LICENTIATE THESIS

Digital Twins for Asset Management of Structures

Vanessa Saback

Structural Engineering

Luleå University of Technology

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LULEÅ UNIVERSITY OF TECHNOLOGY

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Preface

The ongoing PhD program is part of the strategic innovation program InfraSweden2030, a joint venture by Vinnova, Formas and The Swedish Energy Agency. The work is also funded by SBUF (construction industry's organization for research and development in Sweden) and Skanska Sweden in cooperation with Luleå University of Technology (LTU). I would like to gratefully acknowledge these institutions for financing this project, thus allowing this research to be possible.

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Vanessa Saback

Luleå, October 2022

Summary

This thesis deals with asset management of structures through Building Information Modelling (BIM) and Digital Twins.

Background: Current inspection and management processes for civil structures are time-consuming and can even be inaccurate. There is an increasingly high potential to improve these processes through recent advances in technology. Digital Twins offer a common platform to these technologies, so they can interact and be used to their optimal performance. Other industries have significantly advanced in the development of Digital Twins, however, in the construction industry there are still many gaps and room for improvement.

Aim and objectives: The main aim of this project was to investigate the status of Digital Twins in the construction industry and propose a methodology for a Digital Twin for asset management of structures. The three immediate objectives sought are (i) Perform a literature review to establish the current practice with digital twins, in both construction and other industries, and what are the gaps for asset management of structures; (ii) Participate in a pilot experimental program that yields data to a potential digital twin prototype; and (iii) Define a methodology for a digital twin for asset management of structures which fills the identified gaps.

Methods of investigation: A literature review was performed and served as basis for the development of a methodology for a digital twin. A pilot experimental program was defined and performed, and its results were used for BIM and Finite Element (FE) models. A webapp was also created using Autodesk Forge and Java programming language, and the BIM model was uploaded into it.

Results: The literature review provided insight into the maturity level of digital twins, as well as on bridge inspection, maintenance and monitoring, BIM, facility and asset management, and Bridge Management Systems (BMS). A methodology to achieve a digital twin for asset management was proposed, and the conducted experimental program yielded data results to be used in future research.

Conclusion: There has been significant progress in technology to improve structural assessment and analysis, however, their full potential is still under-explored. A digital twin created in a common data environment can provide a platform for these technologies to improve efficiency of current practices. Nonetheless, the construction industry is still significantly behind other industries such as aerospace and automotive.

Keywords: Digital Twins, BIM, Asset Management, Common Data Environment, Finite Element Modelling, Fiber Optic Sensors.

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List of Abbreviations

Abbreviation	Description
API	Application Programming Interface
BI	Business Intelligence
BIM	Building Information Modelling
BMS	Bridge Management System
BrIM	Bridge Information Modelling
CDE	Common Data Environment
DIC	Digital Image Correlation
DT	Digital Twins
FE	Finite Element
FOS	Fiber Optic Sensors
IFC	Industry Foundation Class
IoT	Internet of Things
LCCA	Life Cycle Cost Analysis
ML	Machine Learning
NDT	Non-destructive testing
RC	Reinforced Concrete
SG	Strain Gauges
SHM	Structural Health Monitoring
TRL	Technology Readiness Level
UAV	Unmanned Aerial Vehicles
UI	User Interface

1. Introduction

1.1 Background

Planning for maintenance and performing repairs on damaged structures rather than replacing them entirely is usually a better alternative both financially and environmentally. For new structures, including structural health monitoring (SHM) sensors during construction provides information about structural behavior, which facilitates future maintenance and can be a valuable investment in the long term. SHM sensors can measure traffic, deformation, vibration, displacement, wind, temperature, etc. Therefore, for both existing and new structures, there are tangible benefits in implementing technological improvements and automation to asset management strategies.

For civil structures such as bridges, tunnels, dams, etc., asset management is here defined by four main processes: inspection (damage detection), assessment of current condition from inspection data, prediction of future degradation and maintenance planning. Therefore, asset management focuses on maintenance and rehabilitation with the goal of extending the service life of assets and improving its quality. There have been significant advances in technology that can improve the efficiency of each one of these fours processes separately. If they are combined in a Common Data Environment (CDE), an integrated solution for life cycle management in the form of a Digital Twin (DT) can be achieved.

To determine the current health situation of a structure and plan for maintenance accordingly, the first step is to perform an inspection. For bridge structures, routine inspections are arranged periodically by administrating agencies. In current inspections, damage detection is mostly based on visual examination, and inspection procedures and annotations are performed manually. Therefore, these inspections are often time consuming, human dependent and sometimes even inaccurate [1]. The impracticality of visual inspection for large and complex civil infrastructures has promoted the incorporation of condition-based assessment techniques, SHM has thus emerged to provide the transition from offline damage identification to near real-time and online damage assessment [2]. Among the different non-destructive testing technologies that can improve manual inspections, the most common identified in the literature were: photogrammetry, laser scanning, ground-penetrating radar, ultrasound, infra-red scanning, fiber optic sensors (FOS), unmanned aerial vehicles (UAV), light detection and ranging scanning, total station.

The data acquired by these damage detection and monitoring systems are usually used for condition assessment and decision-making regarding maintenance. Often the data are presented only in spreadsheets and graphs; however, if presented directly on Building Information Modelling (BIM) models, they gain geometrical and spatial context, facilitating their interpretation [3].

Current practices apply probabilistic methods to predict future deterioration from a current condition diagnostic, obtained from the inspection data [4]. However, this analysis can be improved by automated assessment tools that employ artificial intelligence algorithms [5], combining BIM and Finite Element (FE) models [6], [7], and geographic information systems [8].

Concerning maintenance planning and bridge management practices, the main suggested improvement to current system is the inclusion of an interactive geometric representation of the asset through a BIM model. So far, no existing bridge management system (BMS) includes this kind of geometric representations of bridges [4], [9]. The link between BIM and BMS can be achieved through different methods, most commonly through Industry Foundation Class (IFC) and/or programming languages (SQL, C#, Java, Python, MATLAB etc.). IFC is an open, neutral standard usable across a wide range of hardware devices, software platforms, and interfaces for many different use cases [10]. Allowing remote access to data from the system through cloud-based, mobile and/or portable technology would also facilitate information access. Furthermore, in a CDE, FE models for prediction of future degradation can be incorporated to enhance this analysis.

The biggest challenge in obtaining a functional digital twin that serves as an integrated platform for asset management of structures is the development of a CDE for the different data sources. Therefore, the full potential of BIM models post-construction and digital twins is still under explored. In other industries, significant applications of DT can be found, such as in aerospace, automotive, manufacturing, smart city, and healthcare applications [2]. The maturity of development of DT in such industries is much more advanced than in the construction industry, in which the concept of what constitutes a digital twin is not overall clear, and there is still no consensus as to its formal definition. This leads to frequent misconceptions and mislabeling of BIM models and calibrated FE models without any significant automation or data flow as digital twins. In this context, this study investigates digital twins and how to obtain a CDE for a DT for asset management of civil structures.

1.2 Hypothesis, aim, objectives and research questions

Hypothesis:

> Digital Twins provide a more efficient and effective alternative to current practices in asset management of structures.

Aim:

Investigate the status of Digital Twins in the construction industry and propose a methodology for a Digital Twin for asset management of structures.

Objectives:

(i) Perform a literature review to establish the current practice with digital twins, in both construction and other industries, and what are the gaps for asset management of structures.

(ii) Participate in a pilot experimental program that yields data to a potential digital twin prototype.

(iii) Define a methodology for a digital twin for asset management of structures which fills the identified gaps.

Research questions:

(i) What are the current challenges in asset management of structures identified in the literature?

(ii) What is the current maturity level of Digital Twins in the construction industry?

1.3 Scientific approach

Different aspects are involved in the development of a digital twin for asset management of civil structures. It should consider the needs of asset management, the problems with current approaches, how they can be improved, the existing technology for each task and how they can work together to compose the DT. Therefore, the first step of this research process was a systematic literature review, presented here in the first appended paper.

The conclusions from the literature review were the basis for the proposed digital twin methodology, most importantly related to:

- BIM: the potential uses of BIM post-construction are still under-explored. BIM provides 3D geometry visualization in a semantically rich model that can contain information on materials, construction, design, schedules, etc. Geometric representations of the bridges under management (e.g., BIM) should be integrated into existing BMS. Autodesk Revit [11] was the BIM software endorsed by most authors.
- Structural Health Monitoring (SHM): essential to provide current condition information about the structure, usually through visual inspections, data from sensors and Non-Destructive Testing (NDT). The data can reveal unknown information for reverse engineering of existing structures, or can follow the structure from its initial conception, in the case of new structures. There have been major advances in SHM and NDT technologies for bridge inspection,

automated damage detection, monitoring, and maintenance. SHM data should be introduced and linked to the BMS, preferably directly to a BIM model.

- Future behavior: an indispensable aspect of a digital twin for asset management is the ability to simulate scenarios for future behavior of the structure from current degradation to assist decision making in maintenance planning. Life cycle analysis should be incorporated into the systems, including integration of construction information for comparison with current condition from inspection data, and prediction of deterioration to enable better planning of interventions. This can be achieved through degradation models, machine learning algorithms and Finite Element modelling.
- Data flow: the development of functional digital twins requires a very complex automated data flow, a challenge which has hindered the exploitation of their full potential. The use of IFC as a neutral language for communication between different platforms is a potential solution for this issue.

In the second appended paper, the main technologies identified in the literature to perform inspection, BIM, damage identification, data transmission and facility management of bridges are presented in a framework. From the framework proposed in Paper II and further research investigation, in this study a methodology for a DT is proposed, divided into three components: BIM model, SHM data, and prediction of Future Behavior. Figure 1 shows these three components in a Venn diagram, illustrating how they are combined to compose the proposed digital twin.

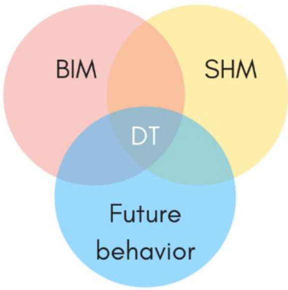

Figure 1: Three components to the Digital Twin for asset management of structures.

Besides the function each component has in the DT, a working data flow between each connection is essential. Each one-on-one connection between the different components in the DT serves to a different purpose. Figure 2 presents the three different connections between the components and their role in the data flow of the digital twin.

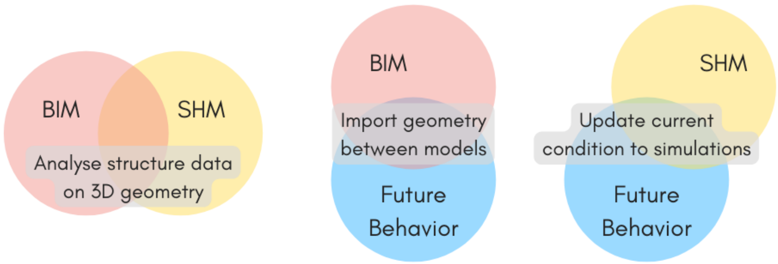

Figure 2: Connection between different components of the DT.

After the literature review and the definition of the methodology for the DT, including the components, connections, and their respective functions, the first step towards the development of the DT is to create a CDE connecting BIM and SHM data. As a pilot study for the DT, a reinforced concrete beam specimen was analyzed.

To obtain SHM data, a pilot experimental program named FOS-Beam was designed. The program consisted of two reinforced concrete beam specimens tested in three-point bending and instrumented with FOS, Strain Gauges (SG) and a Digital Image Correlation (DIC) system. This experiment is described in detail in the third appended paper and in section 3. Experimental program.

The BIM model was created using Revit [11], and Autodesk Forge [12] and IFC [10] were defined for the CDE. The development of the CDE for the FOS-Beam is described in section 4.3 Common Data Environment, along with details on each technology. It is worth mentioning that, in the research process, other programs and alternatives were investigated and tested before the methodology was defined as it is. Figure 3 illustrates the CDE for BIM and SHM data, the technologies employed for each component and their connection.

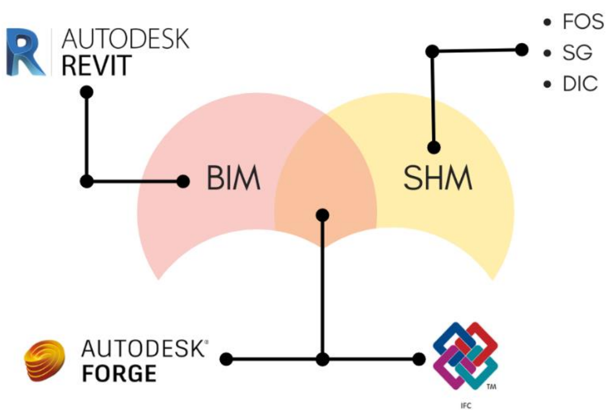

Figure 3: First approach: connection between BIM model and SHM data.

For future research, the next step will be the connection of the SHM data, obtained from the FOS-Beam experimental program, in the designed CDE though the Data Visualization Extension, as explained in section 4.3.2 Data Visualization Extension. Then, the methodology will be applied in a case study, a more complex experimental program here named *Trough Bridges*. For this program, two trough bridges have been cast in laboratory, instrumented with SG and FOS, and will be subjected to a series of tests in 2023 (more details in section 7. Future research). The last component of the proposed DT, i.e., Future Behavior, will be included in the CDE, which will be adapted accordingly to asset management needs and requirements. Figure 4 presents a flowchart with the activities concluded and planned to achieve the proposed digital twin for asset management.

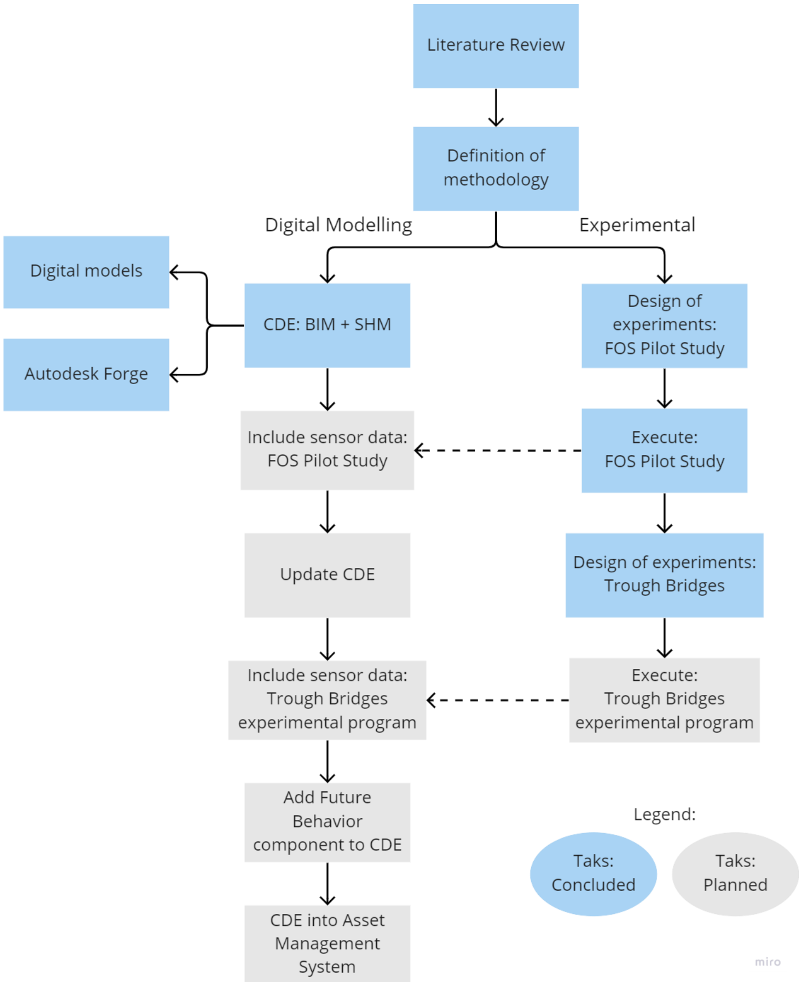

Figure 4: Flowchart of scientific approach to develop the proposed digital twin.

1.4 Outline of the thesis

This licentiate thesis is composed by a compilation of articles appended to an extended summary of their content. The summary consists of **Chapters 1-6**, briefly described in this session as follows:

Chapter 1 – Introduction: presents the background, objectives and research questions, describes the scientific approach to achieve them and introduces the appended papers.

Chapter 2 – Literature review: definition and brief history of digital twins, different approaches and projects towards CDE and DT.

Chapter 3 – Experimental program: describes the experimental program and test setup.

Chapter 4 – Digital Twin approach: presents the digital models and common data environment for the pilot digital twin.

Chapter 5 – Discussion: discusses the results and future research in terms of technology readiness levels (TRL).

Chapter 6 – Conclusions: concluding remarks, answers to the research questions and proposed hypothesis.

Chapter 7 – Future research: future tasks and plans to achieve them, presentation of the Trough Bridge experimental program.

1.5 Appended papers

The core of this thesis consists of four papers: one published journal paper, one journal paper manuscript under review and two conference papers. The appended papers are briefly presented in this session, including my contribution to each of them.

PAPER I

Saback, V., Popescu, C., Blanksvärd, T., & Täljsten, B. (2022). Asset Management of Existing Concrete Bridges Using Digital Twins and BIM: a State-of-the-Art Literature Review. *Nordic Concrete Research*, 66, 6, pp. 93-113. DOI: 10.2478/ncr-2021-0020.

The first paper is a systematic review of the literature, in which a thorough methodology was adopted to review topics related to digital twins for asset management of bridges. The main topics covered by the review were bridge inspection, Bridge Information Modelling (BrIM), digital twins and bridge management systems. This review constitutes the first step in the scientific approach towards the development of digital twins from asset management. From its results, the methodology for the proposed digital twin was established. My contribution to this paper included defining the methodology, performing the review, and writing the manuscript.

PAPER II

Saback de Freitas Bello, V., Popescu, C., Blanksvärd, T., Täljsten, B. (2022). Framework for Bridge Management Systems (BMS) Using Digital Twins. *Lecture Notes in Civil Engineering, 1st Conference of the European Association on Quality Control of Bridges and Structures, EUROSTRUCT 2021*. Padua, Italy, pp. 687-694. DOI: 10.1007/978-3-030-91877-4_78.

The main result of this paper is the proposed framework for facility management of bridges using digital twins. The framework is divided into five tasks that compose the digital twin: inspection, BIM model, damage identification, data transmission and facility management. The main technologies identified in the literature to perform these tasks are presented as options to conduct each one of the technologies. My contribution to this paper was performing the research, developing the framework, and writing the manuscript.

PAPER III

Saback, V., Mirzazade, A., Popescu, C., Blanksvärd, T., & Täljsten, B. (2022). Correlation between surface deformation and reinforcement strain for RC structures: a comparative study between Finite Element and Machine Learning models. [*under review*].

This paper presents an analysis of correlation between surface deformation, measured by a DIC system, and reinforcement strain, measured by FOS. The correlation was evaluated through different machine learning (ML) algorithms and a FE model, and the accuracy of both methods was compared. The data for the analysis was provided by the FOS-Beam experimental program, which is presented in detail in the paper. I contributed to this paper in the design and execution of the experimental program, analysis of results, FE simulations, research and writing the manuscript.

PAPER IV

de Freitas Bello, V. S., Popescu, C., Blanksvärd, T., Täljsten, B. (2021). Bridge management systems: Overview and framework for smart management. *IABSE Congress, Ghent 2021: Structural Engineering for Future Societal Needs*. Ghent, Belgium, pp. 1014- 1022.

This paper presents a review on current BMS. The review covered different BMS in the world, modules of a BMS, and current practices on bridge management. The results were analyzed in terms of identified gaps and potential improvements, and a set of management activities that compose the scope of a BMS was proposed. My contribution to this paper was designing and performing the review, analyzing the results, and writing the manuscript.

1.6 Additional publications

Two additional conference papers have been published by the author but are not appended to this thesis; they are listed in this section and briefly described below.

IABSE Congress, Ghent 2021

de Freitas Bello, V. S., Popescu, C., Blanksvärd, T., Täljsten, B. (2021). Framework for facility management of bridge structures using digital twins. *IABSE Congress, Ghent 2021: Structural Engineering for Future Societal Needs*. Ghent, Belgium, pp. 629-637.

This paper presents a review on digital twins, focused on digital twins for bridge structures. The paper addresses the concept of digital twins, studies that have proposed digital twins for bridges, DT in other industries, and other literature reviews on DT. My contribution to this paper was designing and performing the review, analyzing the results, and writing the manuscript.

IABSE Symposium, Prague 2022

Saback, V., Mirzazade, A., Gonzalez-Libreros, J., Blanksvärd, T., Popescu, C., Täljsten, B., Daescu, C., Petersson, M. (2022). Crack monitoring by fibre optics and image correlation: a pilot study. *IABSE Symposium Prague, 2022: Challenges for Existing and Oncoming Structures – Report*. Prague, Czech Republic, pp. 437-444.

This paper presents partial results from the FOS-beam experimental program. The results from strain measurements from the FOS in the rebars are compared with those from the DIC system. Strain measurements from FOS positioned inside a groove in the rebar are compared with measurements in the concrete adjacent to the rebar. Strain measurements from the FOS in the rebars are also compared with those from the DIC system. Lastly, crack propagation from DIC images is also analyzed. To this paper, I contributed to the design and execution of the experimental program, analysis of results and writing.

2. Literature review

The development of a digital twin for asset management of structures is a comprehensive process, which involves different aspects. To understand this process as well as the progress made thus far in the construction industry and others, the first step in this research project was performing a systematic literature review. The review covered bridge inspection, maintenance and monitoring, BIM, facility and asset management, Bridge Management Systems (BMS), and digital twins. Issues related to BIM and technologies for bridge inspection have been widely discussed in the literature, so the review of those topics focused on synthesizing the most recent research and summarizing information on best practice. Research on digital twins, on the other hand, is rapidly growing but still in its earlier stages, especially in the construction industry. For civil structures, there is still only very few digital twin models [2]. Therefore, the review focused on establishing ground knowledge on the theme and identifying gaps deserving further exploration. The results from the literature review are presented in the first appended paper. In this section, a brief review is presented on the origin of digital twins, definition of the term, common data environments and different efforts identified to achieve digital twins through that.

2.1 Digital Twins: origin and definition

The origin of the concept now known as the Digital Twin came from a presentation on product life-cycle management given by Michael Grieves in 2002 [13]. Although not yet named "digital twin", the main aspects to its concept were introduced: a real space, a virtual space, and a mechanism for mirroring (or twinning) changes in the real and virtual spaces [13]. The name "Digital Twin" was introduced later, by the National Aeronautics and Space Administration of the U.S.A. (NASA) in its Technology Roadmaps, as digital twins were used to replicate the life of air vehicles [14].

The main aspect that differentiates a digital twin from a digital model is the data flow that links digital and real entities throughout the physical system's life cycle. A more recent definition given by Kritzinger et al. [15] separates digital models, digital shadows, and digital twins, as illustrated in Figure 5. According to Kritzinger et al. [15], a digital representation of an object that lacks any form of automated data exchange with the physical object is a digital model. If there is an automated one-way data pathway transferring information from the physical object to the digital representation, that is a digital shadow [15]. If the automated data pathway is bidirectional, allowing exchange of data between the two objects, that consists of a digital twin [15]. Therefore, if there is no form of automated data exchange between physical and digital, a digital model should not be called a digital twin. Although the research on digital twins is rapidly growing, there is still a significant amount of misconception and wrongful categorization of digital models as digital twins.

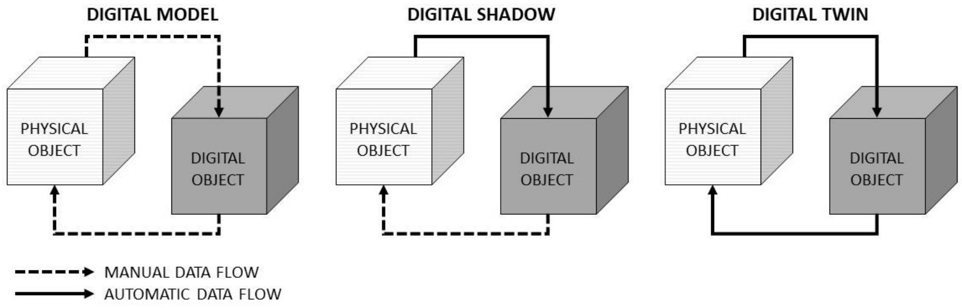

Figure 5 - Data flow in a Digital Model (left), a Digital Shadow (center), and a Digital Twin (right). Adapted from Kritzinger et al. [15].

2.2 Common Data Environment: BIM and SHM

Besides obtaining a CDE that supports the required data flow for a DT, other practical challenges also contribute to hindering their application. There is still a lack of tangible understanding of the potential benefits (e.g., business models) of DT, a high level of expertise and computing demand required, and security concerns with data privacy [16]. Pregnolato et al. [16] argue that further advances in modelling and simulation are needed to establish DT in architecture, engineering and construction practice.

Within the construction industry, the research on digital twins for buildings is currently ahead of other civil structures. Transmission of sensor data related to user comfort, such as temperature and humidity, from physical to digital and vice versa, benefits from commercial technology advances for smart home improvements. For civil structures, structural assessment and management require different kinds of sensor data, which can also face additional challenges, such as remote locations deprived of signal and exposure to the elements. The data flow from digital back to physical is also distinct, as remotely controlling an aspect related to a bridge is not as straightforward as controlling a thermostat, for example. This data flow can be achieved through actuators [17] or through the maintenance strategies that are employed due to analysis of the sensor data.

As established with the definition of Digital Twins in the previous section, the data flow from digital and physical entities is required to obtain a proper digital twin model. The achievement of this data flow is currently the biggest challenge in this process, as it requires interaction in a CDE of data from different platforms that often do not communicate directly. In a DT for asset management, a user interface connecting the data is also often required so the information can be accessed and retrieved for decision making and management.

In this study, the first step towards obtaining a DT for asset management of structures is the connection of sensor data and BIM model in a CDE. Some strategies towards this goal were identified in the literature, most importantly: IFC, "one-stop-shop" commercial software, data extracting tools associated with cloud-based servers, and programmable interfaces, like Autodesk Forge.

As defined in section 1.1 Background, Industry Foundation Classes, or IFC is a neutral standard that can be used across a wide range of platforms. According to buildingSMART International [10], IFC can be used to:

- Describe how a facility or installation is used, constructed, and operated.
- Define physical components (buildings, manufactured products, mechanical and electrical systems).
- Define abstract models (structural analysis, energy analysis, cost breakdowns, work schedules, and more).
- Exchange information between different parties in a project (architects, owners, contractors, etc.).
- Archive project information (design, procurement, construction phases, and "as-built" for preservation and operations).

The IFC data can be encoded in various formats, such as XML, JSON, and STEP, and transmitted over web services, imported/exported in files, or managed in centralized or linked databases [10]. Software vendors of BIM tools (for design, simulation, analysis, and viewing) provide interfaces to end users to export, import, and transmit data in some IFC format [10]. Sensor data can be imported to IFC via the IfcSensor class, which supports the following predefined sensor types: conductance, contact, fire, flow, gas, heat, humidity, ion concentration, level, light, moisture, movement, PH, pressure, radiation, radioactivity, smoke, sound, temperature, wind, CO_2, frost [18]. There is no kinematic IfcSensor type, so to work with sensors that involve motion measurements it is necessary to create a new type from a pre-existing one [19].

For manufacturing, industrial, and other purposes alike, several companies offer their solution in commercial software for digital twins, such as IBM [20], GE [21], AVEVA [22], TCS [23], Autodesk TANDEM [24], and Ericsson [25]. For civil engineering, Bentley [26] has the iTwin platform for digital twins. Like Autodesk Forge Viewer [27], the iTwin Viewer is a customizable viewer that offers basic tools for viewing a civil structure digital twin, which can be further improved with JavaScript iTwin extensions [28]. Still in civil engineering, some other projects with purposes which align with the objectives of this research are:

(i) IM-SAFE [29]: the project aims at supporting the European Commission and the European Committee for Standardization in preparing new standards in monitoring, maintenance and safety of transport infrastructure, and promoting the adoption of these new standards. IM-SAFE seeks the improvement of the rules in the structural design codes by approximating standard and practice in monitoring of structures [29].

(ii) IoT BRIDGE [30]: is a platform for bridge monitoring and health condition assessment. The provided services include instrumentation of sensors on the bridge, continuous measuring, data transfer to cloud for analytics, visualization, and decision support. The data streamed are fed into algorithms to automatically assess the condition of the bridge. The platform includes user applications, and the data is in open formats so the results can be exported to external applications for asset management and maintenance.

(iii) SeeBridge [31], [32]: Semantic Enrichment Engine for Bridges, or SeeBridge is a platform for survey and assessment of bridges. Remote sensing technologies are used to capture the state of a bridge in point cloud data, then a bridge model is automatically generated by a point cloud processing system, which includes a damage measurement tool for the identified defects. The process covers data acquisition, 3D geometry reconstruction, semantic enrichment to BIM models and defect identification and assessment. In Sacks et al. [32], the formal specification of the overall system concept is presented in an Information Delivery Manual and a Model View Definition.

(iv) PhDC4D [33]: is a Digital Twin platform specialized in maintenance management of critical assets such as ports, ships, tank farms, smart cities, fixed platforms and plants. PhDC4D automates and integrates data from human inspections and from drones, robots and sensors into the same digital twin [33]. Futai et al. [34] developed a framework for a FE-based DT for predictive maintenance of bridges using PhDC4D. The features of the DT include 3D model, material properties, drawings, spreadsheets, documents, inspection reports, sensor data, automated tools for assessment, and machine learning algorithms to model degradation. Cloud Computing is used to store and manage data in real-time. The authors state that the monitoring system was employed to a case study bridge to support its restoration, which proved the potential benefits of a cloud computing monitoring system, and that the digital model associating these DT features is currently under development [34].

In addition, in Berrocal et al. [35] results from the ongoing project named SensIT are presented, which aims at developing a digital twin concept to improve asset management of RC structures. The authors presented a case study of a RC beam, in which FOS data are analyzed and integrated into a web application to be visualized in a 3D geometry model of the beam [35]. Pregnolato et al. [16] developed a generic workflow process for developing a DT for existing assets, including a proof-of-concept case study of a suspension bridge in the UK. The "real-virtual" link in this case study was obtained through a Python based linking software [16].

As opposed to a CDE for different data formats, a "one-stop-shop" software solution that does not have a programmable interface might face additional challenges. For instance, dependency on one software that needs updating and learning (unlike, for example, Revit for BIM that many offices might already know), competing with specialized software that might perform better, and the need to replace current systems entirely for it to be implemented.

Cloud computational service platforms, like Azure [36] and AWS [37], can be associated with different programs in a CDE to connect BIM models and sensor data. Business intelligence (BI) platforms, like PowerBI [38], take data from different sources to create interactive reports; platforms such as Vcad [39] connect BI data with BIM. COBie, or Construction-Operations Building Information Exchange is a non-proprietary data format for the exchange of information between the construction and operations phase [40], [41]. Key information (drawings, bills of quantities and specifications) is pulled into one format and shared between the construction team at defined stages in a project [40], [41]. For this study, Forge [12] was chosen to be the CDE for the proposed digital twin for being considered the most complete approach, since it has programmable interface and extensions, and is compatible with cloud services, BIM and IFC. More details about Forge are given in section 4.3 Common Data Environment.

3. Experimental program

3.1 Design of experiment and purpose

The primary objective of the FOS-beam experimental program was to provide SHM data from sensors to be included in the CDE for the pilot digital twin. Two reinforced concrete (RC) beam specimens were instrumented with FOS and SG and subjected to a three-point bending test. During the test, a DIC system was set in place to perform strain measurements through image acquisition. Secondary objectives of the FOS-beam program included:

i. Establishing an opportunity to practice working with a FOS system, including mechanically bonding fibers before testing and analyzing outcome data afterwards.
ii. Evaluating two different positions to place the optic sensors: inside a groove carved in the reinforcement bar, and in the concrete immediately outside the rebars. This analysis found the measurements from the FOS inside the groove to be more reliable; the discussion and the conclusions drawn from this analysis can be found in the additional publication "*Crack monitoring by fiber optics and image correlation: a pilot study*", published in the IABSE Symposium 2022.
iii. Establishing an opportunity to practice working with a DIC system, including testing speckle pattern and surface preparation techniques, and data analysis.
iv. Providing geometrical data and information for a BIM model for the proposed CDE.
v. Providing experimental data to calibrate a Finite Element model, that can be later employed for prediction of future behavior in similar structures.
vi. Providing experimental data for an analysis of correlation between surface deformation, measured by DIC, and reinforcement strain, measured by FOS. The results from this analysis are presented in the third appended paper.

This experiment design was chosen due to its simple yet realistic representation of the behavior of RC structures, and to the available studies in the literature attesting for the accuracy of FOS and DIC in RC beams under three-point bending, such as [42]–[46]. The placement of the FOS in the rebars was chosen because bonding the fibers to the reinforcement can reduce the risk of fiber rupture, as well as idle readings caused by exceeding the strain range of the sensor, since no strain discontinuities occur in the reinforcement [42]. Moreover, by embedding the sensors in a groove along a rib-free side of the rebar, the bond properties should be minimally distorted [46].

The FOS-beam program will also serve as a pilot study for the work with FOS, DIC and digital models that will be applied to the "Trough Bridges" experimental program, presented in section 7. Future research. In this section, the experimental program, digital models, and common data environment for the FOS-beam are presented. More details and data analysis from the tests can be found in the third appended paper. The author actively contributed to this project in different stages of planning, instrumentation, casting, execution of the tests, data analysis and digital modelling.

3.2 Test setup

The FOS-beam experimental program was carried out to evaluate the crack propagation of a reinforced concrete beam tested under a three-point bending scheme. Two beam specimens were tested to failure, instrumented with FOS, SG, and DIC system. The reinforcement consisted of two ϕ16 mm rebars, one in tension and one in compression, and 8 ϕ8 mm stirrups every 80mm. Three cubes were also cast from the same batch of concrete and subjected to a compression test to obtain material properties. Figure 6 presents schematic drawings of the test set up for the beam specimens and cubes, and the beam cross section with the positions of the FOS.

Detailed accounts of the materials and methods of this experimental program are described in the third appended paper. The correlation between surface deformation, measured by DIC, and reinforcement strain, measured by FOS, obtained by numerical analysis through Machine Learning algorithms and Finite Element modelling are the object of study of this paper.

Figure 7 presents a picture of the FOS-beam test, displaying the beam under the machine that applies the controlled displacement, and the DIC system tripod directed at the beam surface, which was prepared with white paint coating and a black speckle pattern. It is also possible to see the FOS outside the beam, where it does a loop out of the first rebar to return to the second.

The goals of this program were to serve as a pilot test for the work with fiber optic sensors, and to provide test data to be incorporated in the digital twin methodology. The complete data output generated from the experimental program was:

- Strain in the rebars in compression and tension measured by FOS in two different positions: in a groove carved inside the reinforcement bars, and in the concrete adjacent to it.
- Strain in the mid-point of the beam, in compression and in tension, measured by Strain Gauges.
- Data extracted from the DIC system, including strain and crack propagation in the surface of the beams.
- Evolution of force and vertical displacement in time from the load-applying machine.

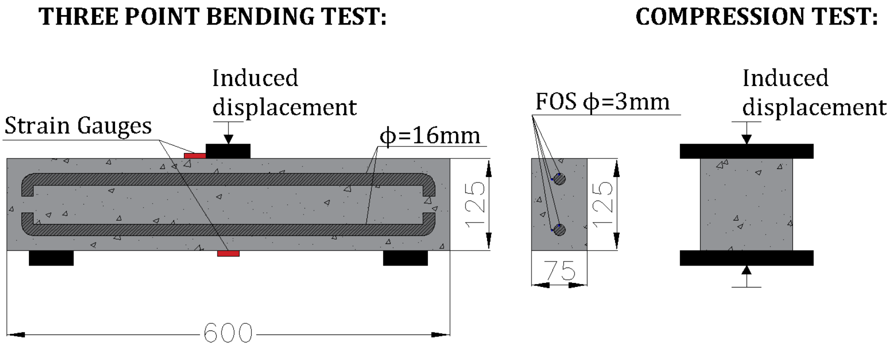

Figure 6: Test set up for the beam specimens (left), cubes (center) and beam cross section with positions of the fiber optic sensors (right).

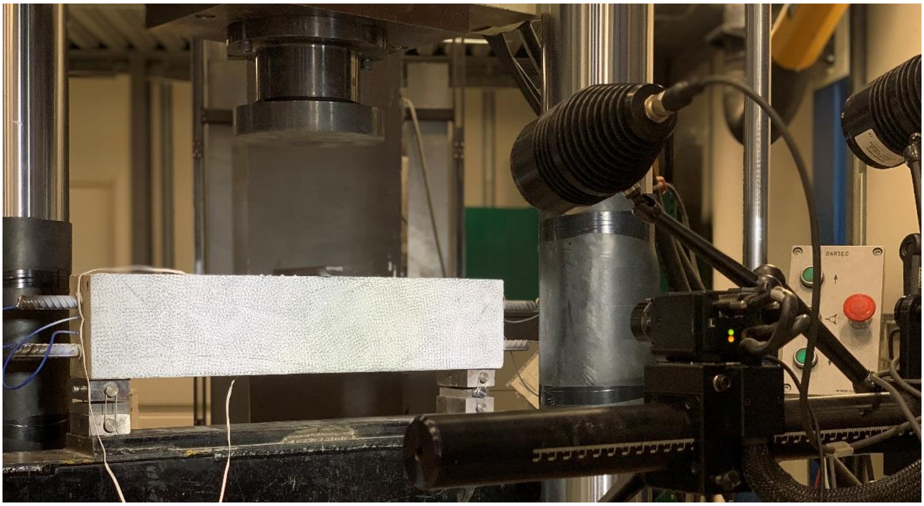

Figure 7: Picture of FOS-beam test, displaying the beam

4. Digital Twin approach

4.1 BIM

A BIM model of the FOS-beam was created using Revit from the design plans and experimental data. Revit is a BIM software from Autodesk for parametric 3D modelling of shapes, structures, and systems, which also enables a unified project environment for multidisciplinary teams. The many advantages of using BIM have already been well established in the literature and in the industry, so a few points worth highlighting as to why Revit is particularly useful for the desired CDE are: Revit allows detailed graphic representation of geometry, including reinforcements, and the inclusion of material information, costs, and schedules. With the multidisciplinary environment, the model and its associated information can be shared and edited between different stakeholders. Revit imports and exports models to different formats, including IFC, and allows the extension of its core functionality through Revit's Application Programming Interface (API) [47].

Besides geometry, the BIM model is a tri-dimensional digital representation of the FOS-beam that can include additional information about manufacturer, cost, and material properties. For concrete, some of the available material properties are compression, shear, and tensile strength, Young's modulus, Poisson's ratio, shear modulus, density, and thermal properties. For the rebar steel, yield strength is also available, besides geometric details such as hook lengths, end treatments (none, threaded or welded) and bending radius. Schedule and material takeoff spreadsheets can also be generated, and different construction phases can be represented in Revit. Figure 8 presents a rendered 3D view, a cross section and an elevation obtained from Revit for the FOS-beam model.

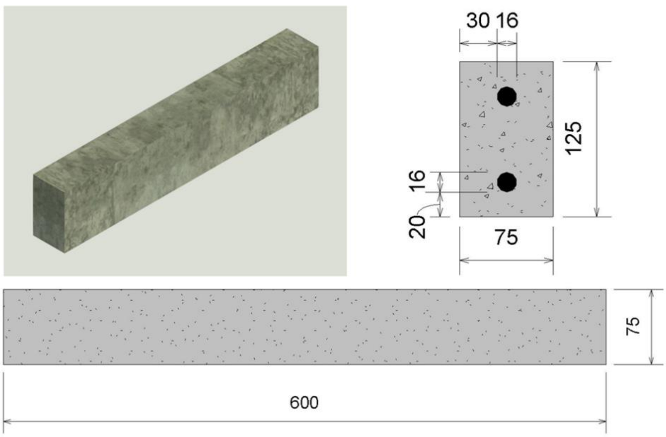

Figure 8: Rendering (top, left), cross section (top, right) and elevation (bottom) of FOS-beam from Revit.

4.2 Finite Element

A tri-dimensional finite element model of the FOS-beam was also created. GiD was used for geometry design and pre-processing, and Atena Studio v5 [48] was used for processing and post-processing analysis. The model properties were included according to those obtained experimentally, as well as the interval data. The induced displacement was applied with a rate of 0,01mm per step, as the experiment had 0,01mm per second. Figure 9 presents the deformed model with the cracks upon failure, and the reinforcement strain.

The failure mode numerically obtained was through shear, similar to what was identified in the experiment. Figure 10 presents the results from the FE model displaying crack width and a picture of the FOS-beam after the test, with emphasis on the shear cracks on both. Details on the development of the FE model, such as elements used, meshing and constitutive models, as well as ML algorithms to evaluate correlation between surface deformation and reinforcement strain can be found in the third appended paper.

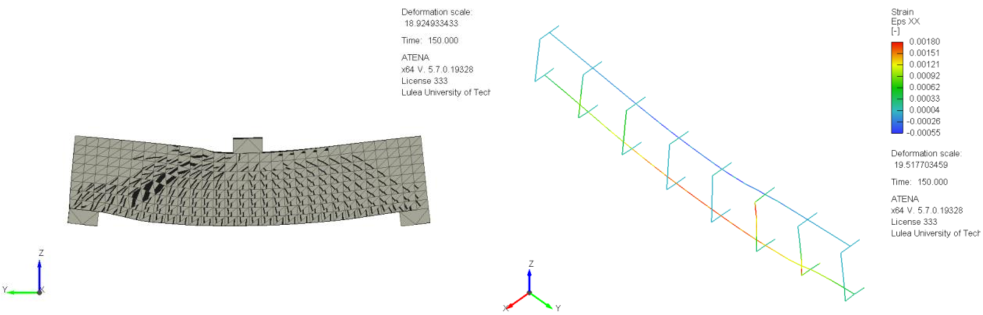

Figure 9: Crack width results from FE model (left) and picture of the tested beam post failure, showing the main shear crack (right).

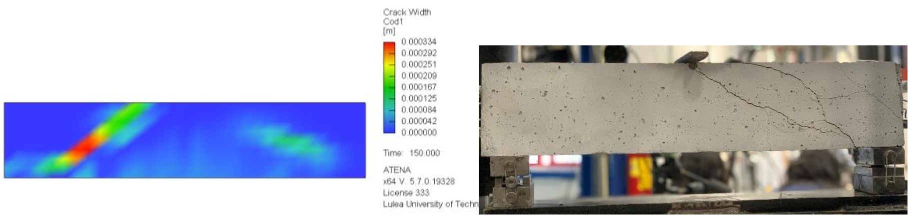

Figure 10: Crack width results from FE model (left) and picture of the tested beam post failure, showing the main shear crack (right).

4.3 Common Data Environment

The first step towards achieving the proposed digital twin for asset management is the creation a common data environment for structural health monitoring data and BIM. First, a BIM model of the FOS-Beam was created using Autodesk Revit [11]. Then, a webapp for visualizing these models was created using Autodesk Forge [12]. Finally, the developed webapp allows sensor data entry to be integrated with BIM through the Data Visualization Extension [49]. This session describes the development of the digital models, webapp and the expected results for the integration of SHM data in the CDE.

4.3.1 Webapp Viewer

Forge is a developer platform from Autodesk that allows access to design and engineering data in the cloud [12]. Applications created using Forge APIs can perform automation of processes, connection of teams and workflows, or data visualization [12]. One of the API solutions available in the Forge platform is the Autodesk Forge Viewer, a WebGL-based, client-side JavaScript library for 3D and 2D model rendering [50]. Web Graphics Library, or WebGL, is a platform-independent way to create interactive graphical applications on the web [51], and a JavaScript library consists of pre-written code to facilitate the development of JavaScript-based applications. Through the Viewer, design models and documents can be displayed, shared, and interacted with on a web page [27].

Eclipse IDE for Enterprise Java and Web Developers [52] was used to handle the code for the webapp created with the Viewer, which was then run using Apache Tomcat v.09 [53] server at localhost. The basic user interface (UI) of the webapp consists of a left panel with a list of buckets and objects, and a 3D or 2D viewer on the right. A toolbar for visualizing and interacting with the models is also part of the basic skeleton of the webapp, including actions such as orbit, pan, zoom, measure, section analysis, document browser, explode model, and properties.

The Viewer API can also be used to customize the appearance of the UI and the contextual behavior of the webapp, as seen in Figure 11. Extensions can be added to the basic code of the Viewer to improve functionalities of the webapp. The Developers Guide for Forge suggests a library in GitHub [54] which contain preexisting code for some extensions, or extensions can be created from scratch by more experienced developers. From the 8 extensions available at the library [54], some worth highlighting are:

1. Camera Rotation: displays the model rotating at a fixed speed, which can be useful for demonstration purposes.
2. Google Maps Locator: displays the geographic location of the model.
3. Icon Markups: presents icon marks for different temperature information.
4. XLS Extension: transposes the data from the Revit file to an Excel format.

The FOS-beam BIM model was uploaded to the webapp, and a PDF design plan was also uploaded to exemplify other types of documents that can be included as layers to the model. Figure 12 presents the webapp created displaying the FOS-beam model and PDF design.

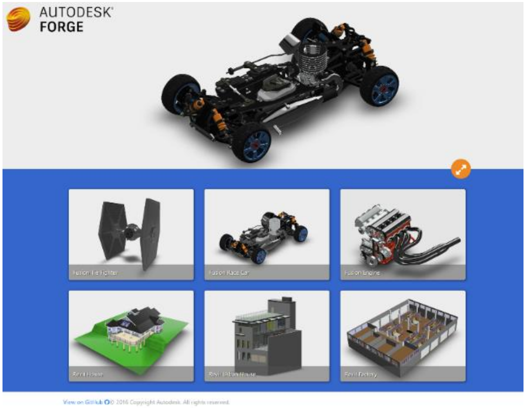

Figure 11: Example of customized Viewer UI [55].

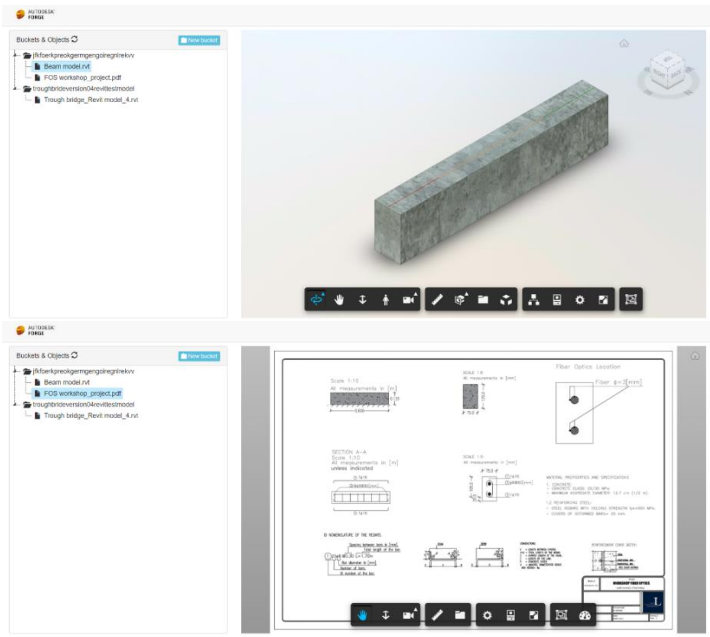

Figure 12: Autodesk Forge Viewer webapp displaying the FOS-beam model (top) and PDF project (bottom).

4.3.2 Data Visualization Extension

The webapp created with Autodesk Forge Viewer serves as a good foundation for the proposed digital twin, since it provides:

- A neutral platform that reads and connects BIM models with other different file formats.
- A programable interface that can be customized in terms of both appearance and functionalities, including the addition of extensions.
- A platform that can be accessed online and interacted with by different stakeholders, in different devices (computer, cellphone, tablets for example).

However, for the Viewer webapp to be considered a functioning Digital Twin, some form of data flow between physical and digital entities is still required. To achieve that, the next step in this research will be to link SHM data from the FOS-beam with the BIM model through the Data Visualization Extension in the created Viewer webapp.

Within the Autodesk Forge solutions, the Data Visualization Extension allows the visualization of data from sensors, and interaction with sprites and surface shading in the context of 3D design models [49]. Heatmaps and sensor data are incorporated into a Digital Twin solution, thus empowering business decisions guided by visual insights. [49]. Design data and business data are combined and visualized together in the webapp platform to form the digital twin, as illustrated by Figure 13.

For the design data, 3D geometry and BIM data can be incorporated through Revit models, a Navisworks [56] model can complement with revision and 4D analysis tools, and IFC files can be included for other types of models. The business data comprises sensor data, from Internet of Things (IoT) devices and other data sources, made available in the cloud through, for example, Amazon Web Services [57] and Azure [36]. The data is finally combined in the Forge Viewer webapp, where sensor data is visualized with the BIM model, along with other elements that can be added, such as graphs, dashboards, and a timeline. The application for the Data Visualization Extension is mostly developed using JavaScript language.

Autodesk provides an example of a digital twin created through the Forge platform and Data Visualization Extension, presented in Figure 14 and Figure 15. Figure 14 shows the main window of the Digital Twin in the webapp, which contains a left panel with the visualization of the 3D BIM model, including the Viewer toolbar, a timeline, and a right panel with a list of sensors separated by level. The right panel is interactive, and by clicking on one of the levels, the sensor graphs of that level are displayed, as shown in Figure 15. The sprites are also interactive, and by hovering the mouse cursor over them the sensor readings are displayed (Figure 15).

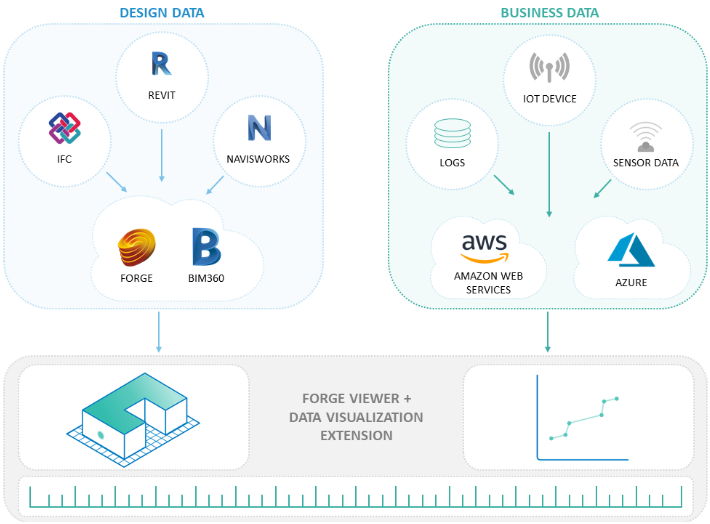

Figure 13: Diagram of how the Digital Twin is created using Forge and the Data Visualization Extension. Adapted from [49].

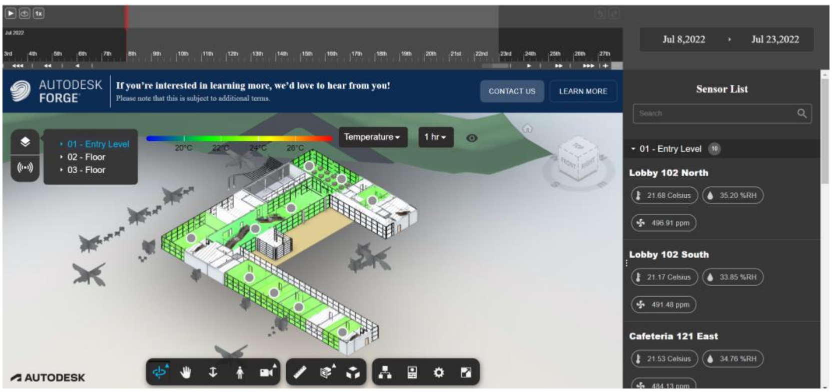

Figure 14: Main window of the Digital Twin webapp on Autodesk Forge [58].

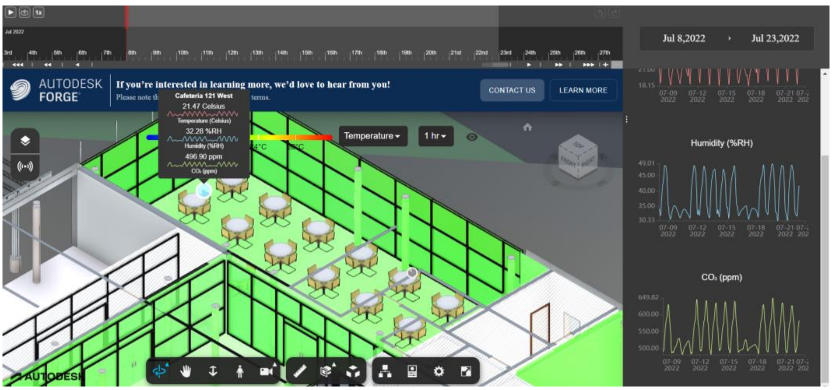

Figure 15: Zooming in the model, hoovering the mouse cursor over a sprite displays sensor readings on the Digital Twin webapp on Autodesk Forge [58].

5. Discussion

A Digital Twin consists of a digital model that represents the geometry and behavior of a physical entity, to which it is connected through a data flow. The goal at the end of this research project is to develop an asset management system of civil structures through BIM and DT. The purpose of DT in asset management is to provide an integrated platform for life cycle management of a structure, efficiently connecting information about construction, geometry and design, materials, current condition, and prediction of future behavior. In this section, the progress of the research towards the development of the system is discussed in terms of technology readiness levels.

Technology readiness level (TRL) scales were developed by the U.S. Department of Defense and NASA in the 1980s. Since then, TRL definitions have been applied and tailored to a variety of industries beyond aerospace [59]. However, the basic idea associated with these other applications remains the same as in the scale proposed by Mankin [60] in 1995, credited with the dissemination of the concept [59]. According to Mankin [60], TRL are a systematic measurement system that supports the assessment of the maturity of a particular technology and the comparison of maturity between different types of technology. Figure 16 presents the TRL definitions for the proposed system, based on the definitions proposed by Mankin [60].

1. **Initial research:** basic principles are observed and reported, scientific research begins to be translated into applied research and development (R&D).
2. **Formulation of concept and applications:** practical applications are defined, but still speculative, without experimental proof.
3. **Concept validation:** active R&D is initiated, including analytical predictions and laboratory-based studies to validate them (proof-of-concept).
4. **Experimental pilot:** validation in laboratory, potential system applications consistent with eventual system requirements, but still relatively low-fidelity.
5. **Demonstration pilot:** the fidelity of the tested component increases significantly, the total applications are tested in a simulated or somewhat realistic environment.
6. **Prototype:** demonstration of an actual system application, or a similar one using the same technologies.
7. **Field test:** system prototype demonstration in its environment.
8. **System qualified:** system completed and qualified through test and demonstration - this is the end level of true system development for most technology elements.
9. **Implementation:** system proven through successful operations, end of last fixes to address problems found following operation, system ready for commercialization.

Figure 16. Definition of Technology Readiness Levels (TRL) for the proposed Digital Twin asset management system. Adapted from [60].

At this point in the research, TRL 3 has been achieved. TRL 1 consisted of the literature review, published in the appended Paper I. The definition of the methodology presented in section 1.3 Scientific approach, as well as the framework proposed in the appended Paper II, represent TRL 2. TRL 3 was achieved through FE modelling, planning and execution of the FOS-beam experimental program, seen in section 3.Experimental program and in the appended Paper III.

For TRL 4, the FOS-beam tests will represent the validation in laboratory environment. The requirements of potential system applications will be achieved once the Data Visualization Extension is added to the webapp created in Forge Viewer, and sensor data from the FOS-beam can be connected to the BIM model. TRL 4 already represents a Digital Twin but is still an experimental pilot with low fidelity compared to the eventual asset management system because a beam is much simpler than a bridge or other civil structure. This is the immediate next step in this study.

In TRL 5, the progress in connecting sensor data to the BIM model in the webapp will be applied to the "Trough Bridges" experimental program, presented in section 7. Future research. Therefore, TRL 5 represents a Digital Twin model of the "Trough Bridges". The application in a bridge structure in laboratory consists of a significant improvement in fidelity of the system in a simulated environment. The trough bridges tests are planned to take place in 2023.

For demonstration of an actual system application in TRL 6, additional aspects of asset management of civil structures will be included to the Digital Twin system. Details are presented in section 7. Future research. The achievement of this level will follow the work in TRL 5 in 2023.

In TRL 7, the DT system prototype is demonstrated in a case study of an existing civil structure. The achievement of TRL 7 withing the time frame of this research project is still under evaluation due to time and logistic constraints.

In TRL 8, the results and improvements from the Trough Bridge tests, representing asset management of new structures, and, if possible, the case study representing the needs of existing structures, are implemented. At the conclusion of TRL 8, the asset management system through BIM and digital twins is completed and qualified.

Lastly, TRL 9 will take place upon the need of improving the proposed DT system to be implemented or commercialized for real structures. This step would most likely occur after the conclusion of this research project.

6. Conclusions

This section addresses the hypothesis, objectives and research questions formulated in the Introduction, based on the literature review and on results achieved thus far in the research project.

Hypothesis:

> Digital Twins provide a more efficient and effective alternative to current practices in asset management of structures.

In sum, managing a structure consists of ensuring its safe operation by periodically evaluating its condition and planning for necessary interventions. Therefore, the efficiency of this process is highly dependent on structural inspection and analysis of future behavior. The literature shows that there has been significant progress in non-destructive testing and automated scanning technology to improve structural inspection, and in digital modelling to analyze structural behavior. However, the full potential of these technologies, particularly post-construction, is still under-explored largely due to the difficulty in communication between different platforms. A common data environment is an alternative that can support different data formats and information exchange. A digital twin created in a common data environment provides a common platform for these technologies to interact, thus allowing them to be explored to their full potential and improving the efficiency of the life cycle management.

Objectives:

As for the objectives, the results can be identified in the appended papers and in different sections of this thesis. The results from objective (i), related to the literature review, are presented in the appended Paper I and Paper IV, and in section 2. Literature review. For objective (ii), related to the experimental program, the results can be seen in the appended Paper III, and in section 3. Experimental program. Lastly, the results from objective (iii), related to the development of the methodology for the proposed digital twin for asset management, can be seen in the appended Paper II, and in sections 1.3 Scientific approach and 4.3 Common Data Environment.

Research questions:

(i) What are the current challenges in asset management of structures identified in the literature?

Asset management for civil structures is highly dependent on inspection data, since this is the information used to create the panorama of the structure's current condition and, consequently, its maintenance needs. For bridge structures, the main challenges in structural inspection identified in the literature are related to inefficiency, inaccuracy, dependency on inspector's personal knowledge and experience, and information exchange between platforms and stakeholders in the project. From the literature review it was also identified that current bridge management systems lack a tri-dimensional geometric representation of the structure, such as a BIM model, integrated and connected to the system to facilitate inspection and management. Other gaps identified in the literature include allowing remote access to the system and its data, adopting automated inspection procedures and NDT that can be linked to a BIM model, Life Cycle Cost Analysis (LCCA) and prediction of future deterioration through digital modelling.

(ii) What is the current maturity level of Digital Twins in the construction industry?

The literature shows that the construction industry is still behind other industries, such as aerospace and manufacturing, in terms of maturity of digital twins. Moreover, within the construction industry digital twins for buildings are more advanced than for civil structures, which present more challenges in terms of access and type of data required from sensor instrumentation. While aerospace and manufacturing are advanced enough to have functional digital twins, or at least a clear vision of concepts, benefits and future plans, there is still not a consensus on what constitutes a digital twin in the construction industry. There have been a few commercial and research initiatives well advanced towards DT for asset management of civil structures, as cited in section 2. Literature review. However, there is often misconception, mislabeling of digital models, and use of the term only as a buzzword in the digital twins presented within the construction industry. The aspects identified as most commonly left out of these mislabeled digital twins are data flow between physical and digital, prediction of future behavior and life cycle management.

7. Future research

The tasks planned for future research in this project are divided into the following three categories, presented in this section: digital modelling and programming, research, and experimental work.

i. Digital modelling and programming

To obtain a functioning digital twin, the software work in the common data environment needs to be completed. The Data Visualization Extension will be added to the created Webapp Viewer to allow sensor data to be visualized and integrated with the BIM model in the CDE. To include the extension, it requires going through its comprehensive JavaScript library. Besides the extension, the Webapp interface can also be customized. Then, prediction of future behavior will be incorporated through FE modelling.

ii. Research

In the appended Paper IV, a review of current bridge management systems is presented, including an analysis on current practices, identified gaps and potential improvements. Once the software work is concluded, the continuation of this research will focus on including asset management aspects to the proposed digital twin. This will include a deeper analysis into the specific needs of the asset owners, with their direct input in potential improvements of current systems. Also, a specific analysis of Sweden's system, BaTMan (Bridge and Tunnel Management system), is planned along with a potential expansion of the analysis to civil structures besides bridges.

Within asset management of civil structures, relevant aspects such as LCCA, environmental and climate impact investigations will be explored. Future discussions in this research include how current management systems can adapt or include the new technology, how the new technology works differently for new and existing civil structures, and the technology readiness level the system will be finalized.

iii. Experimental work: Trough Bridges

An experimental case study that will use the FOS-beam, as a pilot study, is programmed for 2023, named "Trough Bridges". The main application of this project to this study will be the use of extracted SHM data for a digital twin model towards asset management. The author actively contributed to this project in planning, casting of specimens to evaluate material behavior, instrumentation, and digital modelling.

The experimental program for the "Trough Bridges" case study consists in a series of laboratory tests that will be performed in two real scale trough bridges, named TB1 and TB2, cast at Luleå University of Technology (LTU). The main goal of the project is to develop a procedure for evaluating the real structural capacity of bridges. The premise is that a significant number of bridges worldwide are approaching the end of their design life, and how a reliable evaluation of their true structural capacity might extend their life spans. This evaluation can avoid replacing these bridges entirely and prolonging the expected technical life span, which is a more sustainable solution from both environmental and financial aspects. To achieve this, a comprehensive laboratory test plan includes:

- Serviceability load testing: capacity of the bridges defined based on analytical calculations and FE models, which will be calibrated after the tests.
- Fatigue testing: real scale and scaled down model tests to predict fatigue damage more accurately, and investigation of how fatigue decreases the bridge's lifespan.
- Bridge scanning: development of a 3D model based on photogrammetry techniques, including damage information retrieved from point cloud data.
- High temperature testing: evaluation of the feasibility of the tests in the laboratory (definition of the event, position of fire source, exposure time and safety).
- Digital twin: SHM data from tests connected to digital models via Viewer webapp and Data Visualization extension to create a digital twin of the Trough Bridge.
- Strengthening: definition of strengthening technique that causes the least traffic disturbance, perform tests on a strengthened damaged concrete trough bridge and analyze experimental results analytically and through FE modelling.
- Reliability analysis: predict the bridge's true capacity and likely failure modes, including experimental data and probabilistic models.

Besides the laboratory tests, numerical models are also included in the Trough Bridge project scope. These include static and dynamic load distribution models, FE models to capture the structural behavior, and deterioration models to predict the structure's remaining capacity. The project deploys a wide team of researchers to execute all the planned tests and respective digital models. The focus of this study is the use of SHM data to feed the Trough Bridge future digital twin. This digital twin will then be evaluated as a tool for asset management of structures in the larger scope of this research.

So far, both bridges have been instrumented and cast, and modelled in BIM using Revit. Figure 17 presents frontal and lateral elevations of the trough bridge with its dimensions, and Figure 18 shows a 3D rendering of the bridge and its reinforcements from Revit. The total length of the bridges is 7.20m, with 3.80m of width.

Each bridge was instrumented with eight fiber optic sensors, limited by the maximum of eight simultaneous channels in the data acquisition system. The fiber optic system used was ODiSI 6, from Luna Innovations Inc. [61], similarly to the FOS-beam program. The fibers were applied inside a groove carved into the rebars and bonded with an epoxy glue. Besides FOS, some rebars were also instrumented with strain gauges to perform point strain measurements. The rebars that were instrumented with the fibers and the position of the strain gauges are highlighted in Figure 19.

Both TB1 and TB2 bridges were cast outside on 03/03/2022. On 31/05/2022, after the curing process, TB1 was moved to the laboratory. Figure 20 shows the casting of the bridges, transportation of TB1 and the TB1 inside the laboratory. Twelve cylinders were cast from the same concrete batches and kept at the same condition as the bridges to obtain material properties. At the time of testing the bridges, three cylinders will be subjected to a compression test, three to a modulus of elasticity test and six to a fracture energy test.

In this study, the Trough Bridge case study is briefly presented as experimental work planned within future research towards the development of a digital twin for asset management. The research plan for this project includes sharing the future results from experimental testing and digital modelling in journal and conference papers, in which further details on the instrumentation, properties, tests and procedures will be provided.

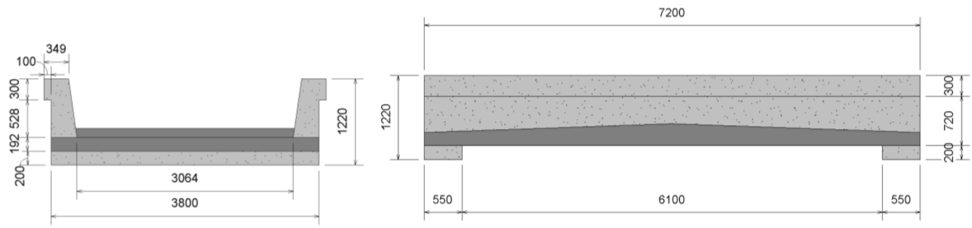

Figure 17: Trough bridge drawings: frontal elevation (left) and lateral elevation (right).

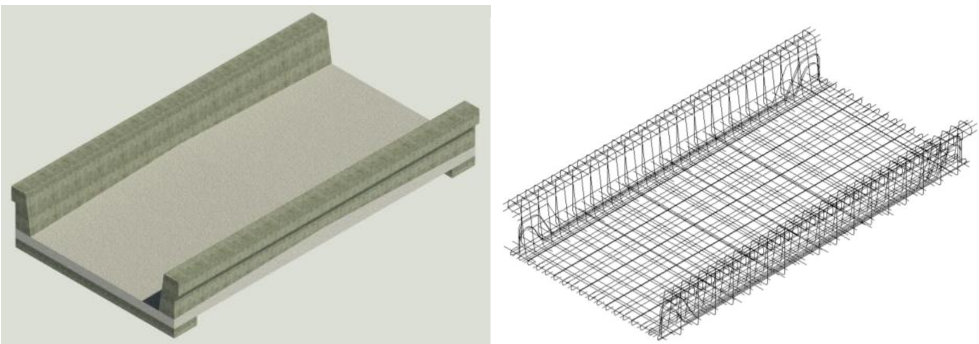

Figure 18: Renderings of Trough Bridge (left), and Trough Bridge reinforcement (right) from Revit.

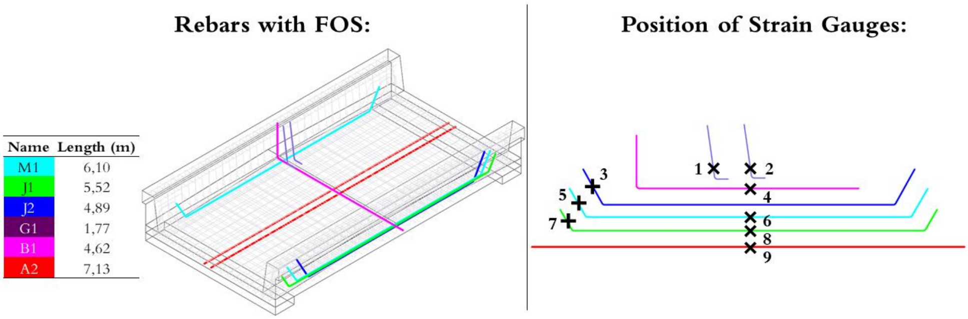

Figure 19: Rebars instrumented with FOS (left) and position of strain gauges in these rebars (right).

Figure 20: Casting Day for the trough bridges (left), transportation of TB1 (right, top), TB1 inside the laboratory (right, bottom).

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PAPER I

Asset Management of Existing Concrete Bridges Using Digital Twins and BIM: a State-of-the-Art Literature Review

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Asset Management of Existing Concrete Bridges Using Digital Twins and BIM: a State-of-the-Art Literature Review

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ABSTRACT
The need to optimize investments in bridge maintenance has created a demand for improved bridge management systems (BMS). Outdated practices in bridge inspection and constant advances in information technology have also contributed to this demand. The use of Digital Twins (DT), although well established in other industries, is still incipient for asset management and structural analysis of bridges. There is a great deal of research on Building Information Modelling (BIM) for bridge inspection, but its post-construction potential is still under-explored. This study presents a state-of-the-art review of the literature on asset management for bridges using digital models such as BIM and digital twins. The review was conducting using a systematic approach. Despite the rapid increase in research on DT and the amount of existing research on BIM, several gaps remain to be addressed, such as the lack of consensus about the definition of digital twins, which has led to wrongful categorisation of digital models as DT. The complex data flow and software compatibility required to develop a functional DT have hindered the exploitation of their full potential so far. The integration of BIM post-construction to BMS and existing automation technologies can also significantly improve current practices of bridge management.

Key words: digital twins, bridges, bridge maintenance, bridge management systems, BIM, review.

1. INTRODUCTION

Bridge structures have long theoretical life spans. Most bridges on the national road networks of the European Union were built within the last 50 years, although some are much older [1]. Deterioration and failures have increased in the already aging bridges due to consistent growth in automobile traffic, environmental exposure, and internal defects such as corrosion of rebars and concrete degradation. In addition, the loads currently applied to many bridge structures greatly exceed those envisaged when they were designed [1]. National guidelines require regular bridge inspection and evaluation to ensure that their operation remains safe and efficient. The processes of managing and scheduling these evaluations, recording and handling bridge data, and making maintenance recommendations have become known as bridge management [2].

Asset management is defined here as the set of activities through which an organization assures the maintenance and optimization of costs, performance, safety, and sustainability of its assets throughout their life cycles. Asset management can be applied to both tangible assets (buildings, infrastructure, equipment) and intangible assets (financial assets, intellectual property, human capital), whereas facility management focuses on maintaining the services that support the organization's primary business and activities.

Bridge management is an essential part of long-term asset management that is applicable to all existing bridges, old and new [3]. The main purpose of a bridge management system (BMS) is to preserve the asset value of the infrastructure by optimizing costs over a bridge's lifespan while ensuring user safety by offering a sufficient quality of service [1]. The expansion of physical infrastructure and improvements in technology have prompted authorities to seek ways of managing maintenance activities more efficiently [4]. In recent decades, the scope of bridge management has grown, and the objective of maximizing the value of maintenance spending to protect investments in bridges has been added to the primary goal of protecting the safety of the traveling public [2, 4]. As a result, the search for more efficient management methods, the appeal of new technology, and efforts to reduce maintenance spending have created a demand for optimized BMS.

Some recent developments in Information Technology (IT) have led to changes in bridge management, through improvements in the quality of inventory and inspection databases as well as the control that can be exerted over deterioration, forecasting, and management models [5]. The proliferation of Industry Foundation Class (IFC) alone has had a major impact on how current tools and methods are developed in research and development [6]. Digital technologies across the board are advancing at an ever-increasing pace, taking advantage of the Internet of Things (IoT) and Artificial Intelligence (AI) agents (data analytics, machine learning, deep learning, etc.) [6].

An approach that has proven useful in many different industries involves the use of Digital Twins (DT). The basic idea behind the DT approach is that a digital informational construct representing a physical system can be created as an entity in its own right, providing a "twin" of the information embedded within the real physical system that is linked to the real system over its entire life cycle [7]. Despite extensive discussion in the literature, no consensus regarding the features and scope of digital twins has yet been established [8]. As a result, the term "digital twin" is often used to describe 3D digital models that lack the relevant data flows. Moreover, despite a growing body of research, the AEC/FM (Architecture, Engineering, Construction/Facility Management) sector still lags behind the manufacturing and aerospace sectors in terms of the maturity of development of digital twins [9].

This context was the main motivation for this state-of-the-art review of the literature on asset management for concrete bridges using digital models such as Building Information Modelling (BIM) models and digital twins. A great deal of research has been done on the use of BIM for inspecting bridges, so the discussion of BIM here focuses on synthesizing the most recent research and summarizing information on best practices. Digital twins, on the other hand, have been studied less extensively, especially in the context of asset management in the construction industry. This review of DT therefore focuses on summarizing the work that has been done and identifying gaps in the literature meriting further exploration.

This review is divided into eight sections: Introduction, Methodology, Bridge Inspection, Bridge Information Modelling (BrIM), Digital Twins, Bridge Management Systems, Discussion, and Conclusion. The methodology section explains the procedures used when conducting the systematic review of the literature. Sections three through six present an overview of key findings from the literature pertaining to their subjects and link those findings to the main thread of the review. The material reviewed in the preceding sections is then discussed in the seventh section, and the conclusions and recommendations for future studies are presented in the final section.

2. METHODOLOGY

This section explains the methodology used when conducting the systematic state-of-the-art literature review. The process was divided into three main steps: (i) defining the search strings, (ii) performing searches in the selected database, and (iii) assessing the retrieved articles. The search strings were defined based on keywords identified in primary references retrieved during a preliminary exploratory literature review. The most commonly recurring keywords in the primary references were divided into five subject groups; each subject group was then assigned a set of strings as follows:

- BIM: ("BIM" **OR** "Building information modelling");
- Bridges: ("Bridge information modelling" **OR** "BrIM" **OR** "Bridge" **OR** "Bridges");
- Digital Twins: ("Digital twin" OR "Digital twins" **OR** "DTM");
- Management/inspection: ("Facilities management" **OR** "Facility management" **OR** "inspection" **OR** "monitoring");
- Maintenance: ("Maintenance" **OR** "Assessment").

16 different searches were then performed in Scopus [10], the selected database, in April of 2020. The search results were only limited by year; the acceptable range was set from 2010 to 2020 to ensure that only publications that could be considered to represent the state-of-the-art were retrieved. Each search used a combination of three (ten combinations), four (five combinations), or five (one combination) groups of strings. The string search was applied to the title, keywords, and abstract of each paper. The combinations and the number of results obtained for each one are shown in Figure 1.

	BIM	BRIDGE	DIGITAL TWINS	MANAGEMENT /INSPECTION	MAINTENANCE
C1	x	x	x	x	x
C2	x	x	x	x	
C3	x	x	x		x
C4	x	x		x	x
C5	x		x	x	x
C6		x	x	x	x
C7	x	x	x		
C8	x	x		x	
C9	x	x			x
C10	x		x	x	
C11	x		x		x
C12			x	x	x
C13		x	x	x	
C14		x	x		x
C15		x		x	x
C16	x			x	x

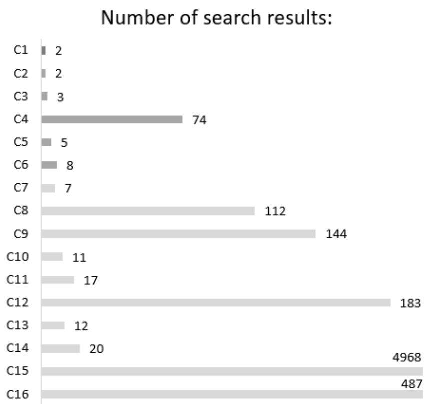

Figure 1 - String combinations (left) and the number of search results obtained for each one (right)

Two of the 16 combinations (C15 and C16) were eliminated for being too broad; the remaining 14 combinations (C1-C14) collectively provided 600 results in Scopus [10]. Some of the papers retrieved in this way were eliminated before assessment because the article had already been assessed while reviewing the results of an earlier string combination, was written in a language other than English, was conference review paper, or dealt with an unrelated area of research (medicine, psychology, etc.).

Each article was then evaluated using three sequential filtration steps; the first focused on the title, abstract and keywords, the second on the introduction and conclusion, and the third on the entire paper. Articles that passed all three steps were included in the review. The main reason for exclusion in all three filters was low relevance of the subject of the paper to the topic of the review;

other reasons for rejection included lack of access to the full paper or low overall quality. An iterative process was applied: all publications cited in the papers that passed all three filtration steps were filtered in the same way and included in the review if they also passed all three filters.

As shown in Figure 1, there were far more search results pertaining to bridge inspection and BIM than to DTs, which is a newer area of research. The five combinations that did not include the search string "digital twins" (C4, C8, C9, C15, C16) collectively yielded 5 785 results, with an average of 1 157 results per combination, whereas the eleven combinations including "digital twins" (C1-C3, C5-C7, C10-C14) only provided 270 results, with an average of 25 results per combination. It is also noteworthy that many of the papers that did include the term "digital twins" in their keywords or text did not actually discuss the creation of DT models. They either used the expression "digital twin" as a synonym for a 3D BIM or stated that the research could support the creation of a digital twin in the future but did not actively contribute to the existing knowledge on digital twins.

The distribution of the selected papers based on their year of publication is indicative of the recent emergence of DTs as a field of study: 50% of the included papers were published between 2010 and 2018, and the remaining 50% were published in 2019 or 2020. The articles selected using the methodology described above are reviewed in the following sections.

3. BRIDGE INSPECTION

The proliferation of road traffic has increased the loads faced by bridges on public roads. Environmental and mechanical damage, besides natural aging, result in decreasing structural performance of the bridges. Regular structural health assessments and maintenance interventions are therefore needed to ensure that the bridges continue to operate safely throughout their intended design life and beyond [11]. The first step in determining the current health of a bridge and planning for maintenance is performing inspections. Routine inspections are periodic quality assessment procedures that are usually scheduled during a bridge's service life to evaluate its health [11, 13]. The frequency at which inspections are scheduled can vary within a country's BMS. Usually there is one principal and more detailed inspection every 3-6 years, one annual or semi-annual follow-up inspection, and more regular superficial routine inspections.

Although the implementation of inspection procedures varies between countries, there are some common basic principles [13]. Current bridge inspection procedures are mostly based on intensive visual investigations and field measurements performed manually by bridge inspectors [14]. During an inspection, the inspector examines each element of the bridge, searching for visible damage. Some non-destructive testing may also be performed to complement the visual inspection. Concrete spalling, cracks, and reinforcement corrosion are the most frequently identified types of damage in reinforced concrete bridges, aside from equipment-related defects (e.g., defects in bearings or expansion joints) [13]. The measurements and observations obtained during the inspection are then documented in the form of field inspection notes, freehand sketches, and photographs [11, 14].

Unfortunately, these procedures present several challenges that make manual inspections time-consuming and inefficient. These challenges may include difficulty in accessing the bridge (due to its large dimensions and/or environmental and traffic conditions), dependence on individual inspectors' knowledge of the bridge's structural behaviour, and transferring information between inspection periods. Consequently, there is a need for new infrastructure inspection and monitoring techniques that reduce disruption while increasing the efficiency of data gathering and the reliability of the acquired data [14].

Approaches based on substituting human visual inspections with automated and systematic 3D point cloud assessments are currently being studied intensively [13]. Much recent research has focused on combining image acquisition techniques with damage detection and feature extraction methods to create automated bridge inspection systems [13]. Figure 2 shows some of the various technologies that have been used for this purpose, which are discussed in more detail below.

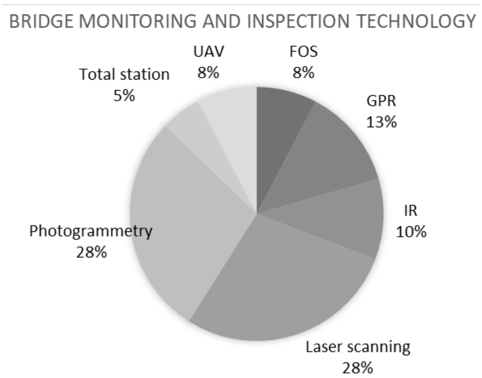

Figure 2 - Technologies used to enhance bridge monitoring and inspections in recently published studies (FOS: Fibre Optic Sensors; GPR: Ground Penetrating Radar; IR: Infrared; UAV: Unmanned Aircraft Vehicle) [11-30].

The evolution of monitoring technology has significantly improved the efficiency of structural health assessment of bridges. Inspections and data collection processes have been automated, leading to significant increases in the accuracy and quality of the inspection data. Technologies used in these automated processes include fibre optic sensors [15, 16], UAV [11, 17, 18], laser scanning [14, 18, 19, 20, 21, 22, 23, 24, 25], photogrammetry [11, 13, 14, 19, 20, 21, 23, 26, 27], and ground penetrating radar [27, 28, 29, 30]. Notable publications in this area are summarized below.

Popescu et al. [14] and Riveiro et al. [19] compared the performance of photogrammetry and laser scanning for bridge inspections; Popescu et al. [14] also included infrared (IR) scanning in their comparison. Their results showed that the two methods achieved similar final accuracies and have great potential to facilitate the 3D reconstruction of bridges. However, laser scanning was found to be more efficient because of its higher data acquisition rate and automated post-processing. The authors found that the main advantage of the photogrammetry technique stemmed from its lower equipment cost.

Riveiro et al. [19] developed an algorithm using MATLAB [31] to automate the measurement of minimum vertical under-clearance during bridge inspections. McGuire et al. [32] developed a method to link and analyse data related to bridge inspection, evaluation, and management using a custom Microsoft Excel [33] tool. Huthwohl et al. [34] used Industry Foundation Classes (IFC) to categorize inspection information on reinforced concrete bridges and to standardize its storage in a format suitable for sharing and comparison by different users. Abu Dabous et al. [28] used cloud-based solutions to sync BIM of bridges so that they could be accessed from tablet computers on-site. Omer et al. [12] used Light Detection and Ranging (LiDAR) to digitize bridges so that they could later be inspected in a virtual reality (VR) environment.

Morgenthal et al. [11] and Xu & Turkan [17] proposed bridge inspection methodologies based on camera-equipped Unmanned Aerial Vehicles/Systems (UAV/UAS). Morgenthal et al. [11] generated flight paths automatically from a basic 3D model and used photogrammetry- and machine learning-based methods to compute automatically geometries and typical damage patterns. Xu & Turkan [17] used computer vision algorithms to collect and process inspection data, storing and managing all of the related inspection information in a Bridge Information Model (BrIM).

Sacks et al. [20] proposed an integrated bridge inspection system called SeeBridge to upgrade the traditional bridge inspection process by producing semantically rich BIM of the inspected bridges. The system uses remote sensing techniques for data collection, software for automated compilation of the remote sensing data, a semantic enrichment engine for converting the 3D model into a semantically rich BIM, and a damage detection tool. Within the system, IFC are used to represent bridge elements, their properties, and the relationships between them.

4. BrIM

Building Information Modelling (BIM) for bridges is commonly referred to as Bridge Information Modelling, or BrIM. BrIM is a novel approach that can be used to manage the whole life cycle of a bridge including its fabrication, construction, operation, inspection, and maintenance [23]. Data gathered using the inspection technologies discussed in the preceding section can be used to generate accurate digital models of bridges using BIM [13, 17, 20, 28, 32, 34]. These BIM can then be used for predictive purposes, for example to predict the future decay of the structure using Finite Element (FE) methods [29]. This is essential for the creation of smart BMS because accurate modelling of the current situation and prediction of future problems are key elements in a digital twin model.

In the case of new bridge structures, the BrIM can be created during bridge's design phase, before its construction. This allows full exploitation of the potential benefits of life-cycle management. If the model is coupled to a structural health monitoring (SHM) system, the sensor data for the bridge can be analysed directly with the model, improving visualization and creating a shared environment that facilitates long-term management [15, 21, 35].

However, because bridges have long life spans, BrIM is often applied to historical bridges [23] [18, 24, 25, 27]. BIM for heritage or historical structures is often referred to as H-BIM. The aim when modelling such a bridge is to create a digital model for recording information that will allow the bridge's cultural significance to be preserved while ensuring its safe operation and providing a virtual tool that can be used to help define effective restoration strategies [18]. The main difficulty in this reverse engineering process is that these heritage bridges often have overly complex geometries and lack detailed formal design documents, which causes challenges when modelling or capturing geometric data on such structures [18].

It should be noted that the modelling of new bridges is also often challenging. A characteristic problem presented by new bridges is that they often have variable curvature and complex cross sections [23]. While commercial BIM software is capable of creating 3D bridge models with highly accurate geometry, there are only a few families of dedicated libraries for the modelling of complex civil structures such as bridges [13, 23, 25]. The lack of existing object libraries may thus necessitate the development of new algorithms and specific families to represent properly the different structural elements of the bridge [23].

Several solutions have been proposed in the literature to tackle the challenges of accurate representation within BIM and interoperability between platforms. In most of the studies included in this review, the commercial software package Autodesk Revit [36] was the tool of choice for generating BIM [18, 23, 24, 25] because it can be tailored and enhanced using its application programming interface (API) [32]. It also offers an inter-operable IFC platform that enables the exchange of data between non-native file types [32]. IFC is a neutral format for exchanging digital building models, and it is hoped that the use of IFC as a standard BIM file format will eliminate or greatly reduce interoperability issues [13]. In addition to IFC, MATLAB [31] and other programming languages have been used to create tailored interoperability solutions [37].

5. DIGITAL TWINS

The first definition of the concept now known as the Digital Twin was proposed by Michael Grieves in a presentation in 2002 [7,38]. Although the context was related to product life-cycle management, it contained all the elements of the Digital Twin concept: a real space, a virtual space, and a link supporting data flow between the two [7]. The premise underpinning the model was that each system consisted of a physical system, a virtual system containing all available information on the physical system, and a mechanism for mirroring (or twinning) changes in the real and virtual spaces [7]. It also implied that the virtual and real systems should be linked throughout the life cycle of the physical system, from its creation and production (manufacture) through to its operation (sustainment/support) and disposal [7]. The Digital Twin concept was first used heavily in the aerospace sector; it was initially used by the National Aeronautics and Space Administration of the U.S.A. (NASA) to replicate the life of air vehicles [8, 39]. At that time, the concept was given the name DT and it was introduced as such to the aerospace world via NASA's Technology Roadmaps [38].

The basic concept of the DT model is based on the idea that a digital informational model about a physical system can be created as an entity in its own right [7]. This digital model then functions as a "twin" of the information embedded within the physical system itself and is linked with that physical system throughout its life cycle [7].

Although much has been published on the topic, there is still little or no consensus among researchers and practitioners regarding the features and scopes of a digital twin [40]. Negri et al. [39] defined a digital twin as a virtual representation of a system that can be used in multiple different kinds of simulations and that is characterized by synchronization between the virtual and real systems based on sensed data and connected smart devices, mathematical models, and real time data elaboration. Kritzinger et al. [38] proposed definitions of Digital Models, Digital Shadows, and Digital Twins that are illustrated in Figure 3 and summarized below:

- Digital Model: A digital representation of an existing physical object that lacks any form of automated data exchange with the physical object.
- Digital Shadow: A digital representation of a physical object with an automated one-way data pathway allowing information on the physical object's state to be automatically transferred to the digital object.
- Digital Twin: A digital representation of a physical object together with an automated and fully integrated bidirectional data pathway allowing exchange of data between the two objects.

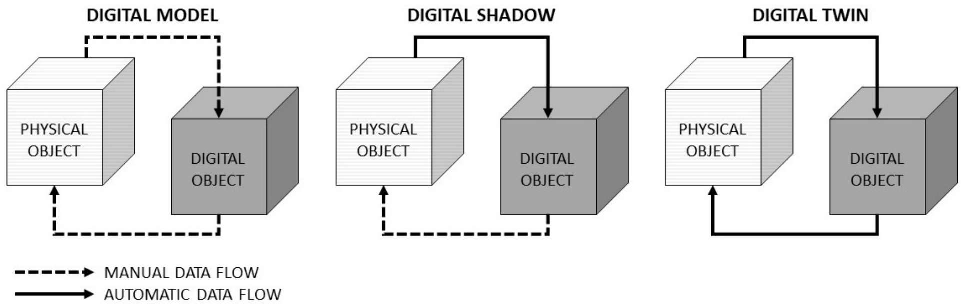

Figure 3 - Data flow in a Digital Model (left), a Digital Shadow (centre), and a Digital Twin (right). Adapted from Kritzinger et al. [38].

Lu et al. [9], Cimino et al. [8] and Khajavi et al. [41] performed literature reviews on digital twins. Lu et al [9]. proposed a framework for achieving smart DT-enabled asset management in the operations and maintenance (O&M) phases. The authors concluded that BIM still has limited adoption within asset management, mostly because in daily O&M management BIM is not enough for complex situations and comprehensive data management [9].

5.1 Digital Twins: bridges

In accordance with the aim of this review, one of the main purposes was to identify studies that propose digital twins for bridge structures. However, only few articles among the ones assessed address digital twins for bridges, namely: Shim et al. [42], Lu & Brilakis [43] and Ye et al. [44]. The following subsections present a discussion on these identified studies.

Shim et al. [42]
Shim et al. [42] proposed a framework for a bridge maintenance system and applied it to a real bridge in a pilot study. The proposed system applies the digital twin concept by creating three models: (1) a physical 3D geometry model (the so-called geometric digital twin, or gDT), (2) a reversed 3D surface model (the reality twin model), and (3) a federated model.

The gDT is based on the as-built documents of the existing bridge; it can be generated using parametric modelling with the aid of an open-source application-programming interface. The reality twin model is created via a 3D scanning procedure and contains information on the current state of the bridge. This model is based on a combination of photo scanning data collected using an unmanned aerial vehicle (UAV) and laser scanning cloud data. Finally, the federated model is created by merging the gDT and reality twin models, which overlap at points bearing predefined marks that are placed on the real bridge before the 3D scanning procedure.

The initial version of the federated model represents the status of the real bridge at the beginning of a maintenance task and is updated as subsequent maintenance tasks are performed. For automated surface damage detection, inspection data from the scanning procedure are automatically converted into technical damage reports and used directly to update the initial model. The general procedure for maintenance work is a closed loop of interactive processes including inspecting, monitoring, performing appropriate repair or rehabilitation work, and importing the resulting feedback into the database.

Lu & Brilakis [43]
Lu & Brilakis [43] proposed an automated method for generating a gDT of an existing bridge from four types of labelled point clusters. Only geometric representations of the four main components of typical RC slab and beam-slab bridges (the slab, piers, pier caps, and girders) were included in the models. Other semantic information including data on the materials, defects, additional relationships, and so on, were considered beyond the study's scope. Lu & Brilakis [43] argue that all of the geometric and property information associated with the gDT should be stored in a platform-neutral data format (i.e., IFC) to support the use of the gDT in the construction industry. This format allows the categorization of inspection information and standardized storage in a format that facilitates sharing and comparison by different users [34]. The output of this study was an IFC file containing the various IfcObjects (IfcSlab, IfcBeam and IfcColumn) that comprise a bridge gDT. Point clusters of the four component types were created, then ground truth gDTs were manually generated and exported into IFC files using Autodesk Revit [36], which was described as one of the most advanced digital twinning software solutions [43]. In conclusion, Lu & Brilakis [43] reported a gain in time saving, better results in six out of ten bridges modelled and that human assistance is still necessary in some challenging scenarios that the current automated method could not handle [43].

Ye et al. [44]
The digital twin framework developed by Ye et al. [44] combines BIM with bridge sensor data, FE modelling, and statistical monitoring. The framework was applied in a case study on two composite (steel and pre-stressed concrete) railway bridges that were instrumented with discrete and distributed fibre optic sensor (FOS) systems during their construction. The sensor data and associated bridge behaviour were visualized in a BIM environment. The FE model was created to investigate the performance of the bridge during construction and operation; it was validated using sensor data and its predictions were verified by FOS strain measurements. The resulting information could be used to help establish a performance baseline that will support long-term condition monitoring and data-informed asset management as further sensor data are collected throughout the bridge's operating life [44]. The conceptual framework was developed by integrating both physics-based (FE modelling) and data-driven (statistical modelling) approaches.

The framework was applied in a case study on experimentally tested and field monitored railway sleepers, with the goal of predicting their operational performance over time. The authors indicate that future work will include developing a working digital twin and improving the level of confidence in the integrated simulation model and its predictions.

6. BRIDGE MANAGEMENT SYSTEMS (BMS)

6.1 BMS in the world

National road administration authorities generally have their own management systems that are used to manage tunnels, culverts, ferry berths, retaining walls, pavements, and quays as well as bridges [45]. These systems are either developed internally by the managing organization itself (with or without the help of private companies), or bought off-the-shelf and modified to suit their needs [46]. Most such systems are only used within a single country, probably due to the differences in bridge management practices between countries [46]. When systems are bought off-the-shelf and adopted by an agency, they are usually significantly modified, creating a new system with a new name (e.g. Eirspan, which was developed using DANBRO as a starting point) [46].

Helmerich et al. [47] listed the best-known software based digital bridge management systems in Europe: BaTMan (Sweden), BAUT (Austria), DANBRO (Denmark), KUBA (Switzerland), SIB-Bauwerke (Germany), and SMIS (United Kingdom). Additionally, the Federal Highway Administration (FHWA), American Association of State Highway and Transportation Officials (AASHTO), and National Cooperative Highway Research Program (NCHRP) of the United States sponsored a scanning study to determine how highway agencies in Europe, North America and South Africa handle bridge maintenance, management, and preservation [45]. The U.S. delegation met with bridge preservation and maintenance experts from these countries (apart from Austria), and with representatives from Finland (BMS: HiBris, Hanke-Siha), France (BMS: LAGORA), Norway (BMS: Brutus), and South Africa (BMS: STRUMAN) [45]. The investigated management systems evaluate the bridges' condition through rating scales, such as a 1-4 point scale [45]. They also establish frequency of bridge inspection, which usually means one principal inspection every 5 to 6 years, some condition evaluation every 2 to 3 years and routine evaluations of damage [45].

The results from research projects on bridge management that have been conducted in Europe contributed significantly to initiating or enhancing the development of national integrated BMS [47]. For example, BRIME (1998-1999) was conducted with the objective of developing Bridge Management Systems for the European Highway authorities [47]. Likewise, Sustainable Bridges (2003-2007) was a consortium of 32 partners from twelve European countries for improved assessment tools, repair and strengthening methods. Guidelines were set to support the railway infrastructure departments with technical background information in the fields of inspection; condition, load and resistance assessment; monitoring; repair and strengthening of railway bridges (including NDT) [47].

In the United States, the FHWA sponsored the creation of two highway BMS, BRIDGIT and PONTIS, which are used to manage bridges on state and interstate highways [2]. PONTIS is the main bridge management system employed in the USA; it is currently managed by AASHTO and has been renamed BrM in reference to bridge management [2, 48]. Some other BMS currently used around the world are: SAMOA, APTBMS (Italy), FBMS (Finland), GBMS (Germany), Eirspan (Ireland), DISK (Netherlands), SMOK/SZOK (Poland), SGP (Spain), OBMS, QBMS, EBMS, PEI BMS, GNWT (Canada), Bridge-ASYST, MRWA and NSW (Australia), MICHI, RPIBMS (Japan), KRMBS (Korea) [46, 49]; GOA (Portugal) [50]; SGO (Brazil) [51]; T-BMS (Taiwan) [52].

6.2 Modules of a BMS

Each of the systems discussed in the preceding section can be used by the corresponding national road administration to perform a different set of management activities. The tasks can vary according to the specific needs and resources of each country, they can be more or less thorough and frequent, and prioritize different parts of the BMS scope. However, all of the BMS have similar scopes based primarily on inspection, structural health monitoring, and rehabilitation [3].

Inspection is the first step in the management process. During inspections, the inspectors establish the physical and functional condition of individual structural members and the entire bridge [53]. Along with the inspectors' experience, the condition is assessed using measurement equipment and well-developed tools and techniques [53]. Rating criteria are then applied to determine the bridge's condition, and rehabilitation procedures are implemented [3].

The management tasks are usually divided into different modules in the systems. For a BMS to function efficiently, the system modules must be integrated internally to minimize duplication and user inputs and thus achieve optimal performance [4]. The modules are usually related to inventory, inspection, condition analysis, and maintenance planning. The main module is the inventory module, which is considered the foundation from which the rest of the BMS operates [4]. According to Woodward et al. [1], a bridge management system capable of fulfilling the various objectives of the managers must be modular and incorporate modules for performing at least the following key tasks:

1. Taking inventory of the stock;
2. Compiling knowledge of bridge and element condition and its variation with age;
3. Evaluating the risks incurred by users (including assessment of load carrying capacity);
4. Managing operational restrictions and the routing of exceptional convoys;
5. Evaluating the costs of the various maintenance strategies;
6. Forecasting the deterioration of condition and the costs of various maintenance strategies;
7. Assessing the socioeconomic importance of the bridge (evaluation of indirect costs);
8. Performing optimization under budgetary constraints;
9. Establishing maintenance priorities;
10. Performing short- and long-term budgetary monitoring.

6.3 Current practices in bridge management

To handle the amount of information required to achieve optimal management of infrastructure, managing agents are using increasingly sophisticated computerized management systems to support their decision-making process [54]. Mirzaei et al. [54] conducted a survey of 25 bridge management systems that are used to manage approximately 1 million (bridges, culverts, tunnels, retaining structures and other objects) in 18 countries. The main results of this survey are presented in Table 1. The results include information on each system's data entry and information access capabilities, stored information, handling of structural information, handling of cost information, predictive capabilities, use of predictions and the systems' contributions to the education and qualifications of their users.

Table 1 - Current practices in BMS [54]

Nº (%)	Item
	Data entry and information access
11	allow data entry through mobile computers
12	allow access to information in the system over the internet.
	Stored information
7	allow basic construction information to be archived in the system (the majority of systems allow the information to be either stored in some way or referenced).
24	allow archiving of inspection information.
23	allow archiving of intervention history.
	Information handled on the structure level
24	handle condition information from inspections.
20	handle information on load carrying capacity.
19	handle information from inspections concerning safety.
18	handle information from inspections concerning risk.
	Cost information
24	can handle intervention cost information.
6	handle inspection costs.
11	handle traffic delay costs.
7	handle accident costs.
8	consider environmental costs.
	Predictive capabilities
19	can predict deterioration; 12 systems use probabilistic methods.
18	can predict the improvement due to future interventions; 9 use probabilistic methods.
19	can identify optimal intervention strategies.
	Use of prediction information
23	are used to prepare budgets.
15	are used to set performance standards.

7. DISCUSSION

The process of creating a BMS for smart asset management of bridges using Digital Twins can be divided into four steps: (1) Inspection/Data acquisition, (2) BIM creation, (3) Digital Twin creation, and (4) Asset Management. The overview of currently operational BMS presented in Table 1 shows that there is room for improvement in many respects. This section analyses the main findings of the systematic literature review presented above.

Most problems associated with current bridge inspection practices relate to time consumption, the limited accuracy and impracticality of manual sketches, knowledge transfer between inspection periods, and issues with access to certain bridge sites. Several technologies that could enhance the quality of inspection data while also improving the efficiency and automation of the inspection process have been proposed in the literature. For example, a synced BIM of the bridge can be accessed from the site to facilitate inspection [28], UAVs can be used to perform inspections with automatically generated flight paths [11], damage detection can be automated with computer vision algorithms [17], and the inspections themselves can be performed using virtual reality bridge models [12]. As shown in Figure 2, photogrammetry and laser scanning were the most widely used methods in the various publications on inspection technologies included in this review.

A very complex data flow is required to transfer information generated during bridge inspections to a BIM that can be used to manage all data on the bridge across its life cycle. The flow must support a semantically rich geometry model, assessment of monitoring equipment and treatment of the resulting data, and visualization of the data in the bridge model while also enabling analysis and predictions. This requires interaction and data transfer between different platforms that do not necessarily communicate directly. Enabling such transfers and interactions is a major challenge, as is establishing interactions between the equipment and its digital mirror. In the literature, the main way of overcoming these challenges was to use IFC to categorize the inspection information and standardize its storage in a format suitable for comparison and sharing with different users.

At present, BIM is mainly used for design purposes and is rarely applied in asset management. The main issue reported in the literature when using commercial software to create BrIM stemmed from the complex geometry of the structures, which can generally not be properly represented using standard libraries. It is therefore often necessary to spend considerable amounts of time to design new families for each modelling effort. Autodesk Revit [36] was the commercial BIM software favoured by most authors because of its interoperable IFC platform and the fact that it is readily modified using its application-programming interface. Most studies included in this review combined a structural health management and/or monitoring system with a BIM [13, 14, 15, 20, 21, 26, 28, 32, 34, 35, 37, 55, 56, 57].

Different solutions can be used to tackle these challenges. Among the reviewed studies, the most common strategy for integrating different kinds of data was to use separate layers or models in the digital twin [42, 43, 44, 58]. These layers often included a data acquisition layer, a layer for 3D representation of geometry and visualization of sensor data, and a layer for transmission/integration of data resources. The 3D geometry can be automatically compiled from remote sensing data and coupled with an engine for converting the 3D model into a BIM [20]. In addition to separate layers, IFC [13, 34, 43 59], MATLAB [19, 37], and machine learning algorithms [11, 26, 41] were also used to facilitate data integration between platforms.

Based on the summary presented in Table 1, some observations about current practices in BMS can be made. First, no existing BMS includes BrIM or geometric representations of bridges of any kind [13, 46]. Traditional paper-based methods of maintaining infrastructure are no longer viable because governments now expect digital tools that leverage information and communication technology [4]. Additionally, fewer than half of the systems allow remote or online access to the BMS; most only allow access through desktop computers, which limits access to information. This should be addressed because many of the technological advances in infrastructure management rely on cloud-based, mobile, and/or portable technology. The BIM can be linked to the BMS using many different methods and tools including Structured Query Language (SQL) statements [60]; C# [60], MATLAB [19, 37] or other programming languages; IFC [13, 34, 43, 61, 62, 63]; or machine learning [11, 26, 41] and artificial intelligence algorithms [64].

Most current systems can manage information on inspections and interventions. However, to enable adequate life cycle management, a BMS should also include budgetary information and data from construction and design plans so that they can be compared to the current condition data obtained from inspections. This enables future deterioration to be predicted more accurately and facilitates the planning of interventions. Many current systems can also predict deterioration – i.e. changes in physical condition or performance indicators [46], mainly using probabilistic methods. However, there have been many advancements in structural analysis using BMS frameworks that could be used to make improvements in this area; examples include the development of automated bridge assessment tools using artificial intelligence algorithms [64] and the combination of BIM with FE models [60, 65] and Geographic Information Systems (GIS) [62]. Figure 4 presents a modular framework of activities that should be supported by a comprehensive BMS based on an evaluation of the data entering a typical BMS [1, 3, 4, 5, 51, 52, 61, 66].

This review identified several papers published over the last decade dealing with the first two processes within the concept presented, i.e. (1) Inspection and (2) BIM creation. Different inspection and monitoring technologies have been tested and compared, and automated inspection methodologies have been developed and linked to BIM. However, the potential uses of BIM and BrIM post-construction remain under-explored.

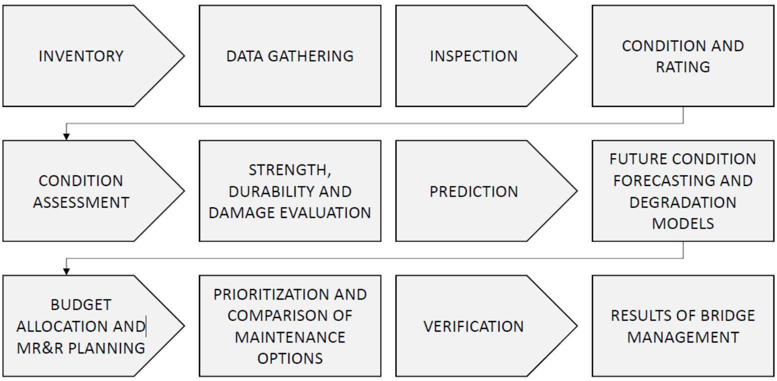

Figure 4 - Management activities within the suggested scope of a BMS.

Research on digital twins in construction is less well established than in other sectors such as aerospace [67], but interest in their application is growing rapidly, as demonstrated by the trends shown in Figure 2. However, there is currently no consensus about what a digital twin model should include and how it should operate. Therefore, the “digital twins” used in many published works would be more accurately described as "digital models" or "digital shadows" (Figure 3) that lack the full capabilities expected of a digital twin. The automation of the two-way data flow between the physical entity and the digital model is a major challenge in the development and post-construction use of digital twins. While there have been some initial studies in this area, much remains to be done.

8. CONCLUDING REMARKS

The growing stock of bridges and the increasing need to optimize investments in bridge maintenance while ensuring safe operation have created a demand for optimized bridge management systems. In recent years, there have been major advances in technologies for bridge inspection, damage detection, digital modelling, and maintenance. This state-of-the-art literature review of asset management for bridges using BIM and Digital Twins summarizes these advances. To this end, the review examined four processes and tools separately: inspection, BIM, Digital Twins, and Asset Management. Each has been addressed in the literature using methods that combine different sets of solutions and technologies. Despite the rapid increase in research on digital twins and the large body of existing research on BIM and bridge inspection, several gaps remain to be addressed:

- The potential uses of BIM and BrIM post-construction are still under-explored;
- There is no consensus concerning the definition of digital twins, which has caused digital models and digital shadows to be wrongly categorized as digital twins;
- The development of functional digital twins requires a very complex automated data flow, which has hindered the exploitation of their full potential.
- There has been little work on the development of asset management and structural health systems using digital twins for bridge structures.

The analysis in this review also revealed some points of improvement in current BMS for asset management of bridges:

- Geometric representations of the bridges under management (e.g. BIM) should be integrated into existing BMS;
- Remote or online access to existing BMS should be made possible;
- Automated inspection procedures (e.g. automated damage detection processes) should be introduced and linked to the BMS, preferably directly to a BIM;
- Life cycle analysis should be incorporated into the systems. This would require better integration of construction information to enable comparisons to inspection data on the structure's current condition, as well as predictions of deterioration generated using structural analysis tools such as FE modelling to enable better planning of interventions.
- Structural analysis and deterioration predictions should be improved; such improvements could have direct impacts on subsequent budgetary analyses.
- Budget analysis throughout the bridge's life cycle should be integrated into the system and should include peripheral costs such as those due to traffic delays, accidents, environmental costs, and inspection and maintenance costs.

This literature review is a part of a project aiming to develop a BMS for asset management of bridges using digital twins. Future work should include studies on the use of IFC with SHM systems, automated damage detection during bridge inspections, and machine learning algorithms to improve the links between the system's modules.

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PAPER II

Framework for Bridge Management Systems (BMS) using Digital Twins

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Framework for Bridge Management Systems (BMS) Using Digital Twins

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Abstract. Bridge structures have significantly long life spans; many medieval and historic bridges remain in operation in the world. The concept of bridge management contains the activities related to managing bridge inspections and condition assessment, which can be gathered into a Bridge Management System (BMS). Deterioration and failures have increased over the years in the already aging bridges; therefore, the importance of BMS to ensure safety of bridge operation and maximize investments in bridge maintenance has also increased. Digital Twin (DT) technology can be applied in the construction industry to achieve smart management through the entire life cycle of structures. Unlike the aerospace and manufacturing industries, the maturity of development of DT models in the construction industry still lags behind. In this study, a literature review was initially performed to gather knowledge on the origins of the digital twin concept and current best practice focused on bridge structures. A systematic approach for the literature review is presented in the methodology. Lastly, a framework for facility management of bridge structures using digital twins is proposed.

Keywords: Bridges · Digital twins · Bridge management systems · BMS · Facility management

1 Introduction

Facility management of bridge structures is usually handled by each country's road administration entity through Bridge Management Systems (BMS). The systems vary according to the specific needs and resources of each country, but the scope itself consists primarily of inspection, structural health monitoring (SHM) and rehabilitation [1]. In order to handle the amount of information required to achieve optimal management of infrastructure, managing agents are using increasingly sophisticated computerized management systems to support their decision making process [2].

In this study, a framework for smart bridge management using Digital Twins (DT) is proposed. The use of digital models, such as DT, adds automation, efficiency and accuracy to the system. The frameworks divides the DT approach into 5 steps: bridge inspection, BIM model, damage identification, data transmission, and facility management.

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A systematic state-of-the-art literature review was performed to identify the main challenges and respective solutions of the processes that compose the proposed framework. This review, along with this study, is part of a broader research on facility management of bridges using digital models.

2 Methodology

In order to develop a framework for facility management of bridges using DT, a state-of-the-art literature review was performed. The review consisted of three main steps: definition of the strings of research, research of the selected database, and assessment of the articles.

The strings of research were defined based on keywords identified in a preliminary exploratory literature review. The most recurring keywords were divided into five groups of subjects, and each group was given a set of strings as follows:

- BIM: ("BIM" OR "Building information modelling");
- Bridges: ("Bridge information modelling" OR "BrIM" OR "Bridge" OR "Bridges");
- Digital Twins: ("Digital twin" OR "Digital twins" OR "DTM");
- Management/inspection: ("Facilities management" OR "Facility management" OR "inspection" OR "monitoring");
- Maintenance: ("Maintenance" OR "assessment").

Different combinations of groups of strings were searched in Scopus, the selected database, limited from years 2010 to 2020 to be considered as state-of-the-art. The search was applied to title, keywords and abstract of each paper, and added up to 600 results in Scopus. Some of the papers were eliminated before assessment, because the article was a repeated result, written language other than English, conference review paper or unrelated area of research (medicine, psychology, etc.).

The selected articles were then evaluated using three different filters: Filter 1 for title, abstract and keywords; Filter 2 for introduction and conclusion; and Filter 3 for the entire paper. The main reason for rejection was low relevance of the subject to the scope of this study, lack of access or overall quality. The articles approved after the third filter were included in the review. An iterative process also occurred and references from selected papers were assessed and included to the study as well.

3 Literature Review

3.1 Bridge Inspection

Regular structural health assessment and interventions are essential to ensure that bridges continue to operate safely throughout their intended design life and beyond [3]. Routine inspections are periodical quality assessment procedures usually scheduled during the bridge's service life to evaluate their health [3, 4].

Current bridge inspection procedures are mostly based on intensive visual investigations and field measurements performed manually by bridge inspectors [5]. However, manual inspections are time-consuming and highly dependent on the inspector's knowledge of the structural behavior of the investigated system [3, 5]. Therefore, the idea of substituting human visual perception with an automated, systematic and quantitative 3D point cloud assessment is currently an intensively investigated topic [4]. The latest research tends to systematize imagery acquisition techniques with damage detection and feature extraction methods into an automated bridge inspection system [4]. Some of the different technologies employed in recent literature to automate bridge inspection and damage detection are presented in Table 1.

Table 1. Inspection and automated damage detection technologies and respective references.

Technology	References
Photogrammetry	10 references [3–12]
Laser scanning	9 references [4–8, 11, 13–15]
Ground Penetrating Radar (GPR)	5 references [12, 16–19]
Unmanned Aircraft Vehicle (UAV)	5 references [3, 13, 20, 23, 25]
Infrared (IR)	4 references [4, 8, 16, 18]
Fiber Optic Sensors (FOS)	3 references [20–22]
Computer vision algorithms	3 references [4, 10, 20]
Light Detection and Ranging (LiDAR)	1 reference [24]
Wireless sensor network (WSN)	1 reference [26]

3.2 Digital Models

Bridge Information Modeling, or BrIM, is a novel approach able to manage the entire life cycle of a bridge: fabrication, construction, operation, maintenance and inspection [11]. Data harvested from bridge inspections can be used to develop digital models using BIM [4, 7, 18, 20, 23, 27, 28], which in turn can be used for prediction of structural decay using FEM [17, 19, 29] and to anticipate the effects of such decay upon structural integrity [17]. This is essential in the context of a smart BMS, since accurate modeling of the as-is condition and prediction of future behavior are key elements in a digital twin model.

Autodesk Revit was the commercial BIM software endorsed by most authors in this review [11, 13–15], and described as one of the most advanced digital twinning software solutions [5]. The program also offers an inter-operable Industry Foundation Class (IFC) platform that allows for the exchange of data between nonnative file types [28]. The use of IFC as a BIM standard file format aims to solve the interoperability issues, since this is a neutral format for the exchange of digital building models [4]. Table 2 presents other solutions to this problem addressed by authors in this review.

Table 2. Technologies for data transmission and respective references.

Data transmission	References
IFC	5 references [4, 7, 30–32]
Machine learning	3 references [3, 10, 26]
MATLAB	2 references [6, 29]
Artificial intelligence algorithm	1 reference [25]
3G/4G/5G and WLAN	1 reference [33]

3.3 Digital Twins

Although much has been published on the topic, a general definition and an agreement over the digital twins' features and scopes has not been reached [34]. Kritzinger et al. (2018) [35] presented a definition which differentiates Digital Models, Digital Shadows and Digital Twins. According to the authors, a Digital Model is digital representation of an existing physical object that does not use any form of automated data exchange between the physical and the digital objects [35]. A Digital Shadow, on the other hand, has an automated one-way data flow between the state of an existing physical object and a digital object. Finally, in a Digital Twin the data flows between an existing physical object and a digital object are fully integrated in both directions [35].

Few studies that employ DT for bridges were encountered in the literature. Andersen & Rex (2019) [36] developed a SHM system backed up by a digital twin able to predict responses from possible critical scenarios during retrofit of the Henry Hudson Bridge in New York. Shim et al. (2019) [37] proposed a bridge maintenance system that applies the concept of digital twins through the creation of three models: a 3D geometry model, a model that contains the current status of the bridge, and a third model created between the first two. Lu & Brilakis (2019) [30] created a geometric digital twin of an existing bridge, which is as a digital twin with only geometry data. The authors also defend the use of a platform-neutral data format, i.e. IFC, to represent all the associated geometric and property information. Lastly, Ye et al. (2019) [38] proposed a DT framework combining BIM with bridge, FE and statistical monitoring, which was tested in a case study of railway sleepers instrumented with fibre optic sensor (FOS) systems.

4 Results and Discussion

Different steps have to be considered in order to develop a BMS. In the literature review section, first the importance of performing regular bridge inspections was established, as well as the main issues with current procedures and respective technologies to improve inspection and damage detection. The second subsection, digital models, approached mainly BIM, FE modelling and technologies to integrate data between different platforms. Lastly, the third subsection addressed digital twins, disclosing the lack of consensus as to the definition of the DT for the construction industry, and that the approach towards bridge management, although growing, is still incipient. Therefore, based on the best practice presented in the literature review section, the desired BMS should include:

- Inspection: automated process combining accurate and reliable technologies that enable the generation of digital models and automated damage identification, with little to no dependence on human eye and access to the site.
- BIM model: semantically rich and thorough model, generated mostly automatically from geometry data, containing the original geometry, current status updated with inspection data and visualization of monitoring points.
- Digital Twin: from the BIM model, the digital twin should be able to be automatically updated with monitoring data from the site and to have a connection with other layers, such as a FE model for prediction of future behavior. For the facility management aspect of the structure in its entire life cycle, the DT system should also:

  o Include analysis of optimal intervention strategies;
  o Predict improvements due to future interventions;
  o Handle costs for intervention, inspection, and peripheral costs such as traffic delay, accident and environmental;
  o Allow archive of basic construction information, inspection information, and intervention history;

The system should also have a user-friendly and include functions such as mindful alerts when certain parameters reach warning or critical levels. For each of these macro-aspects, the possible technologies identified in the literature were summarized in the framework presented in Fig. 1. From this framework, non-destructive testing (NDT) can be applied to identify inner geometry and material properties, and different solutions can be combined to achieve smart facility management of bridges.

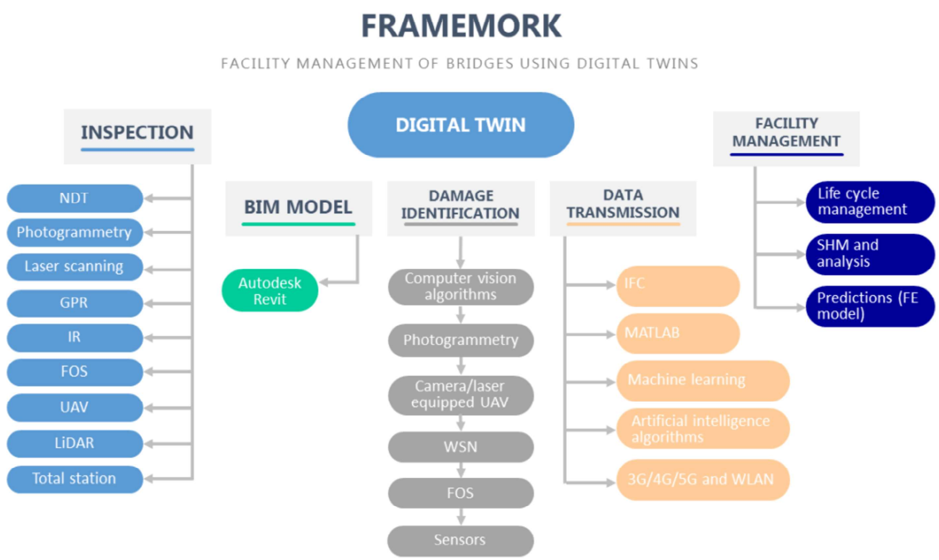

Fig. 1. Framework for facility management of bridges using digital twins.

5 Conclusion

This study aimed at developing a framework for a facility management system of bridge structures using digital twins. This is a highly complex process, mainly due to the integration of a large amount of data from different platforms. To approach this system, a brief literature review covered potential solutions to technological problems related to bridge inspection, digital models and digital twins. The solutions identified in the review were then organized into a framework, which divided the Digital Twin approach into 5 steps: bridge inspection, BIM model, damage identification, data transmission, and facility management.

The proposed framework indicated that, when breaking down the structure for smart bridge management, some aspects have been well addressed by current research. However, this does not apply for the full process, as seen in the literature review, which makes the integration of all the steps and data the main gap to be addressed. This study is part of a broader research, which aims at addressing this gap and constructing a BMS using DT. Future work will include applying this framework initially to a DT of concrete beams under laboratory tests, then to a case study of a bridge.

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PAPER III

Correlation between surface deformation and reinforcement strain for RC structures: a comparative study between Finite Element and Machine Learning models

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Correlation between surface deformation and reinforcement strain for RC structures: a comparative study between Finite Element and Machine Learning models

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Abstract: Structural Health Monitoring (SHM) and Non-Destructive Testing (NDT) technologies have greatly advanced over the last decades, however, obtaining information about internal damage in a structure is still more challenging. In this paper, an experimental program was conducted with two reinforced concrete beams subjected to a three-point bending test. A Digital Image Correlation (DIC) system was used to measure deformation in the surface of the concrete, and Fiber Optic Sensors (FOS) were bonded to the embedded reinforcement bars to measure strain. Correlation between the external deformation from DIC and internal strain from FOS was evaluated through Machine Learning (ML) and Finite Element (FE) models, which were compared in terms of accuracy. As a result, reinforcement strain could be predicted from surface deformation with an accuracy of 86%, and errors in the scale of 10^{-2}. The difference in accuracy and processing time between ML and FE was not significant, but the FE predictions tended to underestimate the reinforcement strain.

Keywords: *surface deformation, reinforcement strain, digital image correlation, fiber optic sensors, finite element modelling, machine learning.*

1. Introduction

Structural Health Monitoring (SHM) might be used as a damage detection strategy that can observe a structure over a period of time, using a series of continuous measuring devices [1]. Features extracted from these measurements and the statistical analysis of such measures can provide the ability to assess the current performance of structures [1]. The fundamental concept behind asset management of reinforced concrete (RC) structures consists of obtaining information about the structure's current condition and applying this information to decision making in maintenance planning. To acquire such information, SHM techniques are usually employed.

Defects that can be visualized externally, such as surface deformation, crack propagation, and excessive displacements, are more straightforward to measure. For these types of damage, non-destructive and non-contact methods can be applied, which normally are less costly. The safety provided by non-contact methods is particularly important when it comes to structures in areas that are harder to access. Investigation of internal damage such as excessive reinforcement strain, voids, delamination, and corrosion, however, is more challenging. It requires specific equipment, like ultrasound, impact echo, electric potential measurement or ground penetrating radar instruments that allow visualization through the concrete exterior. Moreover, existing structures under investigation usually have not been instrumented with any kind of sensor. Techniques that yield information from the structure's inside from its external conditions are not only beneficial, but necessary. Information on current degradation of a structure can be used for prediction of future behavior and to plan maintenance accordingly. This prediction can be achieved through degradation models, by creating a damaged state in a Finite Element (FE) model or by prediction algorithms in Machine Learning (ML) models, for example.

If both external and internal damage are known in a structure, some form of correlation between both can be generated so internal damage can be quantitatively inferred from external deformation. This study has the objective of establishing a correlation between surface deformation, measured by a Digital Image Correlation (DIC) system, and reinforcement strain, measured by Fiber Optic Sensors (FOS) in a reinforced concrete beam specimen tested in laboratory. To establish correlation, a data-driven approach, through Machine Learning algorithms, and a model-driven approach, through a Finite Element model, were tested and compared. Both approaches were compared in terms of accuracy, processing time, and information needed to run the prediction models. The accuracy of the models was established by comparison with the experimental data measured by FOS.

The benefits of DIC and FOS in monitoring of RC structures have been well established in the literature, as shown by examples in this section. Section 2. Experimental program presents the laboratory work conducted to provide data for the analysis. The results from the ML and FE numerical analysis are presented in section 3. Numerical analysis. In section 4. Discussion, the performance of the methods is compared, and final remarks are presented in section 5. Conclusions.

Conventional damage detection techniques are gradually being replaced by state-of-the-art smart monitoring and decision-making solutions; the connection between sensor data and big data processing of critical information in infrastructures through Internet of Things (IoT) is the future of SHM systems [1]. In that sense, this study is part of a broader research project, which aims at improving damage detection and asset management for civil structures.

1.1. Correlation: DIC and FOS

The basic principle of strain-based monitoring is that changes in the physical properties of a structure will cause changes in the amplitudes of strain measurements [2]. Traditional methods for measuring strain are limited, tedious and time consuming, which justifies the need for improved, automated, and non-contact strain measurement methods.

DIC is an optical, non-destructive, and non-contact displacement measuring technique, that measures deformation through comparison of images of random speckle patterns taken before and after surface deformation. In RC structures, DIC has been widely applied to the study of concrete deformation and cracking. Crack monitoring is an important aspect of diagnosing structural health [3]. Most studies identified in the literature employ DIC to predict crack location, crack width and investigate crack propagation [4].

Different studies have investigated the correlation between surface deformation from DIC and strain in embedded reinforcement from FOS in RC [5]–[8] due to the advantages of both methods in comparison to traditional approaches. The suitability of FOS in SHM has been tested in various experiments in the laboratory, as well as field applications, with encouraging results in the field of civil engineering structures [5]. Besides providing continuous strain measurements, FOS are chemically inert, resistant to corrosion, lightweight, and able to operate over a wide range of temperatures [5]. For these reasons, these sensors are believed to have the potential to change the instrumentation industry in the same way fiber optics have revolutionized communications [9].

Barrias et al. [10] presented an extended review covering an introduction to the theoretical background of FOS, the latest developments and improvements of these products, laboratory experiments and their diverse applications in civil engineering structures. Brault et al. [6] proposed an analytical model to estimate reinforcement strain from crack width and compared to experimental results obtained from FOS and DIC, respectively. The model provided accurate estimates of load carrying capacity for a given crack width, however, accuracy was lower when experimental reinforcement strains were estimated from crack widths [6].

Carmo et al. [7] described a method to assess reinforcement strain from surface measurements obtained through photogrammetry and image processing in two concrete ties experimentally tested. Ruocci et al. [8] focused on large structures, describing the use of DIC for crack assessment of RC massive beams and walls. The authors proposed a post-processing noise-filtering technique, validated on a large experimental campaign, to improve DIC results in large RC structures. Feng et al. [11] developed a shear lag–based model for detection of cracks and their location compared to strain distribution measured by FOS in an experimental program. The results indicated that the discontinuities in the strain distribution, such as cracks, based on the theoretical analysis provided the means to accurately pinpoint the location of simulated cracks.

In Berrocal et al. [5], distributed FOS were bonded to the unaltered surface of a reinforcement bar of concrete beams subjected to three-point bending tests. The comparison between the strain profiles provided by the FOS and measurements from a DIC system showed that the cracks were located with most errors below ±30 mm, and the evolution of crack width over time was tracked with most errors below ±20 μm [5]. The authors found that the position of active fully formed cracks, associated to local peaks of strain, could be located based on the strain distribution at the reinforcement provided by FOS. The tested methodology enabled the successful detection of cracks as small as 40 μm, not perceptible to the human eye. However, the determination of the crack position was less apparent than for sensors bonded to the surface or embedded in the concrete and it required a certain post-processing of the strain data to remove the noise associated to the spatial variability [5].

1.2 Numerical modelling and Machine Learning

In a previous study, Mirzazade et al. [12] proposed a semi-empirical equation for prediction of strain in the embedded reinforcement from DIC measurements. The two main aspects in need of improvement of this study were the limited number of collected data, due to point strain gauge sensors, and the large number of variables in the equation, which made it difficult to compute. For these reasons, in this study the FOS were installed for strain measurements, and Machine Learning algorithms were employed for regression analysis.

In the age of the smart city, Internet of Things (IoT), and big data analytics, the complex nature of data-driven civil infrastructures monitoring frameworks has not been fully matured yet [1]. Machine learning (ML) algorithms are thus providing the necessary tools to augment the capabilities of SHM systems and provide intelligent solutions for the challenges of the past. [1]

Crack assessment using DIC is very precise but can require huge computational resources and be very time-consuming [13]. Different approaches to monitoring and evaluation of surface cracks, such as ML algorithms, can be combined with DIC for better description and assessment of concrete elements [13]. However, this kind of research is still scarce in the literature. In Słoński & Tekieli [13], DIC-based monitoring was used to estimate deformation and crack width measurement on the concrete surface, and region-based convolutional neural network (R-CNN) provided accurate automated monitoring and assessment of crack development during laboratory quasi-static tests.

Two different approaches were evaluated in this study: a model driven approach, through a Finite Element model, and a data driven approach, using Machine Learning algorithms. In a model driven approach, the damaged structure is identified from the obtained measurements by comparison with an undamaged state, represented by a physical model, typically FE. An accurate analytical model of the structure requires validation from experimental results, can be computationally intensive and carry model discrepancies, with little to no information about joints and bonds, especially for complex structures [1]. Other than relying on the physical model of the structure, in a data driven approach the model construction is dependent on statistical pattern recognition, which is usually applied by ML algorithms. However, not every ML algorithm is capable of damage prognosis, meaning data-driven approaches are not always predictive models [1].

Therefore, the decision between employing model-driven or data-driven SHM systems or both will depend on the proposed system's requirements, the complexity of the application where the system is deployed, and if the existing data and models can support and provide valuable inferences about the health state of the structure [1].

In recent years, convolutional neural networks (CNN) have been developed and applied for online automatic detection of concrete cracks and structural damage [13]. Zheng et al. [14] reviewed and summarized the development and application of non-destructive testing (NDT) technology for prestressed reinforced concrete infrastructures. The authors concluded that detection visualization, accuracy and efficiency of NDT technology can be improved by combination with artificial intelligence technology, such as neural network deep learning and imaging analysis.

Malekloo et al. [1] provided a very thorough review on SHM and ML, and an outlook on the future of monitoring systems in assessing civil infrastructure integrity. The authors concluded that the extension of ML in SHM dramatically increases the system's capabilities, providing innovative solutions for different research challenges.

2. Experimental program

2.1 Test set up

In the experimental program, two reinforced concrete beam specimens were subject to a three-point bending test. The machine type "Dartec 600 kN" ran in stroke control with an induced displacement rate of 0.01 mm/s for both beams until failure. The reinforcement consisted of two ϕ16 mm ribbed rebars, one in tension and one in compression, and 8 ϕ8 mm stirrups every 80mm. The reinforcement was calculated for a ductile failure mode, through tensile rather than compression strain. Figure 1 illustrates the test set up, differentiating the external deformation seen by the naked eye and measured by DIC, and internal damage represented by reinforcement strain and measured by FOS.

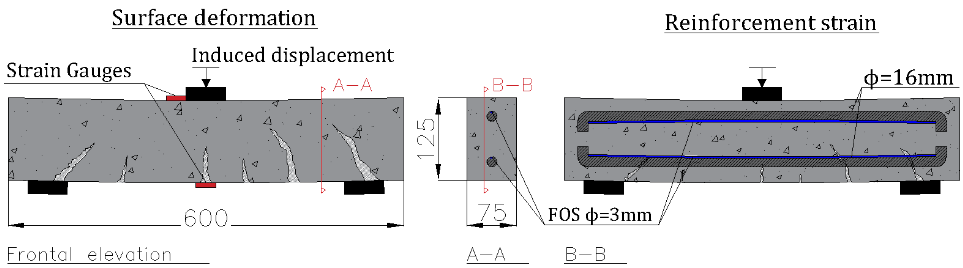

Figure 1. Test set up; frontal elevation (left), cross section (center) and longitudinal section (right).

2.2 Instrumentation

The beam specimens were instrumented with coated FOS, a DIC system and strain gauges. The strain gauges were placed on the concrete surface for point strain measurements, in the center of the lower surface and adjacent to the load cell in the upper surface, as illustrated in Figure 1.

The differences between bonding the sensors to the concrete surface or to the rebars have been studied in the literature – for example, see [5]. In this study, the FOS were placed inside a groove carved in each rebar and bonded with an epoxy glue to measure strain along their length. For each bar, the sensors were also placed adjacent to the rebars and fixated to its exterior with a plastic strip. It was the objective of a companion study by Saback et al. [15] to evaluate the difference in measuring strain inside the rebar and in the concrete adjacent to it. The authors in [15] found the measurements in the concrete to be less reliable, therefore these results were excluded from this analysis and only the measurements in the rebars will be considered. One single five-meter sensor was applied to each beam, including loops in the ends to allow them to exit the formwork and return to cover all the necessary rebar length. The fiber optic system used was ODiSI 6, from Luna Innovations Inc. [16]. Figure 2 presents a picture with the position of the FOS in the beam before casting.

ARAMIS 5M [17] was the chosen DIC system to analyze the specimens. As described in Saback et al. [15], the set up for the ARAMIS system consisted of two 5 MegaPixel cameras rotated to a 25^{o} angle, finely aligned with the embedded laser pointer towards the center of the specimen. The calibration of the cameras was performed using a Calibration Cross CC20/700x560, and the camera's tilt angle, focus, aperture, illumination, and shutter speed were also adjusted to the standards of the test established by the ARAMIS user manual [17]. The facet size used was of 30px, with a point distance of 10px. The facet size was larger than the default value of 15px, which improved the accuracy of the resulting measuring points. The front surface of the beams had to be prepared before the image collection; holes were filled with wall putty, the surface was covered with white contrast spray paint in two layers, and a black speckle pattern was applied using a proper roller. The surface preparation is essential, and its quality can directly influence the precision of the results. A good surface should be smooth, with a good contrast speckle pattern and a dull finish, since reflections can prevent facet computation [18]. The quality of the speckle pattern is also relevant to the results, its most important attributes are speckle size, contrast, speckle edge and speckle density [19]. Figure 2 shows the DIC system tripod and the beam surface with the speckle pattern.

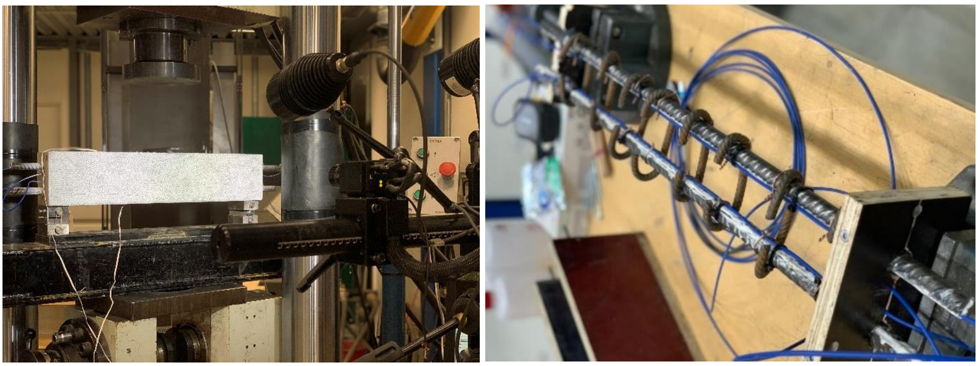

Figure 2. DIC system setup, with speckle pattern on the beam's front side (left), FOS in the rebars before casting (right).

2.3 Material properties

Three cubes were cast from the same concrete as the beams and tested in compression to obtain the resistance of the concrete. The compression test occurred on the same day the beams were tested, more than 28 days after casting, according to the Swedish Standard SS-EN 12390-3:2019 [20]. The average compression strength obtained was $f_{cm} = 50.1\ MPa$, with a standard deviation of 3.08 MPa. The specimens were cast in laboratory. For the ϕ16 mm and ϕ8 mm reinforcement bars, B500B ribbed hot rolled bars were used, with 500 MPa Yield Strength, 1.08 tensile/yield strength ratio, and 200 GPa Young's modulus, as informed by the supplier.

2.4 Results

In the three-point bending test, the maximum load obtained for Beam 1 was 55.70kN, and, for Beam 2, 57.08kN. The machine that performed the test provided measurements of time, load increase and vertical displacement in the center of the upper surface, in the position of the piston. Figure 3 presents the experimental Load x Displacement graph for both beams. The bending reinforcement of ϕ16 mm provided more than enough flexural resistance for this pilot test, therefore, both beams failed due to shear. Figure 4 presents a picture of the beam after failure, with a clear shear crack.

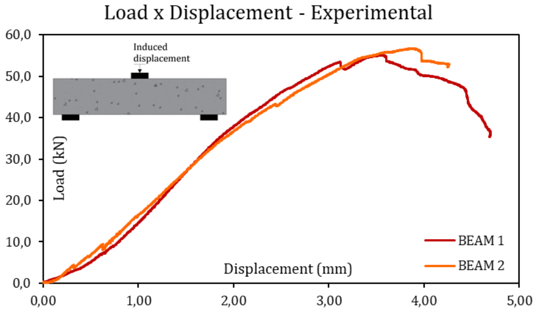

Figure 3. Experimental Load - Displacement graph for Beams 1 and 2.

Figure 4. DIC system setup for test cube with speckle pattern after failure (left), cracking on the back side of the beam after failure (right).

2.4.1 Fiber Optic Sensors (FOS)

The FOS bonded with epoxy inside a groove in each rebar provided continuous strain measurements along the bar length, until the end of the test. The results from the FOS are here presented in terms of Strain x Position, which corresponds to the horizontal length of the beam, from 0 to 60cm. Four FOS graphs were generated; one for the rebar in tension and one for compression, for both beams. Each graph contains five curves, with the evolution of the strain in the loading levels of 10kN, 20kN, 30kN, 40kN and 50kN. The peaks in the curves correspond to the position of the cracks. In the tension graphs, five peaks can be distinguished in Beam 1 and six peaks in Beam 2, especially in the higher loads closer to failure. The FOS Strain x

Position graphs for the rebars in compression and tension in Beam 1 are presented in Figure 5, and in Beam 2, in Figure 6.

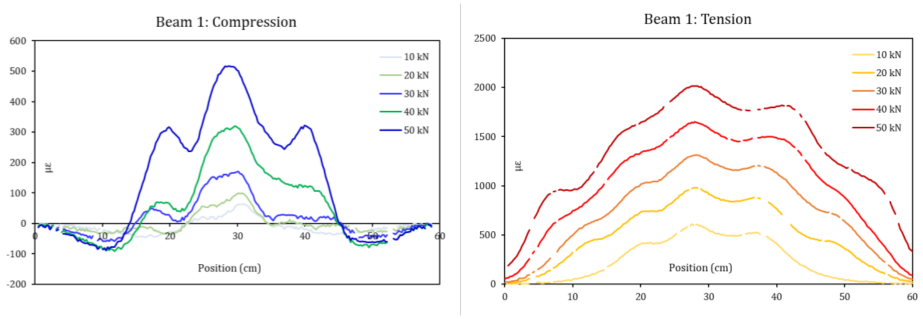

Figure 5. Strain measurements from FOS in Beam 1 for the reinforcement bar in compression (left) and tension (right).

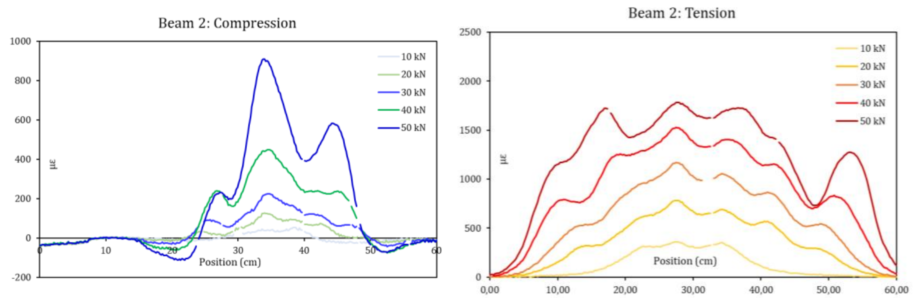

Figure 6. Strain measurements from FOS in Beam 2 for the reinforcement bar in compression (left) and tension (right).

2.4.2 Digital Image Correlation (DIC)

Besides crack propagation, easily observed in Figure 7, Deformation x Position measurements were also obtained from the DIC system data. In Figure 7, it is possible to see two horizontal lines representing where the surface deformation measurements were taken; the black line corresponds to the position of the upper rebar (compression), and the yellow line of the lower rebar (tension). The DIC results are also presented in two Deformation x Position graphs for each beam, one for tension and one for compression, and in 5 different loading levels from 10kN to 50kN (Figure 8 and Figure 9). The DIC curves present more noise than the FOS curves, especially those for compression measurements. In the tension graphs, the peaks which represent the position of the cracks are identifiable.

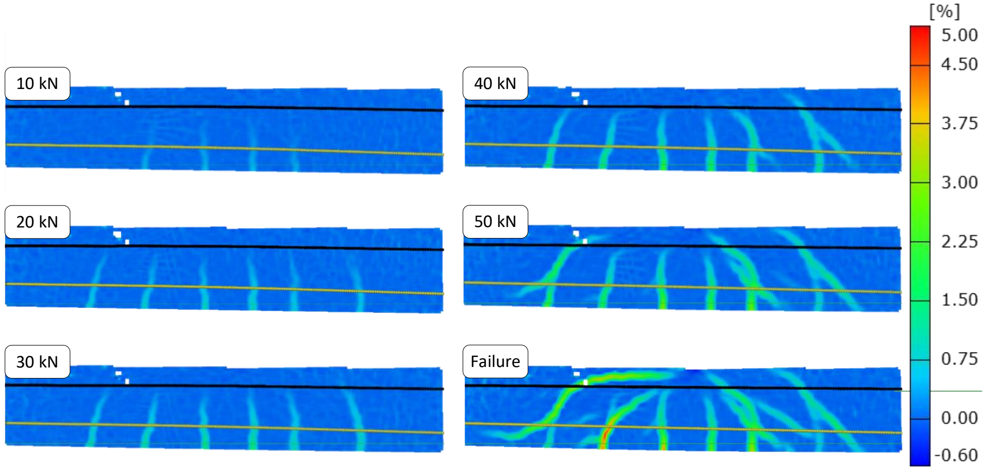

Figure 7. Crack propagation from DIC in Beam 2.

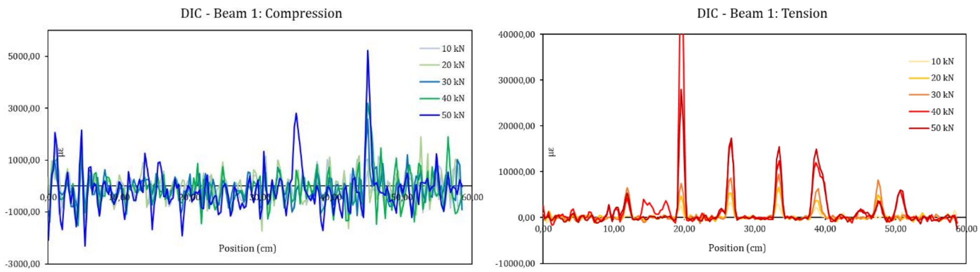

Figure 8. Surface deformation from DIC in Beam 1 in the position of the reinforcement bar in compression (left) and tension (right).

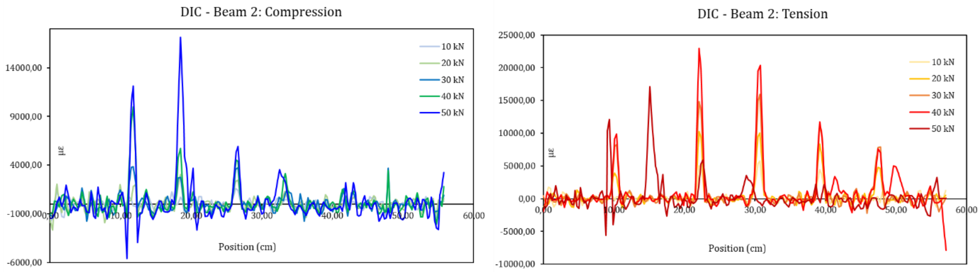

Figure 9. Surface deformation from DIC in Beam 2 in the position of the reinforcement bar in compression (left) and tension (right).

3. Numerical analysis

3.1 Machine Learning

The first numerical analysis performed in this study deployed the following machine learning algorithms: Decision Tree, Support Vector Machine (SVM), Convolutional Neural Networks (CNN), Ensemble (Bagged Trees), and Gaussian Process Regression (GPR). In this section, the models and algorithms used are presented as well as the results from the analysis.

3.1.1 Model parameters

The precision of the models fully depends on how well the dataset has been lined up to find the optimum hyperparameters. The best parameter for both training and validation sets was selected to counter underfitting and overfitting. Therefore, in the Decision Tree model, first the optimized hyperparameter, minimum leaf size of 1, is obtained. Then, Bayesian optimization method is performed as an optimizer in training epochs. Finally, the model was trained for 30 iterations. In the Gaussian SVM method, Gaussian was considered as Kernel function with the scale of 0.43.

The application of CNN in data regression was studied for five different architectures. The first was a Narrow Neural Network (NN) with one fully connected layer including 10 nodes. The second, a Medium NN with one fully connected layer including 25 nodes. The third NN was Wide, with one fully connected layer and 100 nodes. The fourth NN was a Bi-layered NN with two fully connected layers and 10 nodes in each. The fifth and last NN was a Tri-layered NN with three fully connected layers and 10 nodes in each. The activation function used in the defined NN was ReLU, and all the models were trained for 1,000 iterations.

Gaussian Process Regression (GPR) is a nonparametric, Bayesian approach to regression analysis that is creating a significant impression in machine learning. There are several benefits to GPR, including working well on small datasets and providing uncertainty measurements on predictions. The hyperparameters of the Kernel are optimized by a Bayesian optimizer during the GPR fitting. For this model, the prior's covariance was specified by passing a Kernel object in an optimized scale of 0.0597. The noise standard deviation used by the algorithm, called Sigma, was optimized on 0.00917. Therefore, constant, and non-isotropic Rational Quadratic functions were used as covariance and Kernel functions, respectively.

The parameters which served as input to the methods were position (x coordinate in the beam length), loading level and surface deformation in the tension rebar from DIC data, and the output was the predicted response for reinforcement strain in the tension rebar as well. All the models were trained using input data and their corresponding output data. Before the training stage, the datasets were divided into training and validation groups at an 80/20 ratio, to validate and test the methods. The training was carried out using an Intel Core i9-9880H CPU, running at 2.30 GHz.

3.1.2 Results from ML

Table 1 presents the results from the validation of the ML methods, with the training dataset from Beam 1. The reinforcement strain predictions generated from each method were compared to the strain values measured by the FOS and validated according to statistical parameters, besides prediction speed and training time. The statistical parameters presented in Table 1 are coefficient of determination (R^2), Root-Mean-Square Error (RMSE), Mean-Squared Error (MSE) and Mean Absolute Error (MAE). These parameters were chosen for being common in statistical analysis to compare predicted and true responses, and are briefly explained as follows:

- Coefficient of determination (R^2) indicates the proportional amount of variation in the response variable y explained by the independent variables x in the linear regression model (Equation 1). Larger values of R^2 are desired, as it means more variability is explained by the linear regression model.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(\Delta\varepsilon_{i,tru} - \Delta\varepsilon_{i,pre}\right)^2}{\sum_{i=1}^{n}\left(\Delta\varepsilon_{i,tru} - mean\left(\Delta\varepsilon_{i,tru}\right)\right)^2}$$

Equation 1

Where, $\Delta\varepsilon_{i,pre}$ and $\Delta\varepsilon_{i,tru}$ are the estimated and true values of strain in the embedded reinforcement, respectively.

- Root-Mean-Squared Error (RMSE) is a risk function used in regression analysis. It represents the average squared difference between the predicted and the true values, given by Equation 2. Smaller RMSE values are desired, as they indicate closer predictions to the true values, and, therefore, well trained models. The RMSE is considered a measure of quality for the prediction model.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(\Delta\varepsilon_{i,pre} - \Delta\varepsilon_{i,tru}\right)^2}{n}}$$

Equation 2

- Mean-Squared Error (MSE) measures the quality of an estimator. It is derived from the square of Euclidean distance, so it is always a positive value that decreases as the error approaches zero. Therefore, smaller values are desired. MSE is calculated with Equation 3.

$$MSE = \frac{\sum_{i=1}^{n}\left(\Delta\varepsilon_{i,pre} - \Delta\varepsilon_{i,tru}\right)^2}{n}$$

Equation 3

- Mean Absolute Error (MAE) is calculated in Equation 4 as the sum of absolute errors divided by the sample size.

$$MAE = \frac{\sum_{i=1}^{n}\left|\Delta\varepsilon_{i,pre} - \Delta\varepsilon_{i,tru}\right|}{n}$$

Equation 4

Table 1. Validation of ML methods, training dataset: 80% of test data (Beam 1).

Model	R^2	RMSE	MSE	MAE	Prediction speed (obs/sec)	Training time (sec)
Gaussian SVM	0.90	1.61E-02	2.59E-04	8.49E-01	~80,000	1.80
Narrow NN	0.90	1.67E-02	2.79E-04	9.55E-03	~150,000	3.98
Medium NN	0.91	1.55E-02	2.42E-04	8.85E-03	~230,000	3.16
Wide NN	0.91	1.53E-02	2.34E-04	8.15E-03	~200,000	11.78
Tri-layered NN	0.91	1.56E-02	2.43E-04	8.16E-03	~200,000	4.87
Bi-layered NN	0.92	1.49E-02	2.22E-04	8.07E-03	~220,000	4.00
Decision Tree	0.95	1.17E-02	1.36E-04	5.05E-03	~94,000	36.09
Ensemble	0.96	1.00E-02	1.01E-04	4.41E-03	~38,000	143.41
GPR	0.99	4.83E-03	2.33E-05	2.01E-03	~22,000	4283.30

Figure 10 to Figure 16 present graphs comparing the true and predicted responses, and residuals for the evaluated ML models. The precision of the models can be evaluated graphically by analyzing the distance between the predicted response (blue dots) and the true response (straight black line). For the residuals' graphs, the distance between the points and the zero line are the errors. The horizontal axis represents the position in the beam, from 0 to 60cm; it is expected that the errors are higher in the position of cracks.

From analyzing the numerical parameters in Table 1, confirmed visually by Figure 16-17, it was possible to conclude that the three models with the most accurate predictions were GPR, Ensemble and Decision Tree. These models were then tested with the remaining 20% of test data, previously unseen by them, and compared with the same statistical parameters in Table 1. The results from this evaluation are presented in Table 5.

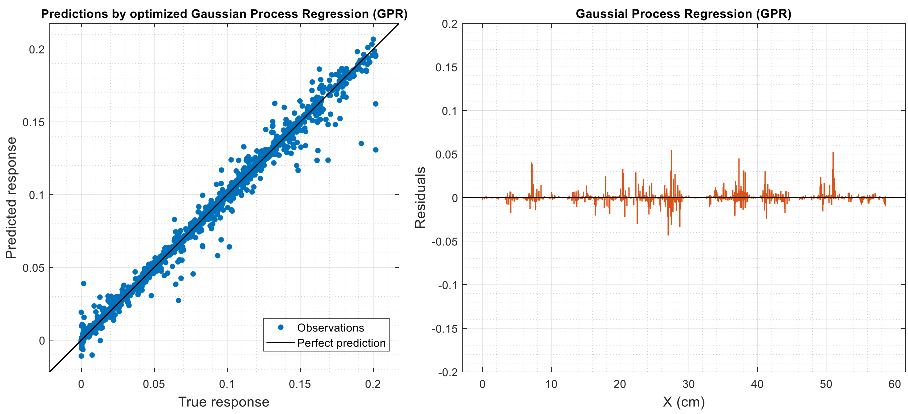

Figure 10. Predicted x True responses (left) and Residuals for the GPR model.

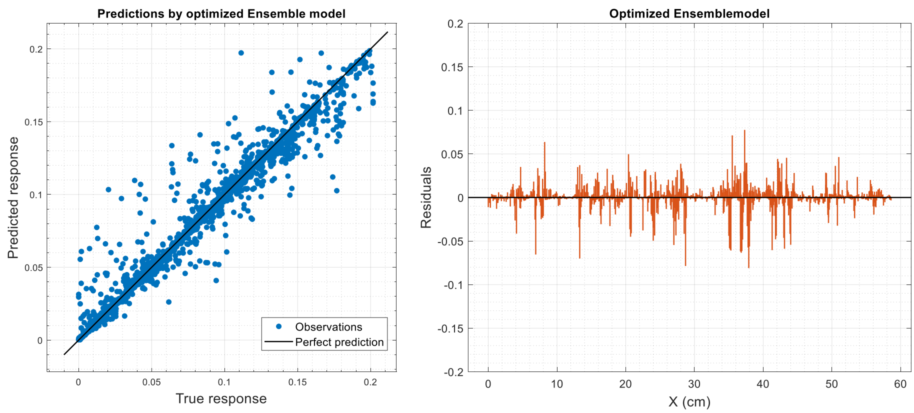

Figure 11. Predicted x True responses (left) and Residuals for the Ensemble model.

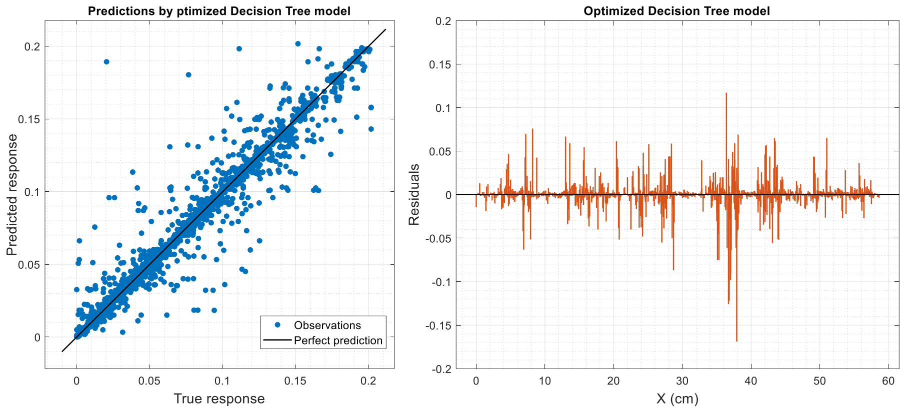

Figure 12. Predicted x True responses (left) and Residuals for the Decision Tree model.

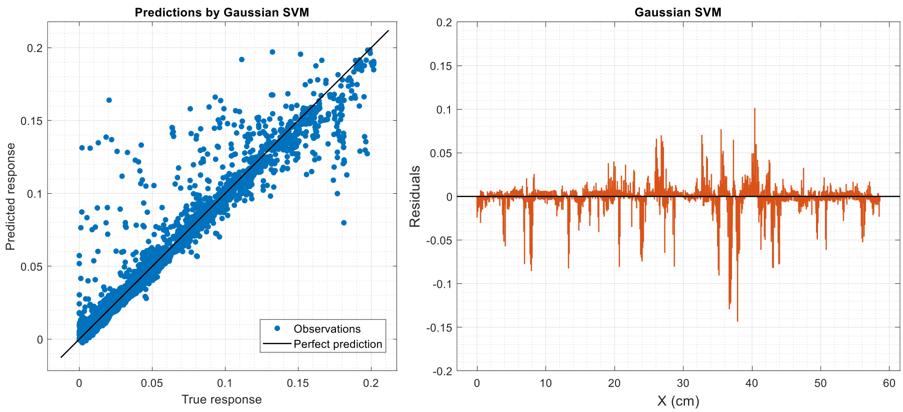

Figure 13. Predicted x True responses (left) and Residuals for the Gaussian SVM model.

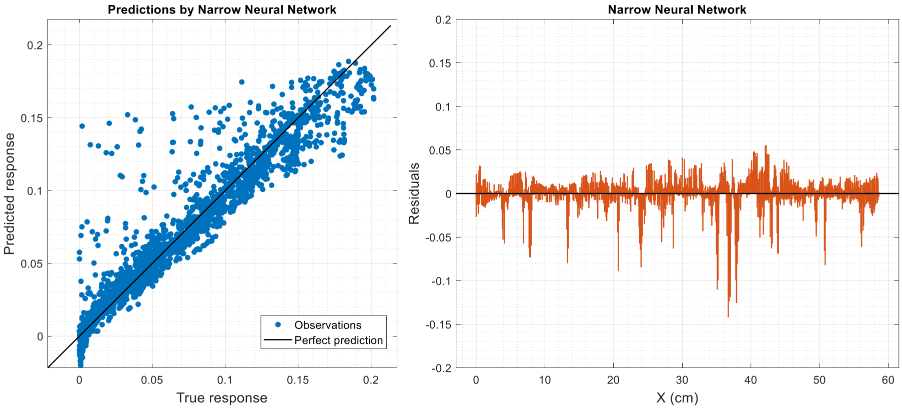

Figure 14. Predicted x True responses (left) and Residuals for the Narrow NN model.

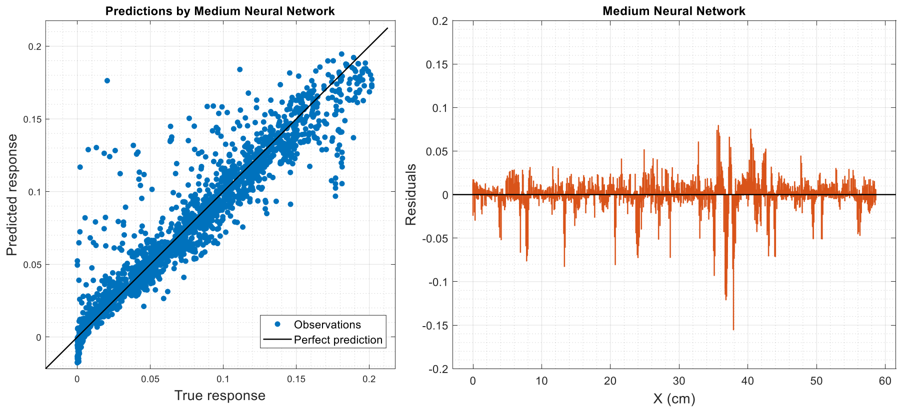

Figure 15. Predicted x True responses (left) and Residuals for the Medium NN model.

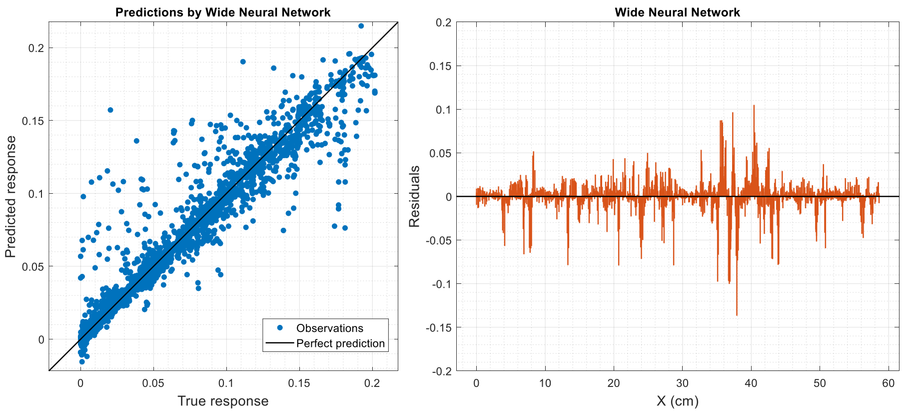

Figure 16. Predicted x True responses (left) and Residuals for the Wide NN model.

Table 2. Comparison of best performing ML models with dataset of 20% of test data (Beam 1).

Model	R^2	RMSE	MSE	MAE
Decision Tree	0.96	1.14E-02	1.29E-04	4.71E-03
Ensemble	0.98	8.52E-03	7.27E-05	3.68E-03
GPR	0.99	2.52E-03	6.35E-06	1.24E-03

The first step of the correlation analysis was to train and test the models with experimental data from Beam 1, as explained. Upon evaluation of the results in Table 5, the GPR, Ensemble and Decision Tree models presented low errors and accurate predictions, and therefore remained in the analysis. Next, surface deformation data from DIC measurements in Beam 2 were fed into the models to perform predictions on reinforcement strain. Then, the predicted response was compared with true values, i.e., the measurements taken by FOS instrumented in the tension rebar in Beam 2. This process is illustrated in Figure 17; Figure 18 presents comparative graphs between reinforcement strain in the tension rebar as predicted by the GPR method and measured by FOS in Beam 2, for loading levels 20, 30, 40 and 50kN; and Table 3 presents the statistical errors.

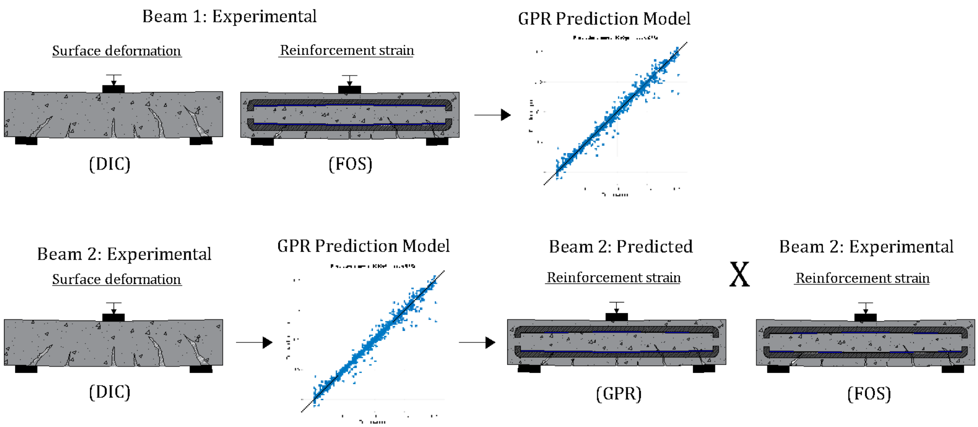

Figure 17. Process of developing a prediction model from Beam 1 experimental data, using this model for Beam 2, and comparing prediction and true results.

The models were trained with data from Beam 1, then used to predict the reinforcement strain from the surface deformation in Beam 2. The errors from these predictions, presented in Table 3, are higher than those presented in Table 2, that correspond to a prediction from the same dataset with which the models were trained.

Visual analysis of the graphs in Figure 18 shows that the correlation increases with the increased loads, which is particularly useful when lower loads are known and used to predict future behavior with increased loads. The peaks, which represent the position of cracks, easily identified in the FOS curves are not as straightforwardly seen in the Prediction curves. However, the overall shape of the curves is similar if noise in the Prediction curve can be reduced. The red dotted lines represent the position of the cracks measured by the DIC system, therefore, cracks in the surface of the specimen. It is worth noting that a slight difference between the position of the cracks in the surface and in the reinforcement level can be expected, considering that these measurements occur at different depths, and that the crack planes might not be perfectly perpendicular to the direction of the reinforcement [5].

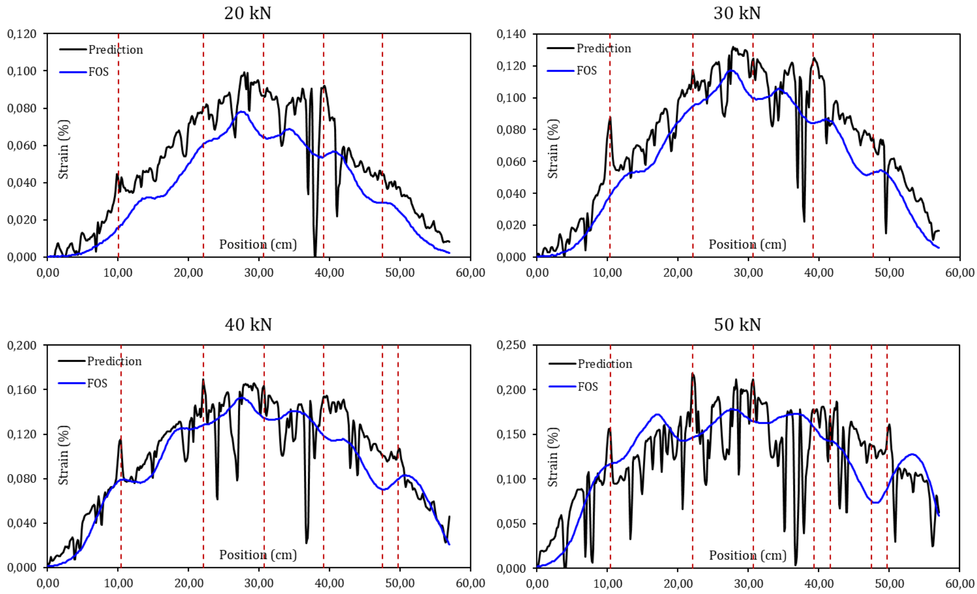

Figure 18. Comparative graphs between reinforcement strain predicted by GPR model and measured by FOS for Beam 2, including crack positions identified by DIC (dotted red line).

Table 3. Statistical errors in reinforcement strain predictions (dataset: Beam 2).

Model	R^2	RMSE	MSE	MAE
Decision tree	0.83	2.20E-02	4.85E-04	1.64E-02
Ensemble	0.86	2.00E-02	4.02E-04	1.54E-02
GPR	0.82	2.21E-02	4.90E-04	1.63E-02

3.2 Finite Element Modelling

This section presents the numerical model and analysis performed using Finite Elements. The programs used were GiD, for geometry design and pre-processing, and ATENA, for post-processing. The aim of the analysis was to numerically predict the reinforcement strain and compare its accuracy with the measurements from the FOS and the predicted response from the ML model.

3.2.1 Material characteristics

The model of concrete behavior used in this analysis combines constitutive models for tensile (fracturing), which employs the Rankine failure criterion, and compressive (plastic) behavior. The fracture model employs the Rankine failure criterion and bases on the classical orthotropic smeared crack formulation and crack band model, which assumes crack spacing larger than a finite element size. The hardening/softening plasticity model is based on Menétrey-Willam failure surface. The model uses return mapping algorithm for the integration of constitutive equations [21]. The plasticity model is combined with the fracture model through an algorithm based on recursive substitution, which allows the models to be formulated and developed separately. The algorithm can describe cases in which failure surfaces are active for both models, and to simulate concrete cracking, crushing under high confinement, and crack closure due to crushing in other material directions.

The mechanical properties of the concrete were determined using standardized concrete cube tests. The mean compressive (f_{cm}) cube strength obtained in laboratory was 50.13 MPa. Based on this value, a compressive cylinder strength (f_c) of 35.8 MPa, a tensile strength (f_{ct}) of 2.28 MPa, a Young's modulus (E_c) of 35,180.2, and a fracture energy (G_f) of 139 N/m were derived and used for FEM analysis.

Discrete bars were used to model the steel reinforcement. After the peak strength (f_u), the stress was reduced to 1% of f_u so that internal stress redistribution could be assured in the numerical computations. The support and loading plates were modelled using a linear, elastic, and isotropic material.

3.2.2 Boundary conditions

The load was applied as a predefined displacement of 0.01mm per step, through a plate of elastic material located on the center of the top surface of the beam. Two loading intervals were used, the first for self-weight, and the second for the induced displacement. A point monitor was used for displacements in the center of the bottom surface of the beam, and a linear monitor was used for strain in the bending rebars. Plates of linear elastic materials were also used to represent supports of the beam, and the interface between the plates and the beam was modeled using a fixed contact for surface condition. Figure 19 illustrates the described boundary conditions in the FE model.

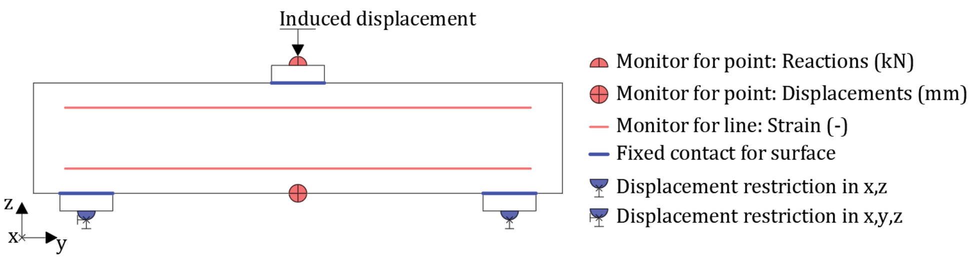

Figure 19. Boundary conditions in FE model.

3.2.3 Numerical methods and finite elements

A standard incremental and iterative Newton–Raphson method is used to compute the model stiffness in the FE model. Four solution errors were used to check the following convergence criteria in this study: displacement increment, normalized residual force, absolute residual force, and energy dissipation. Details about the convergence criteria and Newton–Raphson equilibrium iterations can be found in Cervenka et al. [21].

3D solid, hexahedral elements were used for the concrete beam. After a parametric investigation, adequate convergence was obtained for a structured mesh with element size between 15.6mm and 20mm. For the reinforcement, linear elements of 5.6mm were used, which implies a mesh resolution of 100 elements per rebar to provide a more accurate account of the strain.

3.2.4 Results from FE

The numerical model presented failure due to shear, as did both beams in the experiment, which can be seen by the distinct shear crack in Figure 20. The maximum load obtained in the FE model was 55.9kN, against 55.2kN for Beam 1 and 56.7kN for Beam 2. Figure 21 presents comparative graphs between reinforcement strain in the tension rebar measured by FOS and obtained in the FE analysis, for loading levels 20, 30, 40 and 50kN; and Table 4 presents the calculated statistical errors.

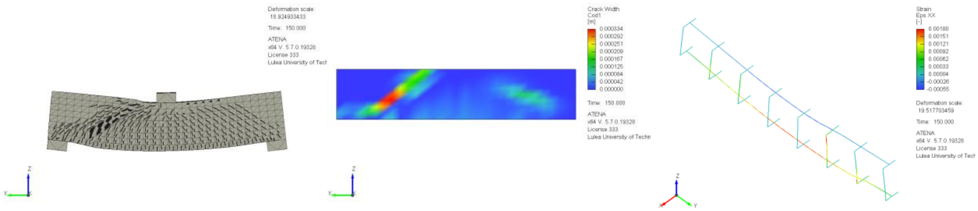

Figure 20. Deformed 3D FE model displaying cracks and mesh (left), undeformed model displaying crack width (center), and strain in reinforcement bars (right).

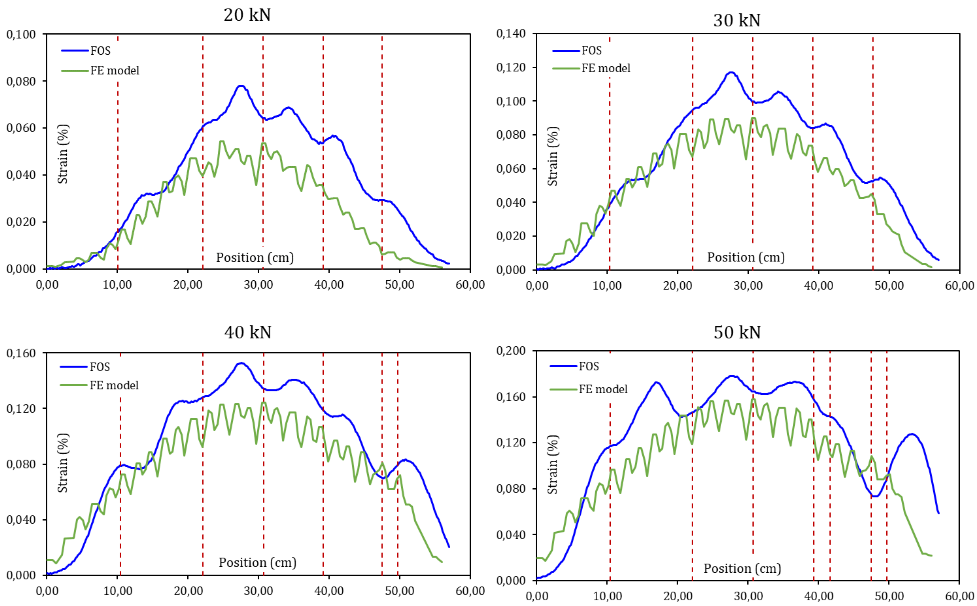

Figure 21. Comparative graphs between reinforcement strain in FE model and measured by FOS for Beam 2, including crack positions identified by DIC (dotted red line).

Table 4. Statistical errors in FE model for reinforcement strain predictions.

Model	R^2	RMSE	MSE	MAE
Finite Element	0.82	2.22E-02	4.84E-04	1.39E-02

Figure 21 shows that the accuracy of the predictions is higher under elastic behavior in lower loads and further from the center of the beam, in the left and right edges of the length, where there is lower cracking. Reinforcement strain was underestimated by FE in the center of the beam, unlike ML predictions which presented a better agreement or an overestimation, preferred in terms of safety.

The FE curve contains more peaks and valleys than the FOS curve, which has a lower number of peaks representing only the main cracks. In Figure 20, the deformed model to the left displays several cracks, even those with smaller crack width values by comparison with the color-coded model in the center. The FE curve, therefore, is more sensitive to crack width, and this is reflected in the number of irregularities in its shape. Finer meshes produce more irregular strain curves, as a higher number of nodes allow for the representation of cracks with lower distance between one-another. As mentioned in the ML analysis, the red dotted lines representing the cracks on the concrete surface measured by DIC are expected to have a slight misalignment with the peaks in the FOS curve, due to the non-linearity of the cracks.

4. Discussion

From the presented experimental and numerical results, the discussion focuses on establishing a correlation between surface deformation and reinforcement strain using ML and comparing the accuracy of ML and FE models to predict reinforcement strain in a RC beam. The accuracy of the models can be compared quantitatively through the statistical parameters in Table 5, and visually from the Strain x Position graphs in Figure 22.

The numerical comparison from Table 5 shows that all the evaluated methods presented similar accuracy in predictions. The Ensemble method provided the most accurate predictions among the ML methods, with slightly higher R^2 and lower values for all three errors. Its results were also more accurate than the FE model. The 4.88% higher R^2 value means the Ensemble method was able to explain the variability of results to a slightly higher extent. Taking the RMSE as a measure of quality of the models, the 9.91% lower RMSE of the Ensemble implies this difference in quality. The same can be stated about the 16.94% lower MSE. The MAE value, however, was 10.79% higher in the Ensemble model than in the FE.

From the graphs in Figure 22, both predictions increased in accuracy with increased loads, and neither was accurate in predicting the position of main cracks. Both predictions presented a general trend in shape similar to the experimental data, even overlapping with its curve and each other at some points.

In both ML and FE methods, pre-processing was longer than processing time. For this small specimen, processing was in the scale of <10 minutes and therefore not a relevant comparison parameter. It is worth noting that the FE model can predict other aspects of structural behavior besides reinforcement strain, isolated here only for the purpose of this analysis and comparison with the ML model. Therefore, it requires more information about the structure to perform accurate predictions of its behavior, unlike the ML algorithm that worked with the three aforementioned variables – position, load and surface deformation. Relevant information required by in FE modelling include detailed geometry, boundary conditions, material properties, and load increment.

Table 5. Statistical comparison between ML and FE models' predictions for reinforcement strain and FOS measurements in Beam 2.

Model	R^2	RMSE	MSE	MAE
Decision tree	0.83	2.20E-02	4.85E-04	1.64E-02
Ensemble	0.86	2.00E-02	4.02E-04	1.54E-02
GPR	0.82	2.21E-02	4.90E-04	1.63E-02
Finite Element	0.82	2.22E-02	4.84E-04	1.39E-02

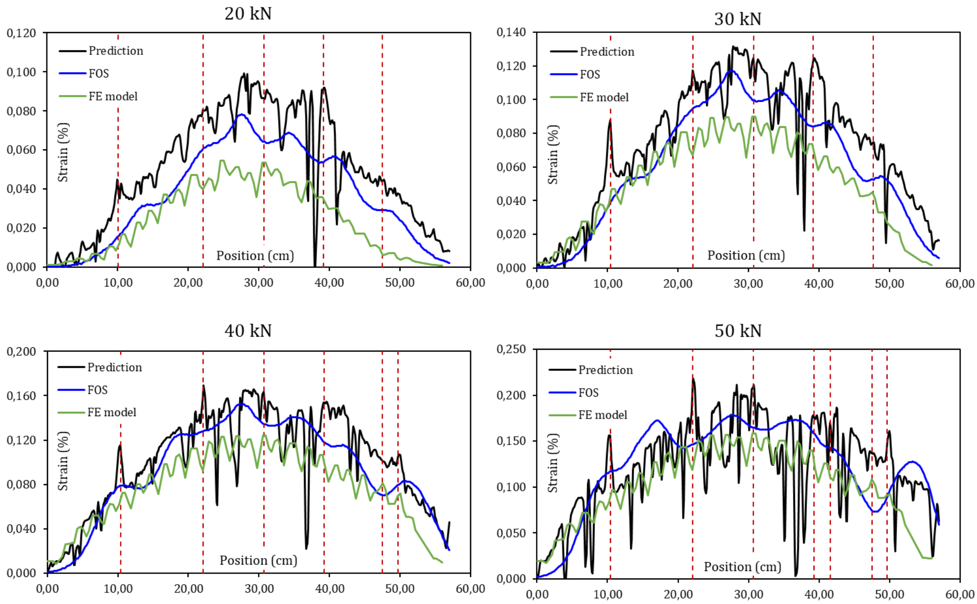

Figure 22. Comparative graphs between reinforcement strain predicted by GPR model, FE model and measured by FOS, including crack positions identified by DIC (dotted red line).

5. Conclusions

The objective of this study was to obtain a numerical correlation between surface deformation and reinforcement strain in a RC beam specimen. To achieve that, ML and FE models were used, and their results were compared for accuracy. The novel contributions of this research can be summarized in these three aspects: presenting a quantitative correlation between surface deformation and reinforcement strain, using ML predictive algorithms with DIC technologies, and comparing the accuracy of ML and FE to predict structural behavior. From the presented experimental and numerical data, discussion, and comparative statistical parameters, it can be concluded that:

- Reinforcement strain could be predicted from surface deformation with an accuracy of 86%, and errors in the scale of 10^{-2}.
- The most accurate prediction was obtained using ML methods, from the Ensemble model. The FE predictions tended to underestimate the reinforcement strain. However, the difference in accuracy and processing time from the predictions obtained by the other ML and FE models was not significant. Therefore, the prediction method can be chosen according to available data, user preference and other results wished to be obtained.
- The location of the main cracks can be identified by the peaks in the FOS strain curves, however, this could not be achieved by the predicted strain curves produced by neither one of the two methods. Nevertheless, crack propagation on the surface is clearly provided by the DIC system.

For future research, this analysis is planned to be replicated in a comprehensive experimental program that will be carried out at Luleå University of Technology, where two full scale trough bridges cast in laboratory will be tested to failure. This program is part of a broader research which aims at improving automated damage detection in bridge inspection and asset management using Digital Twins. The prediction of future behavior achieved in this analysis contributes as a module for Bridge Management Systems currently under study.

Acknowledgements

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PAPER IV

Bridge Management Systems: overview and framework for smart management

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Bridge Management Systems: overview and framework for smart management

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Abstract

Throughout the world, many medieval and historic bridges remain in operation. Deterioration and failures have increased in the already aging bridges due to consistent growth in traffic volume and axle loads. Therefore, the importance of Bridge Management Systems (BMS) to ensure safety of operation and maximize maintenance investments has also increased. Recent improvements in technology also contribute to the demand for optimized and more resource-efficient BMS. In this study, a literature review was performed to map current bridge management practices and systems in operation in the world. The outcomes identified Bridge Information Modelling (BrIM) and Digital Twins as novel approaches that enable efficient management of the whole lifecycle of a bridge. From these outcomes, a framework of an ideal BMS is proposed to achieve automated and smart management of bridges.

Keywords: bridges; bridge management systems; BMS; BrIM; review.

1 Introduction

Bridges on public roads faced lighter loads before the proliferation of road traffic. The reaction to the then increased accounts of failure was to establish national standards requiring regular bridge inspections and evaluations. The activity of managing and scheduling bridge inspections and evaluations, recording and handling bridge data, and making maintenance recommendations became known as bridge management [1].

Bridge management is an essential part of long-term asset management, applicable to all existing bridges, old and new [2]. The main purpose of management is maintaining the bridges by identifying deficiencies and ensuring the continued safety of traffic through rehabilitation [2]. In the past few decades, the scope of bridge management has grown, and the goal of maximizing the effect of maintenance funds to protect the investment in bridges has been added to the primary goal of protecting the safety of the traveling public [1].

Expansion in physical infrastructure and improvements in technology have lead government authorities to find ways to enhance efficiency in managing maintenance activities and maximize the value of maintenance spending [3]. Recent developments in Information Technology (IT) promote changes in bridge management, better quality of inventory and inspection databases, and more control over deterioration, forecasting, and management models [4]. Together with the constantly improving technology, the concern with investment in bridges has created a demand for optimized bridge management systems (BMS).

This context motivated this study, which provides an overview on current bridge management practices and discusses improvements on BMS with regard to recent technologies development. The overview was conducted through a state-of-the-art literature review on BMS, covering BMS in the world, modules of a BMS and current bridge management practices. The systematic approach to the literature review is described in the methodology section of this paper.

The discussion section then covers all aspects comprised in a BMS. The current situation is analysed from the perspective of the data presented in the review, and improvements are proposed based on technologies identified in the literature. Closing the discussion, a thorough modular scope for a BMS is proposed to further promote improved frameworks for bridge management. Lastly, the conclusions of the study are drawn in order to summarize the identified gaps in BMS and respective suggested improvements, besides recommendations for future studies.

2 Methodology

The state-of-the-art literature review of bridge management systems presented in this study is part of a broader review on facility management of bridges using digital models. The methodology for the review comprised three main steps: definition of the strings of research, research of the selected database, and assessment of the articles. A similar methodology is used in companion paper "Framework for facility management of bridge structures using Digital Twins".

The strings of research were defined based on keywords identified in the primary references, which were the result of a preliminary exploratory literature review. Upon assessment of the primary references, the most recurring keywords were divided into five groups of subjects. Finally, each group was given a set of strings as follows:

- BIM: ("BIM" **OR** "Building information modelling");
- Bridges: ("Bridge information modelling" **OR** "BrIM" OR "Bridge" **OR** "Bridges");
- Digital Twins: ("Digital twin" **OR** "Digital twins" **OR** "DTM");
- Management/inspection: ("Facilities management" **OR** "Facility management" OR "inspection" **OR** "monitoring");
- Maintenance: ("Maintenance" **OR** "assessment").

Sixteen different searches were then performed in Scopus, the selected database. The search results were only limited by year, with the acceptable range set from 2010 to 2020 for the results to be considered as state-of-the-art. Each search contained a combination of three (ten combinations), four (five combinations) or five (one combination) groups of strings. The string search was applied to title, keywords and abstract of each paper.

Two of the sixteen combinations were eliminated for being too broad, and the remaining fourteen combinations added up to a total of 600 results in Scopus. Some of the papers were eliminated before assessment, because the article had already been assessed in a previous string combination result, written language other than English, conference review paper or unrelated area of research (medicine, psychology, etc.).

The selected articles were then evaluated using three different filters: Filter 1 for title, abstract and keywords; Filter 2 for introduction and conclusion; and Filter 3 for the entire paper. The main reason for rejection in all three filters was low relevance of the subject to the scope of this study, other than technical reasons such as lack of access to the full paper or overall quality. The articles approved after the third filter, that related to the main topic of this study, were included in the review. An iterative process also occurred and references from selected papers were assessed and included to the study as well.

The distribution of the selected papers over the previously established range of years suggests that this is a rather recent field of research: 50% were published between 2010 and 2018, and 50% in 2019 and 2020. The articles obtained from the aforementioned methodology are addressed in the following literature review section, divided into the subsections: BMS in the world, modules of a BMS and current practices on bridge management.

3 Literature review: BMS

3.1 BMS in the world

Generally, each country's road administration entity has its own management system, with which tunnels, culverts, ferry berths, retaining walls, pavements and quays can also be managed, besides bridges [5]. These systems are either developed internally by the managing organization itself (with or without the help of private companies), or bought off-the-shelf and modified to suit their needs [6]. The majority of the systems are used only within one country, most likely due to the differences in bridge management practices between countries [6]. When systems are bought off-the-shelf and adopted by an agency, they are usually significantly modified, which results in a new system with a new name (e.g. Eirspan that was developed using DANBRO as a starting point) [6].

Helmerich et al. (2008) [7] ranked the best-known software based digital bridge management systems in Europe: BaTMan (Sweden), BAUT (Austria), DANBRO (Denmark), KUBA (Switzerland), SIB-Bauwerke (Germany), SMIS (United Kingdom). The Federal Highway Administration (FHWA), American Association of State Highway and Transportation Officials (AASHTO), and National Cooperative Highway Research Program (NCHRP) of the United States sponsored a scanning study of how highway agencies in Europe and South Africa handle bridge maintenance, management, and preservation [5]. The U.S. delegation met with bridge preservation and maintenance experts from these countries (apart from Austria), and also from Finland, France, Norway and South Africa [5]. Each of these countries' management system, condition rating scale and frequency of bridge inspections are presented in Table 1.

Table 1. Bridge management systems for different countries. Adapted from FHWA (2005) [5].

Country	**Management system**	**Rating scale**	**Bridge inspections (frequency)**
Denmark	DANBRO, DANBRO+	0-to-5	Principal (6 years), Daily (road patrol), Semiannual
Finland	HiBris, Hanke-Siha	0-to-4	Annual, General (5 years)
France	LAGORA	1-to-3	Routine (frequent), Annual, Condition Evaluation (3 years), Detailed (3 to 9 years)
Germany	SIB-Bauwerke	1-to-4	Superficial (3 months), General (3 years), Major (6 years)
Norway	Brutus	1-to-4	General (1 year), Major (5 years)
South Africa	STRUMAN	Four categories*	Monitoring (frequent), Principal (3 to 5 years)
Sweden	BaTMan	Three categories**	Regular (frequent), Superficial (6 months), General (3 years), Major (6 years)
Switzerland	KUBA, UplaNS		Principal (5 years)
United Kingdom	SMIS	1-to-5	General (2 years), Principal (6 years)

*Degree (severity), extent, relevancy (in the load path), and urgency of repair
**Physical, functional and economic condition (related to extent of damage)

In the United States, the FHWA sponsored the creation of two highway BMS - BRIDGIT and PONTIS, and both deal with management of bridges on state and interstate highways [1]. PONTIS is the predominant bridge management system employed in the USA. It is currently managed by AASHTO and has been renamed BrM (in reference to bridge management) [1, 8].

Some of the other BMS currently in operation in the world are: SAMOA, APTBMS (Italy) [6, 9]; FBMS (Finland), GBMS (Germany), Eirspan (Ireland), DISK (Netherlands), SMOK/SZOK (Poland), SGP (Spain) [6]; GOA (Portugal) [10]; OBMS, QBMS, EBMS, PEI BMS, GNWT (Canada) [6]; SGO (Brazil) [11]; Bridge-ASYST, MRWA and NSW(Australia) [6, 9]; MICHI, RPIBMS (Japan) [6, 9]; T-BMS (Taiwan) [12]; KRMBS (Korea) [6].

3.2 Modules of a BMS

Each one of the systems presented in the previous section can be used by their country's road administration agency to perform a different set of management activities. The tasks can vary according to the specific needs and resources of each country, they can be more or less thorough and frequent, and prioritize different parts of the BMS scope. However, the scope itself is similar among different BMS, as it consists primarily of inspection, structural health monitoring and rehabilitation [2].

Inspection is the first step, in which the inspectors establish the physical and functional conditions of individual structural members, as well as the entire bridge [13]. Along with the inspectors' own experience, the condition is assessed using equipment, well-developed tools and techniques [13]. Lastly, after applying a rating criteria to determine the condition of the bridge, rehabilitation procedures are applied [2].

The management tasks are usually divided into different modules in the systems. For a BMS to function efficiently, the system modules need to be integrated internally to minimize duplication and user inputs, and thus achieve optimal performance [3]. The modules are usually related to inventory, inspection, condition analysis and maintenance planning. The main module is the inventory, which is considered the foundation from which the rest of the BMS operates [3]. According to Woodward et al. (2001) [14], a bridge management system that is able to answer the various objectives of the managers must be modular and incorporate at least the following principal modules:

1. Inventory of the stock;
2. Knowledge of bridge and element condition and its variation with age;
3. Evaluation of the risks incurred by users (including assessment of load carrying capacity);
4. Management of operational restrictions and the routing of exceptional convoys;
5. Evaluation of the costs of the various maintenance strategies;
6. Forecast the deterioration of condition and the costs of various maintenance strategies;
7. Socioeconomic importance of the bridge (evaluation of indirect costs);
8. Optimization under budgetary constraints;
9. Establishment of maintenance priorities;
10. Budgetary monitoring on a short and long-term basis.

3.3 Current practices on bridge management

In order to handle the amount of information required to achieve optimal management of infrastructure, managing agents are using increasingly sophisticated computerized management systems to support their decision making process [6]. Mirzaei et al. (2014) [6] conducted a survey which contemplated 25 bridge management systems, used to manage approximately 1.000.000 objects, from 18 countries. Table 2 and Figure 1 present the surveyed systems, their respective countries and the number of managed objects (bridges, culverts, tunnels, retaining structures and other objects).

The main results of the survey conducted by Mirzaei et al. (2014) [6], which contemplated 25 infrastructure management systems currently in operation, are presented in Table 3. The results concern: data entry and information access; stored information; information handled on the structure level; cost information; predictive capabilities; use of prediction information; education and qualification of those that use the systems.

Table 2. Surveyed systems – number of bridges and other objects. Adapted from Mirzaei et al. (2014) [6].

Country	**BMS**	**Bridges**	**Other objects**	**Total**
Australia	MRWA	2 815	83	2 898
Australia	NSW	2 702	3 441	6 143
Canada	eBMS	373	-	373
Canada	GNWT	102	253	355
Canada	OBMS	2 800	2 600	5 400
Canada	PEI BMS	800	400	1 200
Canada	QBMS	8 700	2 400	11 100
Denmark	DANBRO	2 250	-	2 250
Finland	FBMS	13 787	3 278	17 065
Germany	GBMS	10 000	-	10 000
Ireland	Eirspan	2 997	-	2 997
Italy	APTBMS	1 108	845	1 953
Japan	RPIBMS	4 239	779	5 018
Korea	KRMBS	6 192	-	6 192
Latvia	Lat Brutus	934	1 045	1 979
Netherlands	DISK	3 836	1 755	5 591
Norway	BRUTUS	11 500	8 580	20 080
Poland	SMOK	7 902	25 348	33 250
Spain	SGP	24 534	15 511	40 045
Sweden	BaTMan	33 000	12 790	45 790
Switzerland	KUBA	12 574	18 739	31 313
USA	AASHTO	500 000	250 908	750 908
USA	ABIMS	9 728	6 114	15 842
Vietnam	Bridgeman	4 239	-	4 239

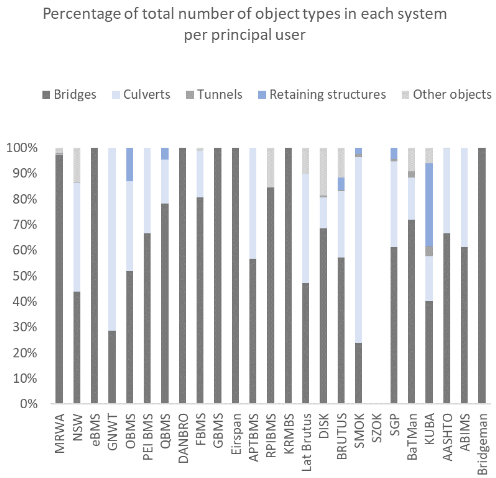

Figure 1. Percentage of object types in each system. Adapted from Mirzaei et al. (2014) [6].

Table 3. Current practices in BMS [6]

Nº (%)	**Item**
	Data entry and information access
11 (44%)	allow data entry through mobile computers
12 (48%)	allow access to information in the system over the internet.
	Stored information
7 (28%)	allow archive of basic construction information in the system (the majority of systems allow the information to be either stored in some way or referenced).
24 (96%)	allow archiving of inspection information.
23 (92%)	allow archiving of intervention history.
	Information handled on the structure level
24 (96%)	handle condition information from inspections.
20 (80%)	handle information on load carrying capacity.
19 (76%)	handle information from inspections with respect to safety.
18 (72%)	handle information from inspections with respect to risk.
	Cost information
24 (96%)	can handle intervention cost information.

6 (24%)	handle inspection costs.
11 (44%)	handle traffic delay costs.
7 (28%)	handle accident costs.
8 (32%)	consider environmental costs.
Predictive capabilities	
19 (76%)	can predict deterioration, 12 of these systems use probabilistic methods.
18 (72%)	can predict the improvement due to future interventions (9 use probabilistic methods).
19 (76%)	are capable of determining optimal intervention strategies.
Use of prediction information	
23 (92%)	are used to prepare budgets.
15 (60%)	are used to set performance standards.
13 (52%)	are used to match funding sources.
Education and qualification of those that use the systems	
25 (100%)	provide education for inspectors that enter data into the system (21 also provide certifications).
22 (88%)	provide education for users of the system (11 also provide certifications).
14 (56%)	have audits to use and verify data and predictions.

4 Discussion

The overview in Table 3 of some of the BMS currently in operation shows that there is room for improvement in many aspects. This section presents an analysis of current practices in bridge management systems, mainly supported from, but not restricted to, the data in Table 3. Improvements are proposed, based on technology identified in the literature, as well as a thorough modular scope for a BMS.

Each country currently handles infrastructure management independently. However, a certain level of standardization in the field of bridge (or infrastructure) management can enhance the exchange of knowledge and experience between managing agents, thus improving the management systems [6]. Figure 2 presents a modular framework of activities that should compose a complete and thorough BMS, proposed after evaluation of different intakes into the scope of a BMS [2, 3, 4, 11, 12, 14, 15, 16]. None of the existing BMS includes geometric representation of bridges [6, 17]. A BIM model offers a comprehensive, accurate and up-to-date digital representation of a building, and many modern researches integrate BMS frameworks with BIM models to achieve smarter and automated management throughout the life cycle of the bridge [17, 18, 19, 20, 21, 22]. Traditional, paper-based methods of maintaining infrastructure, are no longer viable as governments now expect digital tools that leverage information and communication technology (ICT) [3]. Solutions within the Internet of Things (IoT) are increasingly becoming part of bridge inspection, condition assessment, structural analysis and BMS frameworks.

More than half of the systems in Table 3 do not allow remote or online access to the BMS, only access through desktop computers, which represents a limitation to information access. Therefore, this should be a point of improvement, especially since many of the technological advances in BMS include the use of mobile and portable technology. For example, checklists for inspections that are filled on site using mobile technology and uploaded directly to a BIM model using programming language [19]. The connection between a BIM model and the BMS can be done through different methods, such as structured query Language (SQL) statements [19]; C# [19], Matlab [23, 24] or other programming languages; IFC [17, 21, 22, 25, 26]; machine learning [27, 28, 29] and artificial intelligence algorithms [18].

Although inspection and intervention data are contemplated in most of the analysed BMS, information from construction of the bridges is still not integrated well into the majority of these systems. When considering the entire life cycle of the bridge, the BMS should store original construction designs and plans for the bridge so that they can be compared with the current condition data obtained from inspections. From that, future deterioration can me more accurately predicted and planning for interventions can be done accordingly.

Regarding the condition assessment, most systems already seem to deal with information about load

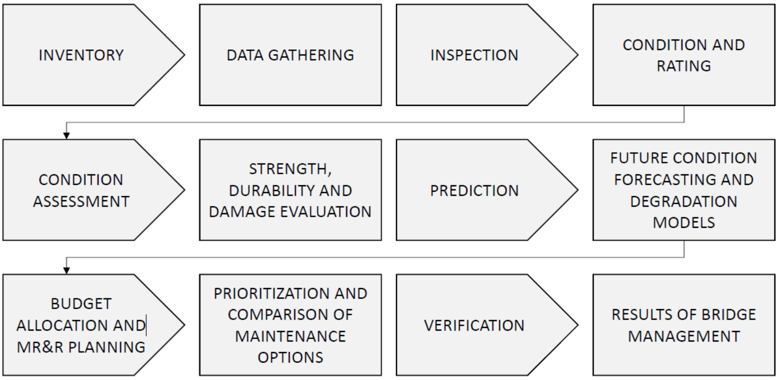

Figure 2. Management activities that compose the scope of a BMS

carrying capacity, safety and risk. Predictions of deterioration – i.e. changes in physical condition or performance indicators [6], are also frequently performed, mainly through probabilistic methods. However, there have been many advancements in structural analysis in BMS frameworks that can be applied to improve this field, such as automated bridge assessment through artificial intelligence algorithms [18] and association of BIM models with FEM models [19, 20], GIS [21] and risk breakdown structures (RBS) [30, 31].

The outcome of these predictions is currently used mainly for budgetary purposes, according to the data in Table 3. Therefore, increasing the quality of the predictions can have a direct impact on budget analysis. Budget information is handled by most systems on a more basic level of analysing intervention cost. Peripheral costs, such as traffic delay, accident and environment costs, are not approached by most systems, and only a few of them handle inspection costs. Recent research on bridge inspection aims at adding automation to the process, which can also improve cost-efficiency. This can be an opportunity for agencies to reduce maintenance costs. Therefore, it would be beneficial to have an integrated system that contemplates budget analysis throughout the bridge's life cycle.

5 Conclusion

Increased bridge deterioration and failures have enhanced the need to maintain the already aging bridges. This necessity amplified the concern with investment in bridge management that, together with the constant improvement of technology, has created a demand for optimized bridge management systems (BMS).

Solutions within the Internet of Things (IoT) are increasingly becoming part of bridge inspection, condition assessment, structural analysis and BMS frameworks. Some of the improvements identified from the analysis of current BMS are:

- Including a geometric representation for the bridge, such as a BIM model, integrated and connected into the system;
- Allowing remote or online access to the BMS;
- Adopting automated inspection procedures, such as automated damage detection, that can be linked to the system, preferably directly to a BIM model;
- Life cycle analysis contemplated into the system. This includes better integration of construction information, to compare with current condition obtained from inspections, and deterioration predictions, performed with structural analysis tools, such as FEM, so that planning for interventions can be done accordingly.
- Improved structural analysis and deterioration predictions, which can have a direct impact on budget analysis.
- Budget analysis throughout the bridge's life cycle integrated into the system,

contemplating also peripheral costs, such as traffic delay, accident and environment costs, inspection and maintenance costs.

The broader research that contains this study aims at developing a BMS for facility management of bridges using digital twins. This system, or systems, should have modules or layers that connect among themselves to perform thorough life-cycle management. Future work will then include a deeper insight into automated damage detection for bridge inspections, machine learning and algorithms to improve the links within the system.

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