional holism to current condition assessment techniques, but also provide more objective decisions for remedial planning. The concept of employing this system/methodology is then explored in the development of a BrIM-oriented BMS plugin. The workflow of this methodology is depicted in Fig. 5-1 and is divided into two main subsections: the first comprises an overview of TLS-derived BrIM development and the second is its incorporation with novel BMS workflow as the focus of this research study, which is detailed in the following sections. TLS-derived BrIM development is divided into two phases of CAD model creation, and data assignment, as outlined in another study of our research team conducted by Mohammadi et al. (2022). To further describe the entire process and demonstrate the reliability of the proposed methodology, and developed plugin, the research is extended to an actual bridge case study after TLSing the Werrington bridge located in Penrith, New South Wales (NSW), Australia.

5.2.1. Integration of BrIM into BMS

Nowadays, bridge health assessments are determined using a long-established inspection manual report developed by road authorities worldwide (TfNSW, 2007, FHWA, 2018, RI-EBW-PRÜF, 2017, Chase et al., 2016). During the progress that has been made in recent years, these reports have also been converted to electronic documents and are now stored in existing management systems. However, concerns remained on the quality of inspections and applicability of the acquired information in an effective bridge management system which requires reliable data for making reasonable and correct decisions to determine the best remediation strategy or budget allocation. Therefore, the proposed approach of TLS-derived BrIM integration into BMS can not only provide a unique solution for a quick, intelligent, and reliable bridge inspection over traditional methods, but it can also provide a rich database for management purposes. In another step ahead, the proposed BMS of this research is designed to be based on a requirement-driven framework in a redeveloped Priority Ranking Condition Index, PRCI, for evaluating bridge elements. This index is a supplement ranking system that incorporates not only the general condition state of bridge elements but also takes additional variables such as their structural importance, and material vulnerability into consideration. In addition, PRCI reduces the subjective nature of personal inspections in terms of safety and

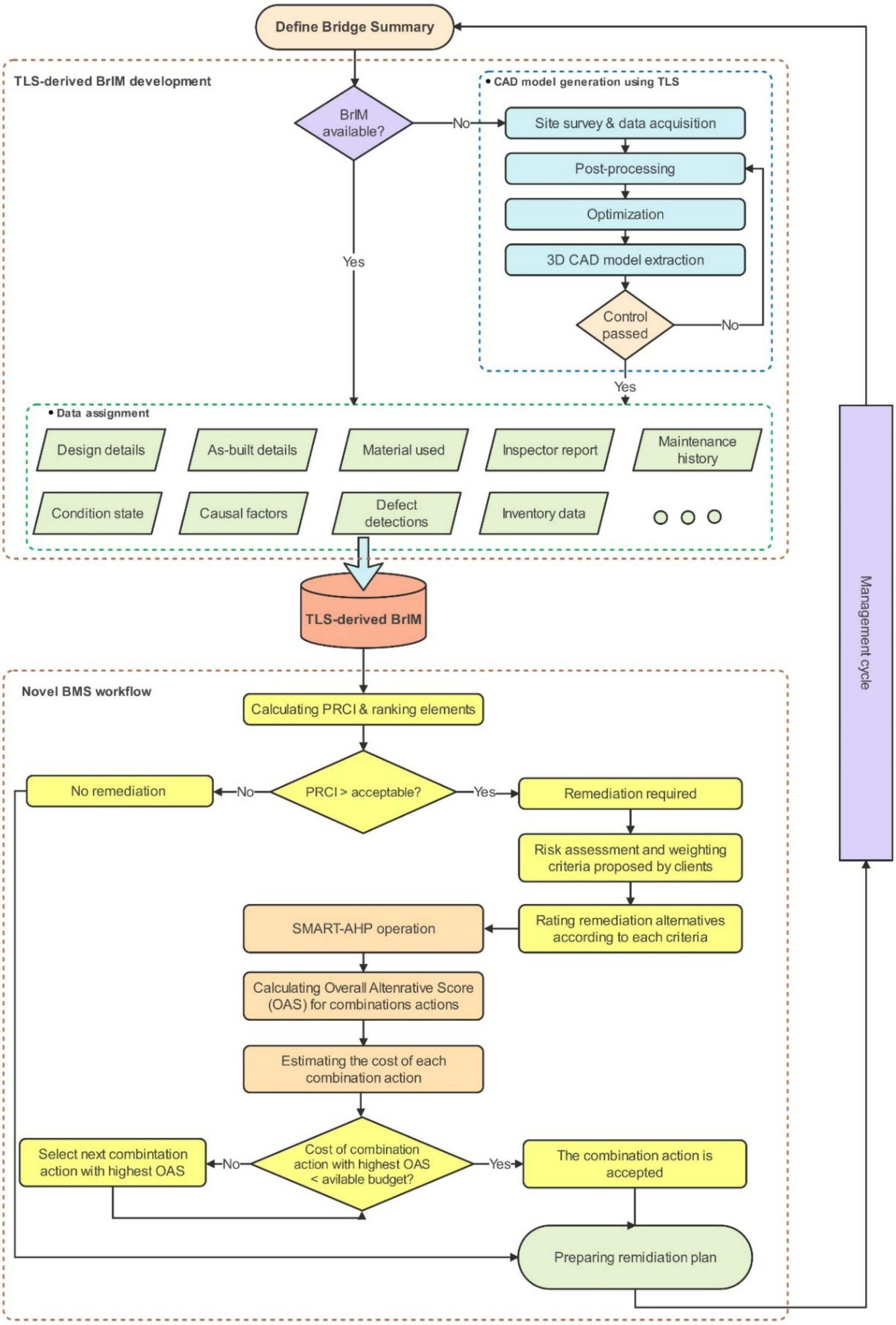


Figure 5-1 TLS-derived BrIM and DSS workflow

serviceability, while also improving the consistency of management decision and remedial actions for each element. As shown in Fig. 5-1, using this ranking system, bridge element types with greater PRCI will be given more attention in terms of bridge structural efficiency, and will be subjected to a risk assessment procedure in a decision-making system to evaluate the possible remedial actions and their costs. In general, management decisions are based on the experience of bridge managers or established rules of thumb achieved over the years. These decisions may also be prone to potential inaccuracy and lack adequate reliability or compulsion that may aggravate dilemmas related to funding and infrastructure needs. Therefore, bridge asset manager needs to get more reliable supports that can assist them in identifying suitable actions and strengthening their credibility with prospective stakeholders. Therein, this research study proposed the integration of a Decision Support System (DSS), thereby evaluating the risks and criteria involved and then devising alternative remedial strategies and budget-based planning.

5.2.2. Designed BrIM-oriented BMS plugin

The designed BrIM-oriented BMS plugin of this research study, consists of three main layers of 3D CAD model generation, application development, and report compilation. The first layer is 3D CAD model generation of the bridge using the captured TLS point cloud and the proposed novel sliced based algorithm described in the study conducted by Mohammadi et al. (2022). Using this algorithm in Python language, the bridge point cloud is divided into several point cloud slices, which were then imported into Tekla Structures (Trimble Solutions Corporation, 2021) CAD software for 3D solid modelling using general plane fitting and extrusion techniques. The extracted bridge model is then segmented based on their element types and exported to an exchangeable 3D format such as Industry Foundation Class, IFC. The second layer, application development, consists of user interface design and the implementation of functional modules in Microsoft Visual Studio using Tekla open API (Application Programming Interface). These functional modules are meant to be completed based on expert user input for each bridge element before performing BMS assessment tasks in the evaluation module. The evaluation module is based on the redeveloped condition rating system and integrated DSS, which are explained in Sections 5.3 and 5.4. This plugin is a cloud-based data storage system/platform that allows bridge users, inspectors, and managers to reach documents at various levels of access. In the last layer, report compilation, the output of the BMS plugin assessment is imported back into the Tekla Structures software and visually presented as well as a paper report produced. Fig. 5-2 illustrates the workflow of the BrIM-oriented BMS plugin development.

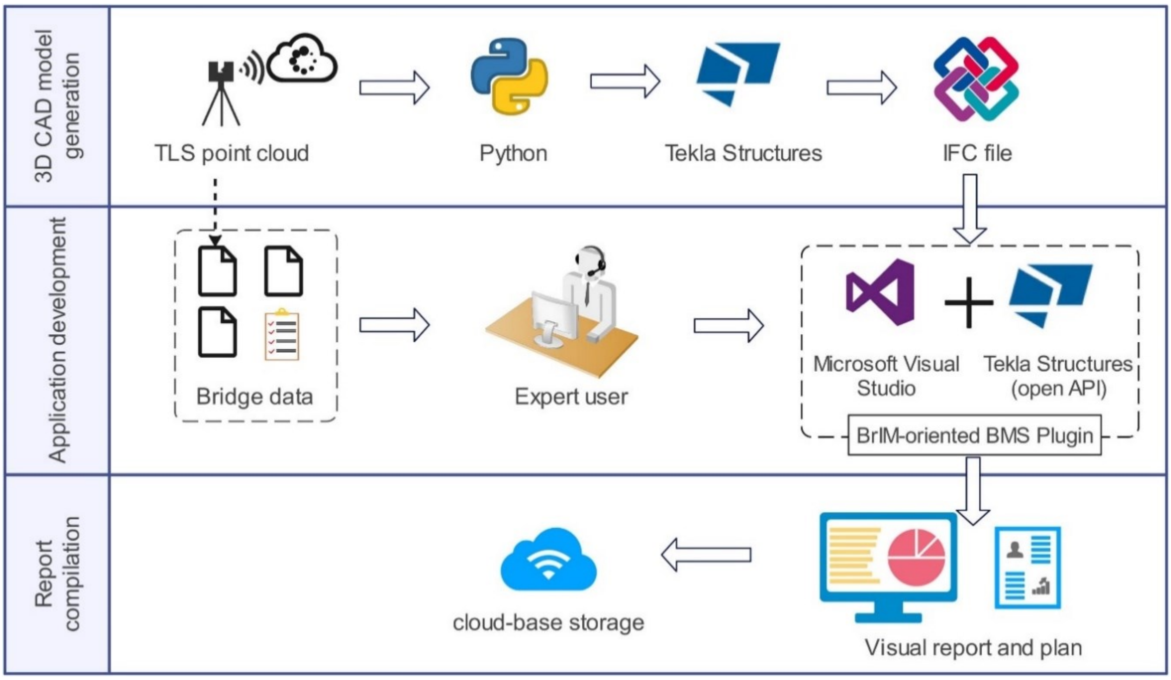


Figure 5-2 The workflow of BMS plugin development

5.3. Key points of novel BMS

The two key operations in the proposed BMS of this research study are based on a redeveloped condition rating system followed by a DSS evaluation, which is elaborated in this section.

5.3.1. Redevelopment of bridge condition assessment concept

The bridge condition or health index is a valuable means of determining a bridge's structural or functional health. This index is generally determined using the structural conditions of the bridge elements and the bridge service supplied, identifying the most deteriorated elements, and determining the necessary repairs in bridge remedial actions (Chase et al., 2016). To be consistent with current trends in both Australian and global bridge inspection standards, as well as bridge inspection procedure manuals established by road authorities such as Transport for NSW (TfNSW) (TfNSW, 2007), the proposed Priority Ranking Condition Index (PRCI) of this research study attempts to use not only the four general qualitative Condition indices (CI), provided in Table 5-1, but also to identify the subjective nature of this process and reduce the uncertainty using a set of weighting factors for ranking elements and maintenance prioritisation. This approach not only provides a detailed picture of how degradation spreads across bridge elements, but it also serves as an effective index to assist bridge engineers to prioritize maintenance and planning rehabilitation for bridge assets.

Table 5-1 General qualitative conduction indices (TfNSW, 2007)

CI	Descriptions
1	The element shows no deterioration. As-new condition or defects has no significant structural and functional effects.
2	Minor defects and early signs of deterioration with no reduction in element functionality.
3	Moderate defects and deterioration with some loss of expected functionality.
4	Severe defects with significant loss of functionality or element on the verge of failure.

In this research study, three factors are considered to be used in the procedure for evaluating the influence of technical indicators and determining a much more reliable bridge maintenance plan. Therefore, the element weighting factor (W_e) is defined, consisting of element Importance Factor (IF_e), multiplying by element Material Vulnerability (MV_e), and Casual Factor (CF_e) scaled by their overall weighted average. The $PRCI_e$ incorporates all the factors/parameters mentioned that influence structural performance and is calculated by following formula:

$$PRCI_e = \frac{CI_e}{\overline{CI}} \times W_e \tag{5-1}$$

where CI_e is the element condition state and $\overline{CI}$ is the overall bridge health index, which can be calculated using Eq. 5-2 (Jiang and Rens, 2010) and Eq. 5-3, respectively. Eq. 5-4 also computes the weighting factor, W_e, where e is the number of elements, and $\overline{IF}$, $\overline{MV}$, $\overline{CF}$ are their overall weighted averages.

$$CI_e = \frac{\sum_i (q_i \times CI_i)}{\sum_i q_i} \tag{5-2}$$

$$\overline{CI} = \frac{\sum_e (CI_e \times IF_e \times MV_e \times CF_e)}{\sum_e IF_e \times MV_e \times CF_e} \tag{5-3}$$

where i is defined as the number of condition states, q_i is the quantity of the elements in ith condition state, and CI_i is the condition state index corresponding to the ith condition state.

$$W_e = \frac{IF_e}{\overline{IF}} \times \frac{MV_e}{\overline{MV}} \times \frac{CF_e}{\overline{CF}} \tag{5-4}$$

As determining the weighting factor and its parameters often requires special knowledge and field testing, particularly for material vulnerability and structural assessments, the inspector can rely on the proposed systematic approach of this research investigated through a semi-structured field interview/survey with experts and engineers in the field of bridge engineering and management. In the following subsections, these factors are elaborated.

5.3.1.1. Importance Factor (IF)

As previously indicated, the current condition state evaluation alone may cause some distortion in evaluating the overall bridge health condition. A minor element with worse condition may unreasonably raise the values and jeopardize the judgments (Dabous and Alkass, 2010, Gorji Azandariani et al., 2022). Therefore, this problem is resolved using the quantified element's structural Importance Factor (IF), which is not dependent on the current condition of bridge components. Based on the above-mentioned expert survey, the bridge components are classified into four categories of primarily, secondary, tertiary, and other elements. As shown in Table 5-2, the higher the value, the greater the influence of the elements on the load-bearing behaviour and safety of the bridge structure.

Table 5-2 Structural Importance Factor (IF) (Dabous and Alkass, 2010)

IF	Bridge elements
1	Other elements; including but not limited to barriers, kerbs, footway, joints
2	Tertiary elements; including but not limited to foundation, abutment, wingwall
3	Secondary elements; including but not limited to deck, bearings, cables
4	Primary elements; including but not limited to beams, girders, piers, pylons

5.3.1.2. Material Vulnerability (MV)

Understanding the vulnerability of various materials can contribute to the durability of the elements under varying hazards throughout time. Although this parameter deserves comprehensive research for various hazards, especially for bridge elements, in general an element made of steel is more prone to deterioration than a precast reinforced concrete element in terms of durability in a harsh environmental condition. Following the studies conducted by Valenzuela et al. (2010), , as well as validating the expert surveys conducted, Table 5-3 shows the vulnerability of common materials used in bridge construction.

Table 5-3 Material Vulnerability (MV) (Valenzuela et al., 2010)

MV	Element Material
1	Precast concrete, non-structural elements
2	Reinforced concrete
3	Steel, iron, and other materials
4	Timber

5.3.1.3. Casual Factors (CF) and calibration

Over time, as the infrastructure used, and is exposed to loading and environmental mechanisms, the health of bridge and its components deteriorates. If this process of deterioration is not well managed, the situation can arise where the bridge ceases to serve its purpose. Besides pre-existing factors, such as design and construction, several post-existing factors such as the environment where the bridge is located, the length of time the bridge has been in service (age), the functional performance that the bridge supports (road type), and the quality of inspection can all have an impact on the bridge's structural efficacy. Although these factors may be comparable for a bridge and its elements, the bridge elements may have different experiences in some circumstances. A bridge element can be upgraded over time, or it can be subjected to harsher environment than others. These factors can subsequently be used to evaluate overall bridge priority rankings when combined with overall functional efficiency factors, political considerations, and other relevant variables. Table 5-4 lists four categories of these factors, each of which is introduced by certain terms introduced in the following paragraphs.

Environmental aggression factor includes but not limited to the natural environmental mechanisms that trigger chemical or physical deterioration to structural elements (Rashidi et al., 2016a). The level of these damages and the time frame for paying them off may vary depending on the severity of the environmental aggression. Sometimes a trace of the aggression or damage might be imperceptible at times, requiring a lab test to identify. Climate change, air, soil, or water pollution, chemical reactions, and human causes are all instances that may be classified at different levels and affect the overall structure's remaining life-time (Byun et al., 2021), as shown in Table 5-4. Moreover, other deterioration triggers, such as fatigue induced by repeated load applied to a structural element over the course of a bridge's lifetime, can promote cracks and fracture expansions. Therefore, the age factor and Annual Average Daily Traffic (AADT) associated with road type, as well as the road importance in network are generally recognized as key considerations not only for bridge design but also for evaluating element durability and bridge remaining lifetime. Besides, bridge inspection and its frequency are critical factors that must not be neglected. In this regard, four different levels of bridge inspection including initial, routine, detailed, and special inspection are defined in this research study. Initial inspection refers to the first inventory inspection following construction for data-driven preparation; however, routine inspection is typically focused on visual observations for general condition assessments. Aside from on-site visual observation, detailed inspection reinforced with non-destructive testing, and special inspection is supplemented with additional structural analysis when a serious incident occurs. It is worth noting that, regardless of the level of inspection, TLS application presented in this research study may be utilized for all different levels of inspection.

Table 5-4 Causal Factor (CF) index (Rashidi and Gibson, 2011)

CF	Causal factors			
	Environmental Aggression (EA)	**Age factor (A)**	**Road type & loading (R)**	**Inspection level (I)**
1	Mild	Recently built (0-25 years)	Minor ($AADT \leq 150$)	Initial
2	Moderate	New (25-50 years)	Local access ($150 < AADT \leq 1000$)	Routine
3	Harsh	Old (50-75 years)	Collectors ($1000 < AADT \leq 3000$)	Detailed
4	Very Harsh	Very old (75-100 years)	Arterials ($AADT > 3000$)	Special

Following the implementation of the research studies conducted by Valenzuela et al. (2010), Rashidi and Gibson (2011), the CF index is calibrated using the results of the aforementioned survey of bridge engineers specialists rating the importance intensity of the casual factors. This rating process was based on the Saaty's nine relative importance scales and development of a pairwise matrix (Saaty, 1990), part of the Analytical Hierarchy Model (AHM), provided in our research team study conducted by Rashidi et al. (2011, 2016a), which is not the main concern of this study. Based on the rating process and the importance scales, the mathematical formulation for predicting the CF was developed as presented in Eq. 4-5.

$$CF_e = 0.12\,EA + 0.41A + 0.11R + 0.36I \tag{4-5}$$

5.3.2. Integration of a Decision Support System (DSS)

Multi-criteria decision-making approaches are among the most robust and reliable analytic systems that have the potential to be integrated into a BrIM-oriented BMS. These approaches frequently use a qualitative relative comparison, to provide a systematic mechanism for weighting the multiple criteria, such as several risks involved, to evaluate and rank feasible alternatives (Wang et al., 2008). In this regard, the Simple Multi-Attribute Rating Technique (SMART) and the Analytical Hierarchy Process (AHP) are two approaches that are widely utilized in many aspects of engineering and have the potential to be integrated into the bridge infrastructure management (Abu Dabous and Alkass, 2008, Abu Dabous and Alkass, 2010, Aflatooni et al., 2015). In this research study, a reasonable balance has been made between the simplicity of SMART and complexity of the AHP. In this case, a combined method of AHP-SMART with the capability of AHP's pairwise comparison of criteria and SMART's cardinal rating of each alternative has been utilized. Using this combined method, the limitation of restarting all calculations after adding a new alternative has been eliminated. During this process, bridge elements with the highest PRCI scores, outlined in Section 5.3, are subjected to AHP-SMART analysis after a risk assessment to evaluate the possible remedial alternatives.

Through the AHP-SMART process, the problem is subdivided into a hierarchy which includes three main levels of an overall goal, a group of alternatives for accomplishing the goal, and a set of criteria that tie the alternatives to the goal. In general, a criterion may not to be equally defined throughout this process, and thus may be graded/weighted based on several aspects of importance in terms of bridge engineering, management, and clients' constraints (Abu Dabous and Alkass, 2008). These weights can vary between projects and must be established by the individual involved in decision-making using the relative pairwise comparison embedded in Saaty's AHP method (Saaty, 1990). Moreover, alternative selection, which in the case of bridge rehabilitation refers to remediation alternatives/actions, entails a case-by-case risk assessment of alternatives and is tied to their associated course of actions. Therefore, bridge maintenance planners require to establish a balance between the relevance of the project's criteria and feasible alternatives.

5.3.2.1. Criteria, remedial strategies, and budget optimization

The primary concept of employing criteria is to evaluate the performance of each alternative in relation to the main goal based on a numerical scale. In the case of bridge rehabilitation, these criteria can be bounded into inclusion of subjective constraints such as functionality, sustainability, and reliability of the structural elements. In this case, the functionality can be extended through the operational efficiency of the elements that can affect the service life of the bridge, or the level of maintenance necessary to avoid the closure of a strategic route.

However, the sustainability refers to the extension of such a service beyond having an effective work operation with a reasonable cost. Besides, element's reliability or safety depends on the structural compliance with the applicable standards while causing less damage to the infrastructure and improving the structural capacity in return.

The majority of real-world decisions involve a combination of alternatives, and solutions out of various possible choices which require a careful evaluation of their pros and cons, the costs involved in making each choice, and the relative benefits (or disadvantages) of each option. Therefore, in terms of bridge rehabilitation, a range of satisfaction alternatives or remedial strategies has to be implemented to make it more feasible to ensure the functional, rational, effective and safe environment for people to travel across the bridges. In this regard, a potential remedial strategy can be classified into three levels (i) major alternatives, (ii) intermediate alternatives, and (iii) sub-alternatives. Major alternatives refer to the fundamental operational functions (including regular maintenance, minor rehabilitation, major rehabilitation, and replacement of the bridge elements), intermediate and sub-alternatives may refer to supplementary (including sub-structure redesign or specific engineering services) or provisional actions. The provisional actions of the sub-alternatives can be evaluated based on a fit to purpose classification after the fundamental/major alternatives have been carried out and endorsed in the form of a technical specification framework. This framework acts as a basis to evaluate various structural problems that may arise or can be found in bridges of different types, as detailed in research studies conducted by Rashidi et al. (2016b, 2017, 2021), and Byun et al. (2021).

Road authorities across the world are dealing with an increasing number of deficient bridges, while their budgets for maintenance are generally limited, making necessary greater investigation and detailed risk assessment. In this respect, identifying vulnerable bridge elements, and providing a reliable maintenance plan with a number of prioritized alternatives can allow for not only a better knowledge of the bridge condition but also a budget optimization and prioritization to preserve bridge safety in a secure state.

5.4. Werrington Bridge case study

In order to further evaluate and demonstrate the procedures discussed, a real case study was conducted to collect the point cloud of a bridge named Werrington bridge which links the north and south campuses of the Western Sydney University (WSU), Werrington campus, built in 1992. The bridge, shown in Fig. 5-3, serves as a passageway for motor vehicles and pedestrians across the Great Western Highway, in Werrington, west of Sydney, Australia. The Werrington bridge is an award-winning architectural structure with an asymmetric cable-stayed system designed out of an A-frame steel pylon with two legs and a composite deck with a reinforced concrete slab and an underlying steel frame. The composite deck is supported by two abutment walls, the pylon's beam, and a set of eight stay cables connected to the pylon's top end.

(a)

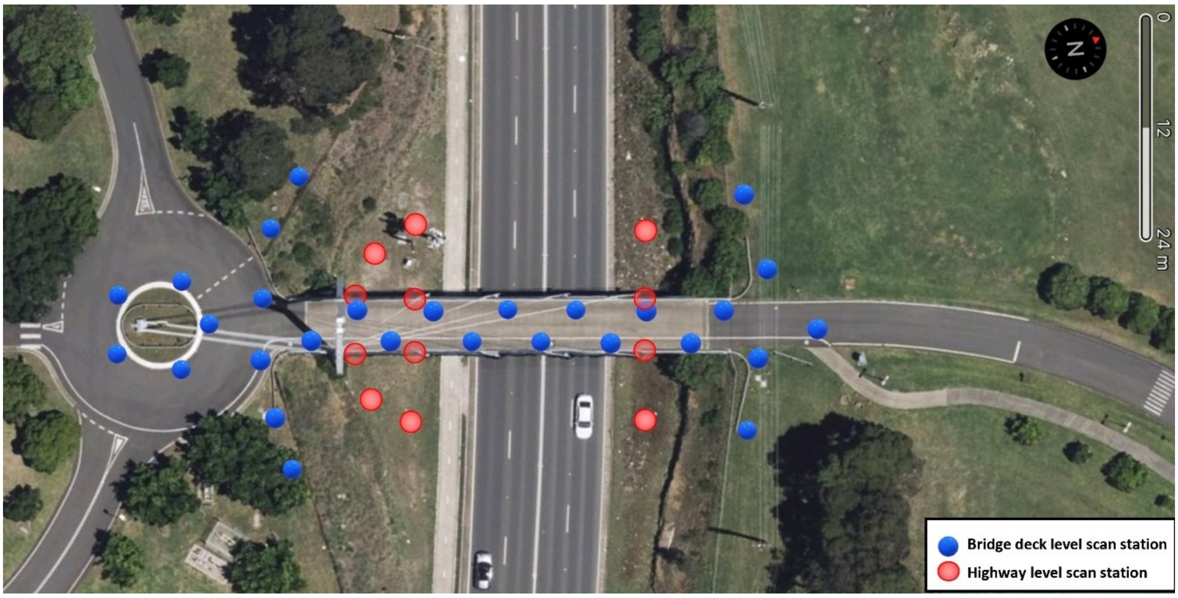
(b)

Figure 5-3 Werrington Bridge case study; **(a)** Navigation map view of the Werrington Bridge, **(b)** Bridge view in 2021.

In this research study, Werrington bridge case study is defined as a part of an asset management project for development of a TLS-derived BrIM, as well as assigning and assessing the soundness of the proposed methodology and implementing the designed BrIM-oriented BMS plugin for future bridge maintenance and management planning.

5.4.1. TLS survey and CAD model extraction

The scanning of the Werrington Bridge took place using Z+F IMAGER 5016 terrestrial laser scanner, shown in Fig. 5-4, following an initial site inspection and investigation to identify the appropriate scan positions and parameters for the scan day strategy plan. Without a reliable strategy plan for selecting scan positions and their numbers, as well as defining scan parameters such as level of accuracy and quality required, the TLS survey result as a point cloud data may be unsatisfactory, noisy, and unusable, failing to cover the main elements' surface condition in detail. Fig. 5-4 (a) depicts 40 scan positions, including 28 on and 12 beneath the Werrington Bridge, that were judged feasible for scanning the whole structure. At the same time, consideration was also given to the positioning of targets, known as common points in scans that were employed to support data post-processing. Table 5-5 shows the scanning details and parameters. Following that, the acquired data points from multiple scan positions have undergone a filtration, registration, and colorization processes using the Z+F Laser Control V9 software (Zoller + Fröhlich GmbH, 2019).



(a) Scan plan strategy

Figure 5-4 Werrington bridge scan plan and data acquisition via TLS

(b) TLS data collection

Figure 5-4 Werrington bridge scan plan and data acquisition via TLS

Table 5-5 Scanning details and parameters

Scanner name	Z+F IMAGER 5016
Resolution	6.3mm at 10m
Quality	273kHz
Average range noise	0.25 mm RMS
Field of view of each scan	The full field of view of the scanner (360 degrees horizontally by 320 degrees vertically)
Maximum distance	No more than 20m to the nearest part of the bridge
Number of scan positions	40 scan positions
Number of targets	29 targets, including spherical and laminated A4 papers
Colour photographs	TLS set to capture colour photographs using its built-in High Dynamic Range (HDR) panorama camera (80 Megapixel)

The outcome of these procedures was an optimized point cloud with around 525 million discrete points, requiring approximately 15 GB of computer storage space, shown in Fig. 5-5(a). In the following, using the quality evaluation approaches presented by Mohammadi et al. (2021b), (2021c), discussed in Chapter 3 and 4, the quality of the point cloud data was checked with the as-designed drawings and as-is measurements conducted on different bridge elements that showed a millimeter-level of relative geometrical accuracy for the captured Werrington bridge point cloud. In the next step, the automatic slice-based algorithm introduced by Mohammadi et al. (2022), discussed in Chapter 4, was utilized to generate a CAD model extraction of the bridge. Using this algorithm, the bridge point cloud is divided into several point cloud slices, which were then imported into Tekla Structures (Trimble Solutions Corporation, 2021) CAD software for 3D solid modelling using general plane fitting and extrusion techniques. Details of the Werrington bridge 3D CAD model extraction are discussed thoroughly in Chapter 4. The Werrington bridge CAD model is illustrated in Fig. 5-5(b).

(a)

(b)

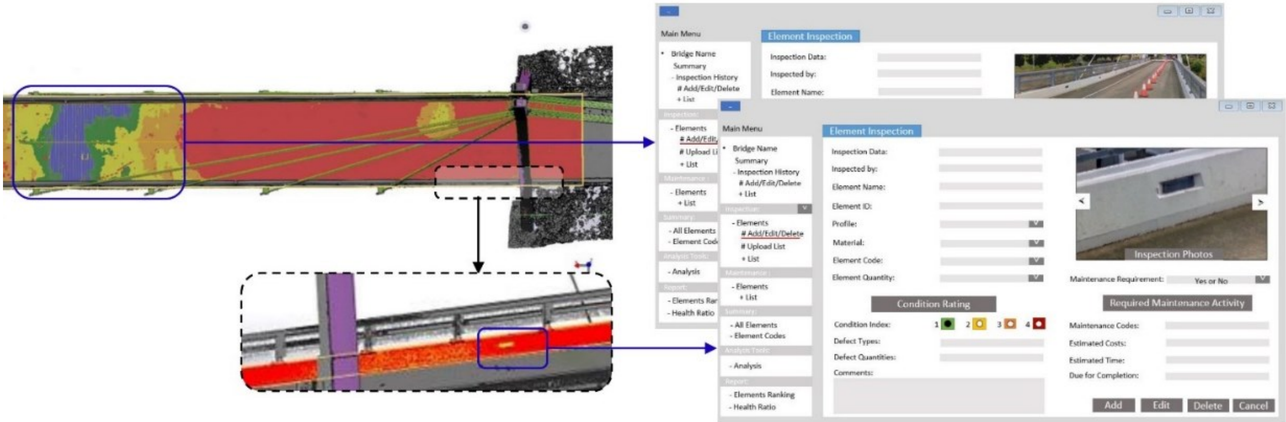
Figure 5-5 Werrington bridge point cloud and CAD model; (a) Optimized point cloud, (b) Extracted 3D CAD model.

5.4.2. Werrington BrIM development

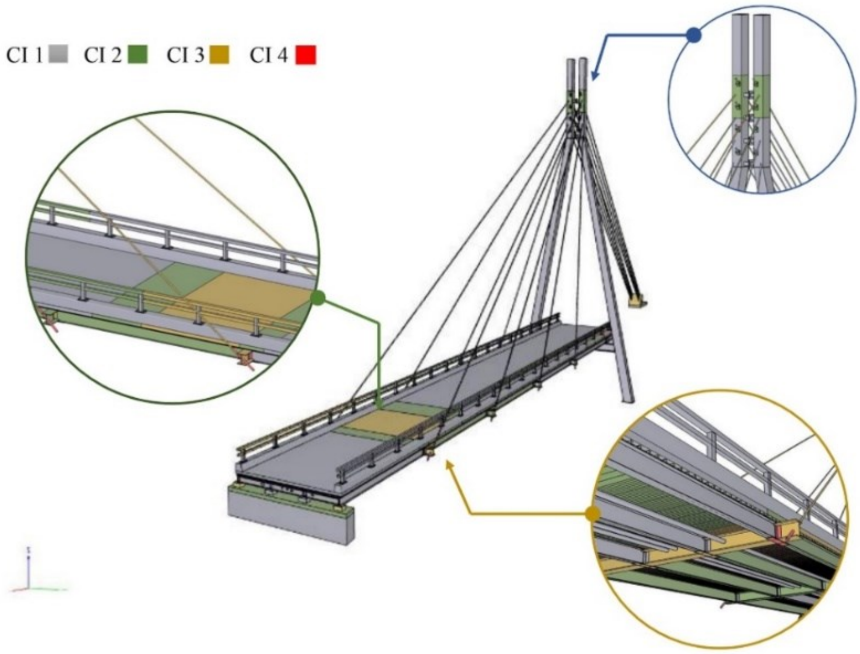
In this stage as illustrated in Fig. 5-2, the extracted 3D CAD model (IFC model) serves as the core of the BrIM, and different non-geometrical information, such as the parameters described in Section 5.3, were allocated to the bridge and its elements to create an information model of the Werrington Bridge. It is worth noting that this procedure is intended to be performed in a Tekla Structures plugin designed after a thorough review of the bridge, employing either the clash detections algorithm (Trimble Solutions Corporation, 2021, Dorafshan and Azari, 2020) or off-site measurements and observations using TLS-based data, or existing reports from an expert engineer on-site. The clash detection and progress tracking algorithms enable bridge engineers to discover changes in the bridge model or TLSed data over time, and the results could be a reliable source of information for bridge assessment in different levels of inspection. The clash detection purpose is to identify potential clashes or interferences between different elements of the structure. The algorithm utilizes the 3D models generated from various sources, including TLS point cloud data and CAD drawings, to identify potential clashes between these elements. The clash detection algorithm works by comparing the geometry and spatial relationships of different elements in the 3D models. It looks for situations where two or more elements occupy the same physical space or where one element intersects with another. When potential clashes are detected, the algorithm flags them as a clash, allowing engineers to review and resolve them. The use of the clash detection algorithm in the BIM methodology provides several benefits. First, it can help prevent costly and time-consuming errors that could occur if clashes are not identified before and after construction. Second, it allows for more effective resolution of any clashes that are identified (Saminathan, 2019, Azhar et al., 2008).

For instance, considering the concrete bridge deck of the bridge as the reference, the deviation of the 3D CAD model and point cloud is analysed using Tekla Structures' built-in clash detection algorithm, resulting in the vertical deformation of the bridge illustrated by colour counters in Fig. 5-6(a).

In the case of the Werrington Bridge, the designed BrIM-oriented BMS plugin is utilized to assign the engineering team's TLS data assessments and existing manual inspection reports to support a digital transformation (digital twinning) of the bridge as a record. The overall distribution of allocated data for various bridge element types are shown in Table 5-6 and illustrated in Fig. 5-6(b). In this regard, the element codes, descriptions, units, and condition state interpretations were considered based on the Australian bridge inspection procedure manual developed by Transport for NSW (TfNSW, 2007).



(a)



(b)

Figure 5-6 Vertical bridge deck deformation using clash detection; (a) Clash detection and data assignment into BrIM-oriented BMS plugin, (b) CI of individual bridge elements.

In this procedure manual, the units rely on the exposed surface area or the number of exposed elements. The elements condition index, CI_e, was derived using Eq. 5-2, and the IF_e and MV_e were specified using their element codes, respectively. Moreover, the CF_e was defined based on previous maintenance records, exposed environmental condition, and level of inspection performed, as this factor was identical to all elements of this case study.

Table 5-6 Distribution of allocated data for various bridge element types

No.	Element code (TfNSW, 2007)	Element description (TfNSW, 2007)	Total quantity, q	Unit	Estimated quantity in each condition index, CI				CI_e	IF_e	MV_e	CF_e			
					1	2	3	4				EA	A	R	I
1	SBGI	Steel Beam/Girder	332	m^2	270	48	14	0	1.23	4	3	1	2	1	2
2	SCBT	Steel Cables	16	ea	10	4	2	0	1.50	3	3	1	2	1	2
3	SPIR	Steel Pier (Pylon)	198	m^2	193	5	0	0	1.03	4	3	1	2	1	2
4	SCOD	Steel Corrugated Deck	285	m^2	243	18	24	0	1.23	3	3	1	2	1	2
5	SCGP	Steel Connection Gusset Plates	26	m^2	18	3.5	4	0.5	1.50	3	3	1	2	1	2
6	CDSL	Concrete Deck Slab	290	m^2	243	18	24	5	1.28	3	2	1	2	1	2
7	CABW	Concrete Abutment	81	m^2	67.7	5	3.8	4.5	1.32	2	2	1	2	1	2
8	RCON	Concrete Railing	92	m	82	0	5	5	1.27	1	1	1	2	1	2
9	RMET	Metal Railing	92	m	45	25	12	10	1.86	1	1	1	2	1	2
10	JASS	Assembly Joint/Seal	12	m	4	0	0	4	1.67	1	1	1	2	1	2
11	BELA	Elastomeric Bearing Pad	12	ea	8	0	4	0	1.67	3	3	1	2	1	2
12	WY	Waterway	5	ea	5	0	0	0	1.00	1	1	1	2	1	2
Weighted Average									1.38	2.83	2.66	1.77			

5.5. Results of BMS plugin implementation

In this section, in order to further investigate the applicability of the proposed BrIM-oriented BMS plugin and DSS integration, the procedures from priority ranking of elements to rehabilitation strategy planning of the Werrington bridge are described.

5.5.1. PRCI-based priority ranking

In the case of the Werrington Bridge, the priority ranking of element types was carried out while calculating the PRCI. Table 5-7 demonstrates the element types in descending order of PRCI. As indicated in Table 5-8, the steel beams, bearing pads, and steel cables have the greatest PRCI among all other types of bridge elements, with 2.60, 2.00, and 1.80, respectively. Hence, those elements require specific attention in terms of budget allocation and remedial actions.

Table 5-7 PRCI-based ranking of Werrington bridge element types

No.	Element Code (TfNSW, 2007)	Element description (TfNSW, 2007)	CI_e	$CI_e/\overline{CI}$	$IF_e/\overline{IF}$	$MV_e/\overline{MV}$	$CF_e/\overline{CF}$	$PRCI_e$
1	SBGI	Steel Beam/Girder	1.23	0.89	1.65	1.77	1	2.60
11	BELA	Elastomeric Bearing Pad	1.67	1.21	1.24	1.33	1	2.00
2	SCBT	Steel Cables	1.50	1.09	1.24	1.33	1	1.80
5	SCGP	Steel Connection Gusset Plates	1.50	1.09	1.24	1.33	1	1.80
3	SPIR	Steel Pier (Pylon)	1.03	0.74	1.65	1.33	1	1.62
4	SCOD	Steel Corrugated Deck	1.23	0.89	1.06	1.33	1	1.25
6	CDSL	Concrete Deck Slab	1.28	0.93	1.24	0.89	1	1.03
7	CABW	Concrete Abutment	1.32	0.96	0.82	0.89	1	0.70
9	RMET	Metal Railing	1.86	1.35	0.41	0.45	1	0.25
10	JASS	Assembly Joint/Seal	1.67	1.21	0.41	0.45	1	0.22
8	RCON	Concrete Railing	1.27	0.92	0.41	0.45	1	0.17
12	WY	Waterway	1.00	0.73	0.41	0.45	1	0.13

5.5.2. Scoring the remedial alternatives and budget-based prioritization

Following the priority ranking of element types, the SMART-AHP was employed to evaluate the major remediation alternatives/strategies for each bridge element types. Considering the goal of Werrington Bridge rehabilitation, alternatives were evaluated using a set of criteria that were defined and weighted to maximize safety and service life while minimizing traffic disruption and costs. Throughout this procedure, as explained in Section 5.3, these constraints/criteria were articulated quantitatively by the experts in this area using Saaty's nine relative importance scales (Saaty, 1990). In this respect, Table 5-8 displays the generated pairwise comparison matrix, which includes the main client criteria identified as well as the relative importance scales of pairs assessed by experts' judgments in relation to the overall bridge rehabilitation objective. In the case of Werrington bridge, this matrix shows the strong importance of safety in the rehabilitation process, over the service life criteria. Moreover, Fig. 5-7 depicts the procedure's hierarchical structure used.

Table 5-8 Pairwise matrix of main criteria in respect to Werrington Bridge remediation

	Service Life	Safety	Cost	Traffic disruption
Service Life	1	1/5	1/3	3
Safety	5	1	3	7
Cost	3	1/3	1	5
Traffic disruption	1/3	1/7	1/5	1

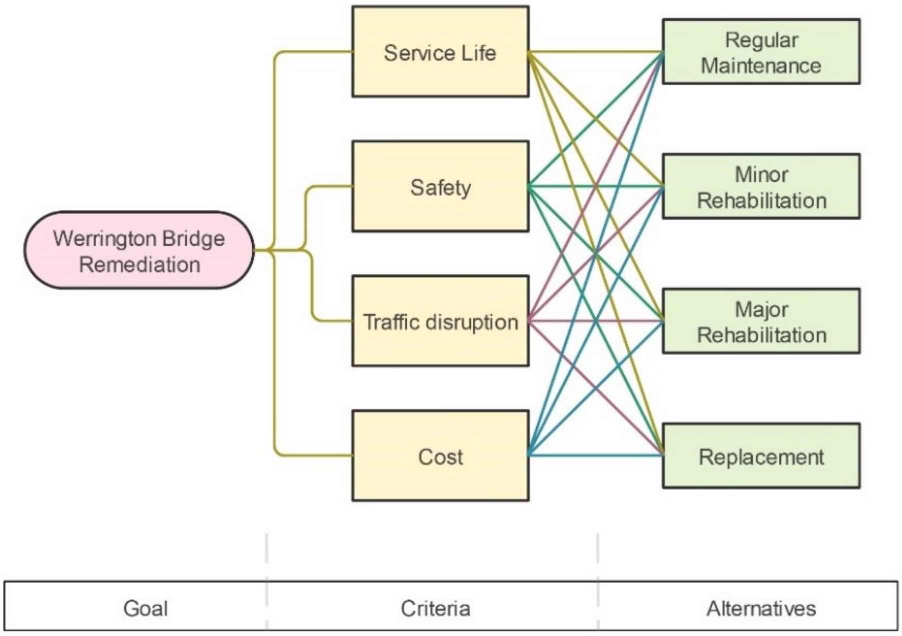


Figure 5-7 Three-level hierarchical framework for remedial planning of Werrington Bridge

Following this procedure, the criterion weights are determined, as shown in Table 5-9, which reveals that safety and cost have the greatest contributions. Moreover, the consistency check resulted in a Consistency Ratio (CR) of 0.0043, which is less than 0.1, indicating that the completed judgement is consistent. With respect to each criterion, the expert judgments were also used to compare the major alternatives for each element type using Saaty's nine relative importance scales (Saaty, 1990). This evaluation needs to be conducted for the element types with the highest PRCI, generally for elements with greater than two scores, which may be varied based on client preferences between projects. For the Werrington bridge, two element types of steel beam/girder, SBGI, and elastomeric bearing pad, BELA, were candidates to be examined. Table 5-9 shows the score of the major remedial alternatives for these two element types. During this procedure, the Overall Alternative Score (OAS) of each activity for specific element types was determined to be utilized for remediation planning priority ranking after the budget allocation. As shown in Table 5-9, OAS for SBGI and BELA replacement were higher than for other activities; nevertheless, for the BELA, similar scores were obtained for minor and major rehabilitation, indicating that BELA major or minor rehabilitation were in same level of effectiveness in terms of Werrington bridge rehabilitation.

Table 5-9 Scoring the major remedial alternatives for element types with highest PRCI

Criteria	Criteria Weights (%)	SBGI, Major remedial alternatives				BELA, Major remedial alternatives			
		Regular Maintenance	Minor Rehab.	Major Rehab.	Repl.	Regular Maintenance	Minor Rehab.	Major Rehab.	Repl.
Service Life	12.19	1	2	5	5	1	1	1	6
Safety	55.79	1	2	3	5	1	2	2	5
Cost	26.33	3	4	5	2	2	4	4	3
Traffic Disruption	5.69	5	5	5	2	5	5	5	2
OAS		175.4	269.7	388.4	403.9	149.1	257.5	257.5	442.5

Following that, budget optimization was accomplished by establishing possible action combinations, calculating the cumulative OAS and actual cost of each combination, and then comparing it to the annual bridge budget. Therefore, the final optimal remedial plan would be a combination of actions with the highest OAS, which can result in more improvement, and a cost within the annual budget range. If the budget was unlimited and sustainability was not a priority, the combination of remedial actions with the highest OAS would be chosen. In this respect, and in the case of the Werrington Bridge, the combination of major SBGI rehabilitation and BELA replacement resulted in a total OAS of 830.9, met the annual bridge budget request. This information can be transferred directly to the project's asset manager for future remedial planning and management.

5.5.3. Visual condition report and remedial plan

During all these procedures, the designed plugin is utilized to assess all the aforementioned information and update the Werrington BrIM by assigning the analysed information to each component of the digital model. The system has the ability to colorize the bridge element types with respect to overall maximum interpreted PRCI, shown in Fig. 5-8, as well as CI values individually, shown in Fig. 5-6(b). Using this plugin, not only can help with identification of the locality and severity of defects through assignment of geometrical and non-geometrical information of the model, but also can generate a reliable report containing several combinations of remedial actions that can be chosen while keeping the allocated budget optimized.

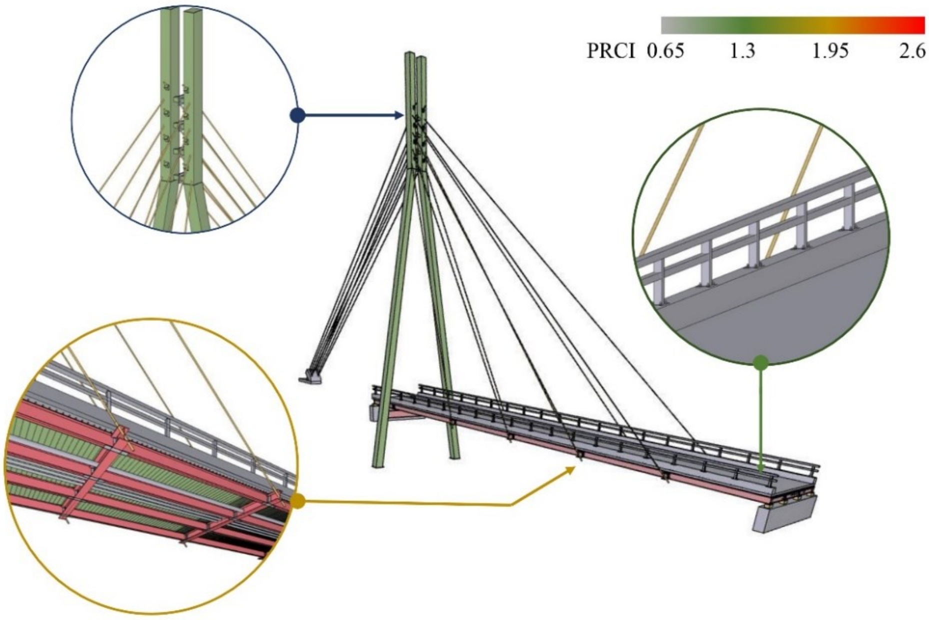


Figure 5-8 Visual condition reports of Werrington Bridge; (a) PRCI of element types, (b) CI of induvial bridge elements

5.6. Discussion and future directions

This chapter of the research study established a comprehensive methodology and a pathway for addressing two concerns of having a reliable digital replica of the bridge with geometrical and non-geometrical information and employing these data in a reliable and objective management system for remedial planning. In these regards, this study introduced the valuable use of state-of-the-art TLS technology in capturing precise geometrical information of the bridges that can be utilised for 3D CAD model extraction, and digital inspections. Unlike paper-based information, these can be stored in a digital format as a reference for future investigations and are particularly valuable in the development of innovative solutions in detecting damages and identifying risks using clash detection algorithms, which can assist bridge engineers or managers in gaining a better understanding of how the bridge interacts.

The study also made an effort to systematize the bridge management in a practical way, further providing a management system that can be linked to the proposed BrIM and offers asset managers with the ability to use the assigned data to more effectively and objectively evaluate the bridge's health condition. In this system, three additional factors were taken into consideration to form a Priority Ranking Condition Index (PRCI), which was used to select those bridge element types that may require more attention in terms of their structural importance, material vulnerability, or other causal factors such as their age or interaction environment.

Besides, in this chapter a Decision Support System (DSS) was developed to accompany the management system conducting the risk assessment and verifying that the bridge rehabilitation is properly managed. In this regard, a SMART-AHP analysis tool was introduced that integrates asset management system with dynamic risk analysis and strategy mapping for bridge elements, in order to provide a more accurate and objective measure of bridge maintenance plan.

In a subsequent step, the proposed methodology of this research study was then implemented into a software plugin to make this procedure more applicable in terms of Information and Communications Technology (ICT) and digitalization. Eventually, this methodology was further evaluated and validated in a real bridge case study on a cable-stayed bridge named Werrington Bridge in New South Wales, Australia. In this case study, the process from bridge survey through TLS application was covered, and then the general procedure of BrIM development, as well as setting up an asset management plan using DSS was described.

Considering the proposed methodology and findings of this research study, future research could potentially target the incorporation of sustainability into the strategic remedial planning, as well as integration of different methods of real-time data extraction and analysis leveraging Artificial Intelligence (AI) (Truong-Hong and Lindenbergh, 2022, Yu et al., 2022, Yu et al., 2021, Liu et al., 2021, Zhen et al., 2022) to form dynamic bridge digital twins, as well as digital platforms to enable network level asset management (Aflatooni et al., 2014), and boost capabilities for smart cities and intelligent urban transformation. Implementation of Internet of Things (IoT) in bridge asset management system (Scianna et al., 2022, Wu et al., 2022), through using remote sensors as a supplement is a suggested solution that not only improves real-time data collection, but also allows for centralizing and correlating data for efficient sharing with network partners and other stakeholders.

5.7. Summary and conclusion

This chapter proposes a novel BrIM-oriented BMS framework integrated with a DSS which not only incorporates the significance of TLS application for accurate and rapid bridge inspection, 3D model extraction, as well as supporting the BrIM development in digital transformation of bridge information, but also provides a comprehensive methodology for using BrIM information in a redeveloped element based condition assessment system while implementing a DSS analysis to address subjectivity in decision making and maintenance planning. This methodology was them employed to develop a software plugin, which was evaluated on a real bridge case study in Australia. The main findings are as follows:

(1) TLS application demonstrates its potential as a ground-based remote system capable of acquiring precise and sufficient data in a timely manner for geometrical bridge inspections. TLS data allows precise surface interpretation which improves the surface condition assessment, as well as 3D CAD model extraction.

(2) Through the proposed BMS framework, the bridge management system has been greatly improved not only by the BrIM-oriented geometrical and non-geometrical information, but also by the proposed priority ranking and decision support systems. This system surpasses traditional inventory management concepts by providing a visual condition report and proposing budget-based remedial strategy.

(3) The BMS plugin described in this study provides a new generation of digital documentation system with the flexibility, visuality, and capability to support bridge information for each element that can be readily transferred/shared and be utilized for long-term bridge condition assessments.

(4) The redeveloped condition index concept and proposed PRCI of this research study generated acceptable results in the priority ranking of the Werrington bridge elements. Using PRCI, element types with higher structural importance and material vulnerability received increasing attention with higher PRCI scores.

(5) The integration of DSS and BrIM datasets allows higher level of objectivity in decision making and asset management. This potential has been validated throughout the case study of Werrington bridge with aim of cost effective, safe and functional remedial planning.

Chapter 6

(Conclusions and future directions)

6.1. Introduction

The development of Bridge Information Model (BrIM) for bridge management Using Terrestrial Laser Scanning (TLS) technology, which is the main focus of this research study, is dependent on a wide range of variables and factors, which attempted to be covered in the chapters presented. In this thesis, the approach of utilising TLS to create a thorough and reliable BrIM is theoretically and practically investigated. Several methodologies for exploiting this database to integrate decision support systems were described, and the validity of the proposed methodologies demonstrated using a real case study. The proposed designed prototype system has a significant potential to be transformed into a thorough computer software that can be utilised by different users and transportation agencies such as Transport for NSW Australia for having a reliable bridge management system. This chapter summarised the research findings and expected future directions.

6.2. Conclusions with respect to literature study

The literature review of this research study investigated the application of laser scanning as an emerging technology in modern bridge surveying, based on a combined scientometric and state-of-the-art review, to evaluate the existing documentation data set and provide a deeper understanding in this field. The following are summary conclusions:

1- Research studies on using TLS as an emerging quantitative tool, providing precise information, dates back to almost ten years ago for bridge engineering. During the last decade, the historical trends show that the number of publications kept rising from an average of 15 papers/year in 2010 and 2011 to 44 papers/year in 2018 and 2019, confirming the growing interest in adopting TLS in the field of bridge engineering.

2- Publications on the subject of this thesis can be found in over 100 different journals and conference proceedings. Although journal publications are evenly distributed, the *Automation in Construction* and *Remote Sensing* journals appear to have published the most research articles in this area, as seen in Table 2-1. This table can also assist new researchers working on bridge point clouds to decide where to publish and discuss their findings. Furthermore, Fig. 2-2 shows a low rate of publication on application of TLS in bridge engineering and asset management.

3- Keyword mapping results revealed the frequency of keyword presence, suggesting concerns and limits in this field of study. In this regard, 3D model generation and quality inspection are the most researched study subjects, accounting for 48% and 27% of total keyword occurrences, respectively, while structural evaluation and construction management are unique and timely themes that deserve to be examined.

4- According to the findings of a scienetometric study of the most productive researchers in this subject, the United States of America is the top country in terms of being the primary contributor in research endeavours. The United States retains substantial research linkages with the United Kingdom and Spain in particular, although there are indications of weaker research links with countries such as Australia and Germany.

5- According to the state-of-the-art study, several methodologies for implementing TLS-point cloud in various aspects of 3D model extraction, quality inspection, structural assessment, and bridge information modelling (BrIM) were thoroughly reviewed, and several research gaps were identified that are discussed in the future direction section (Section 6.5).

6.3. Conclusions with respect to preliminary analysis and TLS quality evaluation

With respect to bridge inspection and monitoring, chapter three of this thesis introduced a comprehensive methodology for having a reliable quality analysis of digital point clouds subjected to the implantation of a detailed 3D reconstruction model. In this regard, a range of general and specific data evaluation approaches was proposed and used for evaluating and comparing two available bridge point clouds captured/scanned via UAV photogrammetry and Terrestrial Laser Scanning (TLS) from a heritage bridge named McKanes Falls Bridge located in NSW, Australia. Here are the summary conclusions:

1- The proposed methodology of this research study, which includes two series of general and specific approaches, provides acceptable comparable results that can be utilized to evaluate and compare the consistency, quality, and precision of two or more bridge size point clouds. The comparative result of the presented McKanes Falls Bridge case study exhibited the capability and applicability of the proposed methodology and evaluation approaches which lead to a reliable and acceptable/fair data quality evaluation and comparison.

2- The quality evaluation of the presented case study using the proposed methodology and approaches showed a higher level of point density, more acceptable agreement with as-is measurements, normal levels of outlier and general noise using TLS when compared to UAV photogrammetry. Moreover, considering similar surveying objects and evaluations, the results exhibited some greater scaling errors with lower geometric accuracy for UAV based point cloud.

3- In overall, the quality evaluation demonstrated that TLS can offer significant advantages in level of geometric accuracy while having a high level of point density which are important considerations in terms of precise 3D model reconstruction for detailed quality inspections of the bridges.

4- Concerns remain including the implementation time, high equipment cost and limited/restricted access of TLS, which all can be compensated using UAV-based photogrammetry techniques.

6.4. Conclusions with respect to BrIM development using TLS point cloud

In terms of BrIM development using TLS point cloud, chapter four of the thesis established a practical methodology for developing a TLS-derived BrIM that contains a 3D CAD model as geometrical information and the ability to connect non-geometrical information of each component of the bridge structure with the objective of bridge asset management. The main conclusions are listed below:

1- Given the time and effort required to collect manual measurements and update the geometrical and non-geometrical information of the bridge, resulted in an efficient and precise approach for data collection and 3D CAD model generation, as demonstrated in Werrington Bridge case study in which the 3D point cloud was captured via TLS.

2- The proposed slicing approach of this thesis demonstrated its reliable potential in the deviation analysis, with the majority of deviations being less than 5 mm between the resulting 3D CAD model, traditional mesh-based model, and captured point cloud. Moreover, comparing with the proposed slicing approach, the process of transforming TLS data into mesh model is significantly time consuming. This time can also vary according to the level of detail required, available computer hardware, available processing/modelling software and their inter-compatibility, as well as the operator involved.

3- The proposed TLS-derived BrIM methodology in this research study can not only be beneficial for asset managers and bridge engineers in potential time saving through overcoming the necessity to frequently revisit a bridge in person, but also can ease the document management through substitution of digital twins over hard formats paper-based documentations.

4- Using the designed plugin presented to link additional non-geometrical information such as bridge reports or any other bridge inspection data to digital replication of a bridge will result in a better understanding and smoother communication of such data being exchanged between the relevant personnel in a digital twin.

5- In the case of Werrington Bridge, presented in Chapter four of the thesis, the use of TLS in capturing the bridge point cloud and a sliced-based approach for creating the 3D geometrical model and linking additional information in the designed plugin demonstrated the soundness and acceptable usage of this methodology for future assessment management planning.

6.5. Conclusions with respect to BrIM-oriented BMS and DSS integration

In terms of Bridge Management System (BMS), the fifth chapter of this research present a comprehensive methodology for using BrIM data in a redeveloped element-based condition assessment model, while integrating a Decision Support System (DSS) to tackle the subjective nature of decision-making by conducting a risk assessment for priority ranking and evaluating the remedial actions. This methodology was further implemented in a designed software plugin and validated by a real case study on the Werrington Bridge, a cable-stayed bridge in New South Wales, Australia. The main findings of this chapter are as follows:

1- The BrIM-oriented BMS and designed plugin provide a new generation of digital documentation system with the flexibility, visibility, and capability to support bridge information for each bridge element that can be readily transferred/shared and be utilized for long-term and accumulative bridge condition assessments. This system surpasses traditional inventory management concepts by providing a visual condition report and proposing budget-based remedial strategy using an integrated DSS.

2- The redeveloped condition index concept and proposed PRCI presented in this chapter produced acceptable results that not only follow the general qualitative conditions indices (CI), but also reduce the subjective nature of this process by using a set of weighting factors for priority ranking of bridge elements.

3- The combined AHP-SMART multi-criteria Decision Support System (DSS) was presented in this study based on a reasonable balance between the simplicity of SMART and the complexity of AHP analysis systems that included the BrIM. This method provides a better level of objectivity in decision making on the available remedial alternatives in terms of bridge rehabilitation for evaluating the bridge elements with higher priority rankings.

4- This study's findings, including the Werrington Bridge case study and BMS plugin implementation, confirm the reliability of the proposed BMS and integrated DSS for prioritizing structural elements that require more attention based on structural importance and material vulnerability, as well as optimizing remedial actions in a practical way while keeping the bridge safe and reliable.

6.6. Future Directions

In the last decade, the terms of digital twin and smart manufacturing have been introduced to define the promising trends of automation process and digitization in the construction industry, especially bridge engineering. During this period, introducing new technologies, such as TLS discussed in this thesis, offers the chance to improve upon the traditional paper-based methods of bridge inspection, assessment, and management, using the generated BrIM from the acquired geometrical and non-geometrical data. From where we are today, the following are some prospective research gaps that have a high potential to be addressed as future directions of this research:

1- According to the presented study, the future research can be focused on developing a comprehensive framework for determining the appropriate level of detail (LOD) in point cloud data acquisition for bridge inspections. This framework can incorporate guidelines for evaluating the quality and accuracy of the collected data to ensure that the LOD level is accurately defined and aligned with the intended purpose of the data. Additionally, future research can investigate the effectiveness of different data acquisition and post-processing procedures in generating high-quality point cloud data at different LOD levels. By doing so, it would be possible to establish a standardized approach to point cloud data acquisition and processing for bridge inspections, resulting in more reliable and consistent data that can be utilized in a wide range of applications.

2- Currently, data acquisition using TLS, as the most crucial phase of generating a 3D solid model, is heavily performed in a manual way based on surveyors' experiences. Collecting sufficient data with complete coverage for a large and complex structure, such as bridge, is an important consideration and where research is still lacking to identify the required optimum scan locations and parameters.

3- Locating, classifying, and quantifying the structural damages and anomalies using Artificial Intelligence (AI) and point cloud data can be further investigated with the aim of bridge quality inspection. In this respect, topological data analysis can be used to analyse the deformations and discontinuities in the structures utilizing point cloud data.

4- Future research is needed on investigating and developing novel algorithms to process TLS data effectively and efficiently in order to generate digital twin models with a higher Level of Detail (LoD) that accurately reflect the structural behaviour of the real-world structure. Combining machine learning and AI techniques could also provide valuable insights for more accurate and efficient data processing in model updating and reverse engineering approaches. Furthermore, structural behaviour can be defined as a layer for BrIM, providing another avenue for future research in this field.

5- Future study is recommended for the development of a BMS that leverages the Internet of Things (IoT) and Artificial Intelligence (AI) technologies to connect all bridge equipment via remote sensors. Such a system would enable real-time data collection and analysis, allowing asset managers to make informed decisions and recommendations based on current bridge conditions. By incorporating AI algorithms into the BMS, the system could be programmed to identify potential issues or vulnerabilities in real-time, automatically alerting asset managers and suggesting strategic plans to address them.

6- The development of a project level and network level bridge management system (BMS) is recommended for future study to manage the operations of multiple bridges within a transportation system. Such a BMS could provide a comprehensive view of the transportation system and its bridge infrastructure, enabling asset managers to make informed decisions regarding maintenance, repairs, and replacements. At the project level, a BMS could monitor individual bridge structures and provide detailed information on their condition and performance. This could include real-time data on traffic volume, load capacity, and structural health, as well as information on maintenance history and future maintenance needs. By aggregating this data across multiple bridges, a network level BMS could provide a broader perspective on the transportation system as a whole, allowing asset managers to identify trends and prioritize resources accordingly.

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