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Title: *A Digital Twin of Bridges for Structural Health Monitoring for* Proceedings of the **12th International Workshop on Structural Health Monitoring 2019**

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ABSTRACT

Bridges are critical infrastructure systems connecting different regions and providing widespread social and economic benefits. It is therefore essential that they are designed, constructed and maintained properly to adapt to changing conditions of use and climate-driven events. With the rapid development in capability of collecting bridge monitoring data, a data challenge emerges due to insufficient capability in managing, processing and interpreting large monitoring datasets to extract useful information which is of practical value to the industry. One emerging area of research which focuses on addressing this challenge is the creation of 'digital twins' for bridges. A digital twin serves as a virtual representation of the physical infrastructure (i.e. the physical twin), which can be updated in near real time as new data is collected, provide feedback into the physical twin and perform 'what-if' scenarios for assessing asset risks and predicting asset performance.

This paper presents and broadly discusses two years of exploratory study towards creating a digital twin of bridges for structural health monitoring purposes. In particular, it has involved an interdisciplinary collaboration between civil engineers at the Cambridge Centre for Smart Infrastructure and Construction (CSIC) and statisticians at the Alan Turing Institute (ATI), using two monitored railway bridges in Staffordshire, UK as a case study. Four areas of research were investigated: (i) real-time data management using BIM, (ii) physics-based approaches, (iii) data-driven approaches, and (iv) data-centric engineering approaches (i.e. synthesis of physics-based and data-driven approaches). A framework for creating a digital twin of bridges, particularly for structural health monitoring purposes, is proposed and briefly discussed.

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INTRODUCTION

Many bridges across the world serve crucial roles in connecting different regions and improving resilience of their associated transport networks. To adapt to changes in the twenty-first century, which can be categorized as technology push (e.g. integrated sensing, Industrial Internet of Things) and demand pull (e.g. change of use, climate change), virtualizing bridges become important for improving their management and sustainability. One emerging field of research is the development of digital twin (DT) (e.g. [1]–[3]). A DT can be thought of as a digital representation of a physical asset which serves as a 'living' digital simulation model and is enabled by the abundance of data (e.g. operational data acquired from the bridges) and advanced data processing and interpretation routines.

This paper discusses two years of exploratory study towards creating a digital twin for bridges. The case study considered two railway bridges in Staffordshire, UK which have pervasive sensor networks installed at the time of construction. The study involves an interdisciplinary collaboration between the Cambridge Centre for Smart Infrastructure and Construction (CSIC) and the Alan Turing Institute (ATI), combining the expertise of bridge monitoring [4], finite element modeling [5], [6], building information modeling (BIM) [7], [8] and statistical modeling [9], [10], with the end objective of creating a working digital twin for the instrumented Staffordshire bridges.

STATE-OF-THE-ART

The complexities of bridge structures and the associated planning, design, construction, and operation and maintenance (O&M) require the adoption of systematic and well-coordinated approaches to ensure their successful delivery, safety and as-intended functioning throughout the lifetime of these bridges. There are many issues with existing practice in whole-life management of bridges, which include: (i) large and heterogeneous datasets are difficult for storage, processing and interpretation; (ii) efficiency in query of relevant data is low, as different data resources are stored in different management systems; (iii) interoperability across different software packages for different stages of a bridge project is low due to incompatible data file formats, and there is often a loss of data and information during project handover; (iv) coordination and integration in various design and construction iterations (e.g. conceptual design, detailed design, quality assurance) is low; and (iv) historical data of past performance is not well recorded and learned to improve future projects and practice; etc.

Meanwhile, the rapid development of sensing technologies has allowed more data to be gathered from our built environment than ever before. Middleton et al. [4] presented a comprehensive review of existing technologies of bridge monitoring. In general, four types of monitoring data can be gathered: (i) response-based, such as strain, displacement and inclination; (ii) geometry-based, such as conventional surveying and laser scanning; (iii) vision-based, such as image and video; and (iv) loading, such as operational and environmental loadings. More recently, the technological developments of Wireless Sensor Networks (WSNs) and the Industrial Internet of Things (IIoT) have enabled enhancement in integrated sensing and analytics.

However, despite years of research, the value case for bridge monitoring in industry practice has not been satisfactorily made to justify the associated cost and effort. This is

TABLE I. KEY CAPABILITIES AND LIMITATIONS OF PHYSICS-BASED AND DATA-DRIVEN APPROACHES

	Physics-based approach	Data-driven approach
Key capabilities	Incorporating engineering physics to perform: • Damage detection • Damage criticality evaluation • Load capacity assessment • Remaining service life prediction • 'What-if' simulation	• Identification of underlying trends, patterns and correlations within the dataset • Anomaly detection • Uncertainty quantification • Spatial/temporal inference and prediction • Dimensionality reduction and data fusion
Key limitations	• Random noises and systematic errors in sensor system response (not the same as bridge response) are not taken into account • Physics-based models often include simplifying assumptions (e.g. linearity in behavior) that produce biases in outputs	• Difficult to distinguish between changes of sensor response and changes of bridge response • Difficult to distinguish between environmental changes and bridge condition changes • Many parts of the bridge cannot be measured, and therefore difficult to assess changes of condition in these parts

often due to ill-defined end objectives and benefits which require sufficient capabilities of (i) turning monitoring data into practical information for decision making; and (ii) managing and processing large monitoring datasets. Middleton et al. [4] noted the often limited consideration of how SHM data would be interpreted before installation of bridge SHM systems. In general, there are two main approaches for processing and interpreting bridge monitoring data: a physics-based approach and a data-driven approach. A physics-based approach relates sensor measurements with prior physics-based model predictions (from e.g. first principles, code formulae, finite element models, etc.) and explains any discrepancies, thereby inferring real structural condition and performance. The current practice typically involves model updating, mostly by updating the parameters within the model, to minimize the discrepancies and to create an "As-Is" model. A data-driven approach is formulated based on the data alone and takes the form of statistical models which are used for identifying trends, patterns and correlations within the datasets and quantifying uncertainties of structural condition and performance. These approaches are often unsupervised and do not include input based on physical intuition. Table I summarizes the key capabilities and limitations of both physics-based and data-driven approaches. Thus far, there has been limited research on the synthesis of both approaches to best leverage their advantages and capabilities.

A DIGITAL TWIN FOR BRIDGES

Currently, there are many definitions of a Digital Twin (DT) under different contexts. For example, in the context of Digital Built Britain, a UK government led program, a DT is defined as "a realistic digital representation of assets, processes or systems in the built or natural environment" [1]. Lu et al. [2] describes DTs as "living digital simulation models that are able to learn and update from multiple sources, and to represent and predict the current and future conditions of the physical counterparts correspondingly and timely" in the context of dynamic DTs at building and city levels. As for bridge applications, based on review of existing literature (e.g. [1]–[3]) and

TABLE II. KEY FEATURES AND CAPABILITIES OF A DIGITAL TWIN FOR BRIDGES

Key features and capabilities of a DT for bridges
• It is a *digital replica* of the physical bridge (asset, process and/or system), in terms of geometry and many other aspects; • *Data* is the key ingredient of a DT, which includes data about terrain, layout, component, material, cost, schedule, inspection, monitoring, energy, carbon emission, etc.; • It is *connected* to the physical bridge in that it can be updated and provide feedback into the bridge (e.g. *monitoring* of current state) in near real time as new data is collected; • It spans the *whole life cycle* of the physical bridge, with data and information flowing through various stages of the bridge project, which includes planning, design, construction, operation and maintenance, refurbishment, demolition, etc.; • It has a *common data environment*, with all data stored in one model and conditionally accessed and modified by various stakeholders of the project; • It is a *visualization* tool which can be used to retrieve data or information in context, aid communication and collaboration, etc.; • It is a *simulation* tool (e.g. physics-based, data-driven, or both) which can be used to perform 'what-if' scenarios for assessing asset risks, predicting asset performance, etc.; • It can *learn* from real measurement data to improve future projects and practice.

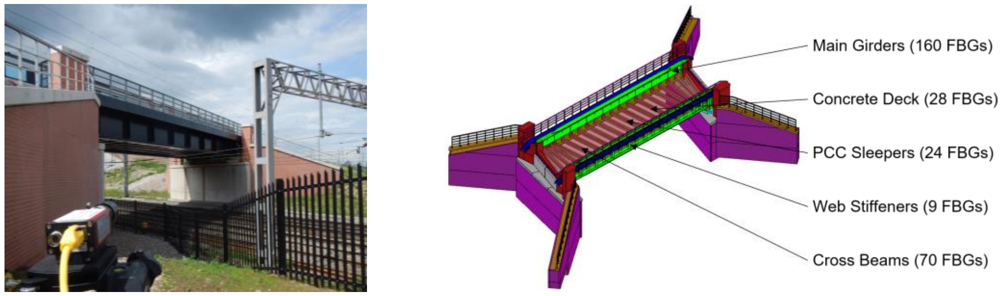
consultation of nine experts (four professors, two directors, one associate professor and two assistant professors) in related fields (BIM, digital construction, asset management, smart infrastructure and bridge SHM), a number of key features and capabilities of a digital twin for bridges are summarized in Table II. In summary, a DT can be used for visualization, monitoring, assessment, simulation, prediction, optimization, management, etc.

Integrating large and heterogenous data resources (e.g. various types of SHM data mentioned in [4]) and integrating different analytical approaches (e.g. physics-based and data-driven approaches) are key to the successful development of a DT for bridges. The interdisciplinary collaboration between CSIC and ATI has focused on developing a Data-Centric Engineering (DCE) approach, a synthesis of physics-based and data-driven analytical approaches, for extracting greater value of information from bridge monitoring datasets and creating a DT of bridges for SHM purposes.

CASE STUDY: STAFFORDSHIRE RAILWAY BRIDGES

Description of Bridges and Monitoring Program

Two newly constructed railway bridges in Staffordshire, UK were instrumented at the time of their construction with fibre optic sensor (FOS) networks which included discrete Fibre Bragg Grating (FBG) and distributed Brillouin Optical Time Domain Reflectometry (BOTDR) sensor systems. These two bridges are Intersection Bridge 5 (IB5), a steel half-through bridge with composite deck and instrumented with 291 FBG sensors, and Underbridge 11 (UB11), a prestressed concrete girder bridge with infill concrete deck and instrumented with 220 FBG sensors and 260 m of BOTDR cables. The primary objective was to perform early-age behavior assessment to inform long-term condition monitoring. In this paper, only the results for IB5 are presented. Figure 1 shows the completed bridge and its sensor instrumentation arrangement.



(a) Completed bridge (b) Monitoring program

Figure 1. Intersection Bridge 5 (IB5)

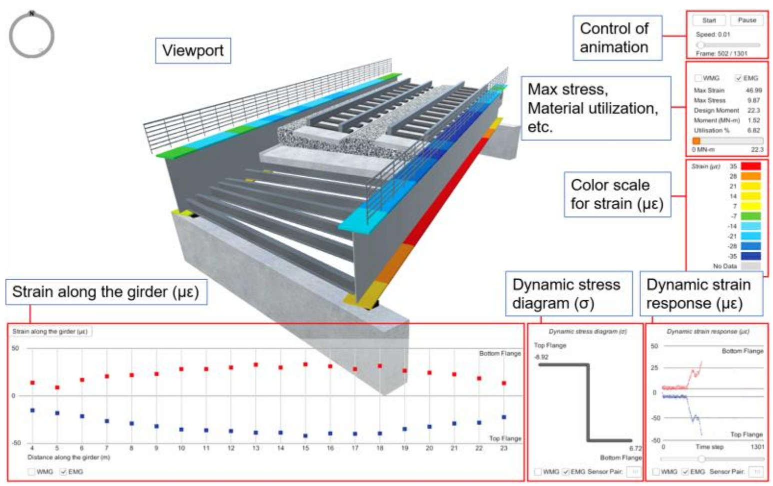


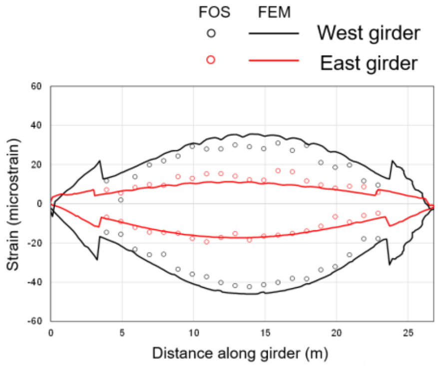
Figure 2. BIM model of IB5 incorporating real-time sensor data (adapted from [8])

Real-Time Sensor Data Visualization Using BIM

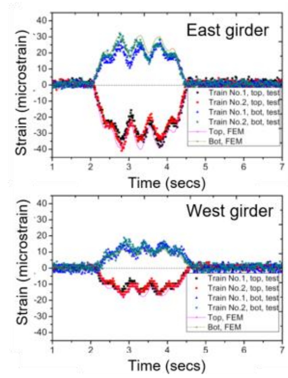
SHM datasets were incorporated into a dynamic BIM environment for visualizing real-time sensor data and associated bridge behavior [7], [8]. Specifically, this can be used to help identify anomalies in the data (due to e.g. faulty sensors, anomalous behavior, etc.) as well as to visualize strain/stress evolution, strain/stress distribution and material utilization. An example dynamic BIM model of IB5 is shown in Figure 2, which presents a colormap of strain/stress distribution and the corresponding structural utilization of the two main girders, both along their longitudinal axes (i.e. spatial variation) and in real time (i.e. temporal change), during a train passage event.

Physics-Based Approach: Finite Element Modeling

The performance of IB5, both during construction and in operation, was investigated through numerical (finite element) modeling which was validated using sensor data [5], [6]. A 3D FE model was constructed incorporating solid, shell and rebar elements, with the consideration of time-dependent concrete properties, staged construction and torsional effects due to the skewed bridge geometry. The FE model predictions were verified by FOS strain measurements, both spatially (e.g. at different locations along the girders) and temporally (e.g. dynamic response during a train passage event), as shown in Figure 3. This information can be used to help establish a performance baseline,



(a) Spatial verification



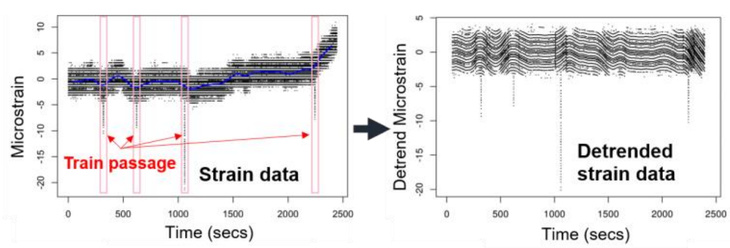
(b) Temporal verification

Figure 3. Physics-based approach (adapted from [6])

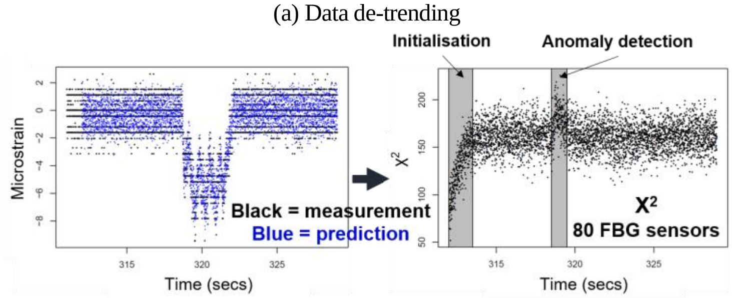
thereby achieving long-term condition monitoring and data-informed asset management as subsequent sensor data are collected throughout the bridge's operating life.

Data-Driven Approach: Statistical Modeling

Meanwhile, the ATI has focused on the data-driven approach, specifically, real-time statistical modeling of sensor data [9], as shown in Figure 4. First, sensor data from a network of 80 FBG sensors in the girders were de-trended through a refined moving average algorithm to remove both short-term and long-term environmental trends (e.g. effects of temperature variations) and to extract individual train-passage events. Linear dynamic (statistical) modeling was then used to perform short-term forecasting and to detect anomalies in the data. A streaming model was developed which could be updated in real time. Specifically, strain from sensor *s* at time step *t* is predicted as a linear combination of strain measurements from all other sensors at the previous time step *t – 1*. The predictions were verified using real measurements, as shown in Figure 4b.



(a) Data de-trending



(b) Linear dynamic (statistical) modeling

Figure 4. Data-driven approach (adapted from [9])

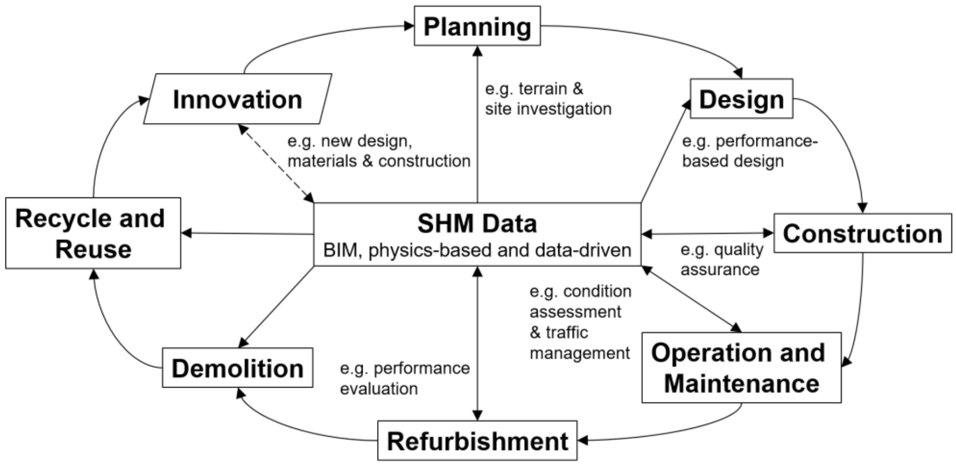


Figure 5. Whole life bridge monitoring and management

Data-Centric Engineering Approach: Towards Creating a Digital Twin for Bridges

Finally, the conceptual framework for a Data-Centric Engineering (DCE) approach, by integrating both physics-based and data-driven approaches to best leverage their advantages and capabilities, has been developed [3]. A DCE approach models the bridge response by integrating and balancing the information from the physics-based model (which has simplifying assumptions and modeling errors) with the incoming information from various monitoring datasets (which have measurement errors), with the objectives of minimizing systematic errors, quantifying underlying uncertainties and combining multiple sources of data which are often heterogeneous in nature. For example, a Gaussian process (GP) based DCE method has been developed by integrating GPs with physics-based models (e.g. FE models) [10]. This work used the experimentally tested and field monitored railway sleepers as a case study, with the goal of predicting their operational performance over time.

As recommended future work, a working DT for the Staffordshire bridges may be created by integrating SHM data, BIM, FE modeling and statistical modeling to improve structural health monitoring and thus to improve whole-life management of the bridge structures, as shown in Figure 5.

CONCLUSIONS

This paper has presented an overview of the necessary capabilities required to develop a digital twin of bridges for structural health monitoring purposes. A case study involving the Staffordshire railway bridges which have been instrumented with a dense array of fibre optic sensors was introduced. A digital twin can be developed by integrating multiple data resources under a unified data structure and integrating multiple simulation models to provide more confident predictions. The key benefits of a bridge digital twin include: efficient query of relevant data, integrated capabilities of data processing and interpretation, collaborative environment for various stages of a bridge project, etc. The emerging field of Data-Centric Engineering (DCE), which involves a synthesis of physics-based and data-driven analytical approaches, has been explored and investigated by civil engineers and statisticians together for extracting greater value of information from bridge SHM data. Future work will require developing the methodology for integrating various information and simulation models as well as heterogeneous datasets into a working digital twin; and improving the level of confidence in the integrated simulation model and its predictions.

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