Structural performance monitoring using a dynamic data-driven BIM environment

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Abstract. Structural health monitoring data has not been fully leveraged to support asset management due to a lack of effective integration with other datasets. A Building Information Modelling (BIM) approach is presented to leverage structural monitoring data in a dynamic manner. The approach allows for the automatic generation of parametric BIM models of structural monitoring systems that include time-series sensor data; and it enables data-driven and dynamic visualisation in an interactive 3D environment. The approach supports dynamic visualisation of key structural performance parameters, allows for the seamless updating and long-term management of data, and facilitates data exchange by generating Industry Foundation Classes (IFC) compliant models. A newly-constructed bridge near Stafford, UK, with an integrated fibre-optic sensor based monitoring system was used to test the capabilities of the developed approach. The case study demonstrated how the developed approach facilitates more intuitive data interpretation, provides a user-friendly interface to communicate with various stakeholders, allows for the identification of malfunctioning sensors thus contributing to the assessment of monitoring system durability, and forms the basis for a powerful data-driven asset management tool. In addition, this project highlights the potential benefits of investing in the development of data-driven and dynamic BIM environments.

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Introduction

Monitoring the structural performance of built assets is one of the primary tasks addressed by what is known as structural health monitoring (SHM), which is essentially an assessment of structural performance and damage identification (Farrar and Worden 2007). SHM systems use sensors to measure parameters that indicate the structural performance of a built asset; these parameters are usually related to the loads that the structure is subject to and its response. Loads caused by environmental conditions such as temperature, humidity, wind, etc. can be measured directly. Loads caused by other conditions, e.g. loads caused by vehicle traffic on a bridge, have to be derived from parameters that measure the response of the structure to the applied loads.

The commoditisation of sensing technologies is reducing costs allowing the wide-spread installation of SHM systems for a wide-range of construction projects. Interest is rapidly increasing within the construction industry for leveraging Big Data to support decision making (Bilal et al. 2016); as it has been done before in –for example– the financial, marketing, healthcare, and manufacturing sectors (Hashem et al. 2015). The importance of easy access and good managed data for construction management has been identified (Martínez-Rojas et al. 2016). However, there are many challenges that limit the effective use of data in the construction and every other industry. For example, poor data management practices, fragmented data sources, non-standard formats, etc. can lead to negative effects such as high operational costs, inefficient decision making, and lower productivity (Haug et al. 2011; Pipino et al. 2006). The difficulties to compile, organise, and analyse data represent an obstacle to adopt advanced data-driven strategies (Lavalle et al. 2011).

Building Information Modelling (BIM), an IT strategy to manage information related to built assets during their entire life cycle to increase quality and reduce costs (Giel and Issa 2013), is intended to be the solution to leverage data in the construction industry (Eastman et al. 2011; Gu and London 2010). But BIM provisions (e.g. software solutions, standards, processes etc.) are not yet sufficient to fully support decision-making for operations and maintenance (Davila Delgado et al. 2015; Gerrish et al. 2015). For example, existing standards can map monitoring data such as hardware specifications, but cannot map the dynamic logic defined by algorithms embedded in intelligent sensors, the configuration and topology of the sensor network, the interaction protocols, or monitoring strategies (Smarsly and Tauscher 2015). This is partly because BIM applications have primarily been implemented within the design and construction phases, which have different data requirements and objectives compared with the operations and maintenance phase (Becerik-Gerber et al. 2012; Liu and Akinci 2009). Additionally, given the increasing amount of data generated in a project's lifecycle, data modelling, visualisation, and simulation have become key aspects to support decision-making for designing, constructing, operating, and maintaining built assets (Leite et al. 2016). The major challenges for effectively employing these aspects include (i) developing as-built BIM models that fit real-world applications, (ii) resolving the disconnect between research outputs and industry needs, and (iii) creating automated methods for updating models based on datasets.

This paper presents an approach that contributes to tackle some of the challenges presented above and advance the provisions required to support decision-making during the operations and maintenance phase of infrastructure assets. This approach enables the compilation, standardisation, integration, and visualisation of monitoring data in a BIM environment to facilitate interpretation, analysis, and exchange of monitoring data. Addressing these aspects will potentially contribute to (i) proactive data-driven decision-making, (ii) wider adoption of new techniques to improve performance throughout the project life-cycle, and (iii) higher levels of automation, as identified by (Leite et al. 2016). More specifically, the approach (i) enables the creation of semantically-rich BIM models of monitoring systems using parametric methods and including monitoring data directly into the BIM model; and (ii) enables the visualisation of the included monitoring data in a data-driven and dynamic BIM environment.

A fibre optic based monitoring system installed in a newly-built railway bridge in Staffordshire, UK, has been used as case study. The system monitors changes in strain in a number of steel structural elements. A set of monitoring data is then presented that describes the structural response of the bridge during the passage of a train. Parametric and semantically rich BIM elements of structural elements have been modelled and the acquired data has been integrated. The developed data-driven and dynamic BIM environment has been used to visualise the critical structural parameters of the BIM elements derived from the acquired monitoring data.

BIM requirements for monitoring of built assets

It is possible to support asset management decisions through BIM if the following conditions are met: (1) a parametric and semantically-rich as-is BIM model is available and populated with condition data; (2) BIM interaction/visualisation functionality is available, which is data-driven and dynamic, such that it enables 4D (3 Dimensions + time) animations. These animations should be dynamic, i.e. respond and be driven by the included underlying time dependent data. And (3) the BIM is integrated with the database(s) that receives and holds the sensor data from the site. This will also make possible coordinated change and the reuse of information as envisioned by the Autodesk's seminal whitepaper (Autodesk 2002). A literature survey indicates that there are not sufficient provisions to fully satisfy these first two requirements (Davila Delgado et al. 2015). This paper proposes a new approach to address them. This section presents a brief description of the context, existing research, and challenges to satisfy these requirements; and the subsequent section presents the developed approach.

Parametric and semantically-rich BIM models

Currently, the data required to describe built asset performance cannot be fully managed in a BIM environment. The benefits of adopting BIM are limited by the lack of interoperability between software solutions (Ferrari et al. 2010), e.g. due to manual re-input of data. One of the major obstacles to address this is the lack of open standard data models that enable robust exchange of information (Davila Delgado et al. 2015). This obstacle is particularly challenging for supporting decision-making given the fragmented nature of the construction industry (Pauwels 2014). Moreover, extending existing standards is a long and laborious procedure as described by (Zhiliang et al. 2011). Thus, alternative solutions are taken that make use of proxy elements and user-defined property sets, e.g. (Rio et al. 2013). These types of solutions are ambiguous and can lead to errors. There are still many challenges to the management of performance data using existing data specifications, e.g. Industry Foundation Classes (IFC), such as: the size of the datasets, accuracy and levels of detail, and interoperability with existing formats employed to store historical performance data (Gerrish et al. 2015). Particularly to SHM systems, semantic information is difficult to include in IFC models, e.g. configuration and topology of the sensor network, interaction protocols, monitoring strategies, embedded algorithms, implicit dynamic relationships and logics, etc. (Smarsly and Tauscher 2015).

Informal and ad hoc approaches are being used to model monitoring systems due to the lack of existing capabilities; which leads to errors and inconsistencies reducing the benefits of employing BIM (Davila Delgado et al. 2015). More importantly, they indicate the lacking capabilities: (i) lack of specific entities and attributes for modelling, i.e. new entities, enumerated types, and property sets are required to fully model monitoring systems; (ii) lack of directives for data management and visualisation; and (iii) lack of guidelines for connection with external sources of data and other standard data models.

An important aspect to consider when generating BIM models for asset monitoring is the appropriate handling and visualisation of the data acquired by sensors. As exemplified in literature (Chen et al. 2014), data collected by temperature sensors has be included in BIM models using an ad hoc method. In the authoring tool, a user-defined element type has been created to represent temperature sensors. The sensor data, which is stored in plain text files, is assigned to instances of the element type using user-defined parameters. These parameters are exported to the IFC specification using user-defined property sets. As this case shows, in practice much of the data still resides in accompanying documents (Dossick and Neff 2010); which limits the full potential of BIM. Basic visualisation of the sensor data has been achieved by generating 2D charts directly in the authoring tool using its API (Application Programming Interface).

Data-driven and dynamic BIM environments

Software solutions have been developed to support the adoption and implementation of BIM. The types of BIM solutions can be grouped into the following categories: (i) BIM authoring tools, which mainly function to generate content such as the BIM model of the asset to be constructed (e.g. Revit, ArchiCAD, MicroStation, Tekla, etc.); (ii) BIM viewers, which enable the visualisation of BIM models to facilitate the communication of the design intent and collaboration among stakeholders –such as clients, authorities, designers, contractors, etc. (e.g. Solibri, xBIM, BIM Vision, BIMx, etc.). Some of these viewers even enable the visualisation of BIM models using a web browser (BIMer, BIMsurfer). BIM viewers are lightweight software tools with limited capabilities, that is, the models cannot be manipulated or new objects cannot be created; (iii) Design review, the objective of these tools is to facilitate the assessment of the design once it has been generated (e.g. BIMReview, BIMestiMate, Solibri Model Checker, Navisworks, Infraworks). Many different aspects of the design can be assessed such as normative compliance, constructability and clash detection, deficiency detection, 4D (3 Dimensions + time) simulation of the construction sequence, material estimation, etc.; (iv) Project management and collaboration platforms, these tools support the management of information and processes during design and construction (e.g. Trimble Connect, Project Wise, Project Wide). Their main functionalities include document management, database implementation, workflow and report management, and support for team collaboration.

BIM software was initially developed to support design and construction only, logically they lack provisions for the operational phase of the built asset lifecycle. Because the requirements to adopt BIM during the operational phase are distinctively different than during design and construction, the existing BIM software solutions are not suitable to implement BIM during the operational phase. For example, they lack capabilities to easily compare as-designed and as-built BIM models; to record and use time-series data, such as data related to performance and degradation; and to allow dynamic visualisation of data (Davila Delgado et al. 2017; Gerrish et al. 2015; Mousa et al. 2016).

Since there are no existing solutions that fully provide the required capabilities, there are two ways to obtain them. The first option is to develop a so-called plug-in or add-in that expands the capabilities and usability of an existing solution. These are pieces of code that interact with the software solution via an Application Programming Interface (API). APIs are interfaces that expose the code of the software solution to automate repetitive tasks, to implement additional features or to create links with other software solutions. For instance, in literature there are examples of plug-ins that facilitate considering accessibility for maintenance (Liu and R.A. Issa 2014), waste minimisation during deconstruction (Akinade et al. 2015), and enabling daylighting simulations (Kota et al. 2014). The main drawback of this approach is that the functionality of the plug-in is ultimately constrained by the capabilities of the software solution, and that not all software solutions provide an open API that is well documented and easy to use.

The second option is to create a custom and stand-alone application from scratch. This approach provides the most flexibility to implement the desired capabilities, but it is time consuming, requires considerable programming experience, and it is not preferred for research purposes. However, to expedite the development of stand-alone applications software frameworks have been developed, which provide functionalities that facilitate the development of software solutions with similar requirements. They include support programs, compilers, code libraries, etc., which allow programmers to direct their efforts on implementing specific software features rather than dealing with low-level functionalities that are common for a wide-range of applications. For example, a web framework would facilitate the development of an online shop without the need to develop entirely all the low-level web-communication functionalities.

Game engines are software frameworks that facilitate the development of video games; however, their main functionalities also make them suitable for developing scientific applications. These functionalities include (i) a rendering engine to visualise 2D and 3D graphics, (ii) a physics engine to simulate real-time physical phenomena (e.g. rigid body dynamics, fluid dynamics, etc.), (iii) animation modules to facilitate the simulation of motion changes through time, (iv) interactive modules to enable the interaction of users with the developed application, (v) an audio engine to process sound inputs and outputs, and (vi) networking modules to facilitate the implementation of communications between server and client applications. Game engines are, therefore, an appropriate platform to develop BIM solutions that include the capabilities required for asset monitoring. Their main advantages are that they facilitate the development of solutions that can handle dynamic visualisation of time-series data (e.g. state and performance data) in an interactive manner and in a 3D environment; and that their network capabilities enable the visualisation of real-time data.

The use of game engines to develop applications in the Architecture, Engineering, and Construction (AEC) area, has been limited. It was focused at first to develop environments that would allow a richer interaction with the developed BIM models via the use of virtual walkthroughs (Shiratuddin and Thabet 2002). Game engines have been used to develop design review systems that facilitate the examination of the generated designs before construction (Shiratuddin and Thabet 2011). These systems are especially useful for complex buildings such as healthcare facilities (Kumar et al. 2011), urban design (Indraprastha and Shinozaki 2009), and for real-time architectural visualisation (Boeykens 2011). Game engines have been used to develop applications for construction safety education (Lin et al. 2011) and to train construction operators (Wang et al. 2011). Lastly, an application to simulate transport systems has been developed using a game engine as well (Miao et al. 2011). But, game engines have not been used to develop solutions to support operations and maintenance or for structural performance monitoring.

Note that there are commercial software solutions for asset monitoring (e.g. Asset Wise), as well as ad hoc solutions that are developed for specific projects. These, however, were not included in the categorisation above, because they are not capable of handling BIM models. The data visualisation only supports 2D graphics and spreadsheets. To the authors best knowledge there are no BIM software solutions that enable the dynamic visualisation of (time-series) monitoring data directly into the BIM models in an interactive and dynamic manner.

Proposed Approach

The proposed approach consists of three main phases (1) the development of a data model –compliant with IFC– to model structural monitoring systems including the monitoring data, (2) the development of parametric and semantically-rich BIM models using automated parametric methods; and (3) the development of a data-driven and interactive BIM environment to interact with the generated models.

Data model for structural monitoring systems

The authors have developed a general approach to model structural monitoring systems and to include and visualise sensor data directly onto BIM models (Davila Delgado et al. 2016, 2017). It enables the creation of BIM models enriched with sensor data that comply and can be exchanged using the IFC specification. The approach was developed drawing inspiration from SensorML –a generic data model for complex monitoring systems (Botts and Robin 2014). An overarching method was used to amend various IFC schemas while trying to use the existing IFC entities as much as possible. This approach allows to describe any other type of monitoring system with minimal additions to the IFC specification. This paper builds up on the previous work and enables the generation of parametric monitoring systems that automatically adjust given the linked sensor data. This represents and step forward in the creation of fully parametric and semantically rich BIM models of monitoring systems.

Automated parametric modelling

A parametric and semantically-rich BIM element (Figure 1) and a (graphical) script (Figure 2) have been developed to: (1) automatically generate a BIM model of the sensor system, (2) load sensor data, residing in external files, into the BIM model, and (3) change the material (colour) of the BIM elements representing the individual discrete fibre optic sensors (FOS) given the sensor data. Note that the parametric modification is applied to the attributes related to the varying monitoring data (temperature, strain, moments, percentage of utilisation, colours, etc.) but not to the geometrical attributes of the structural elements.

The parametric and semantically-rich BIM element, so-called FO_Sensor, has been created using Autodesk Revit to represent each FOS. This special BIM element has the following capabilities: (i) it can be represented using different geometries, (ii) it can store sensor data such as strain, temperature, time stamp, etc., (iii) its material (i.e. colour) changes based on the values of the sensor data, (iv) it can be dynamically placed at equidistant locations along a polyline, and (v) it can be exported to the IFC 4 specification.

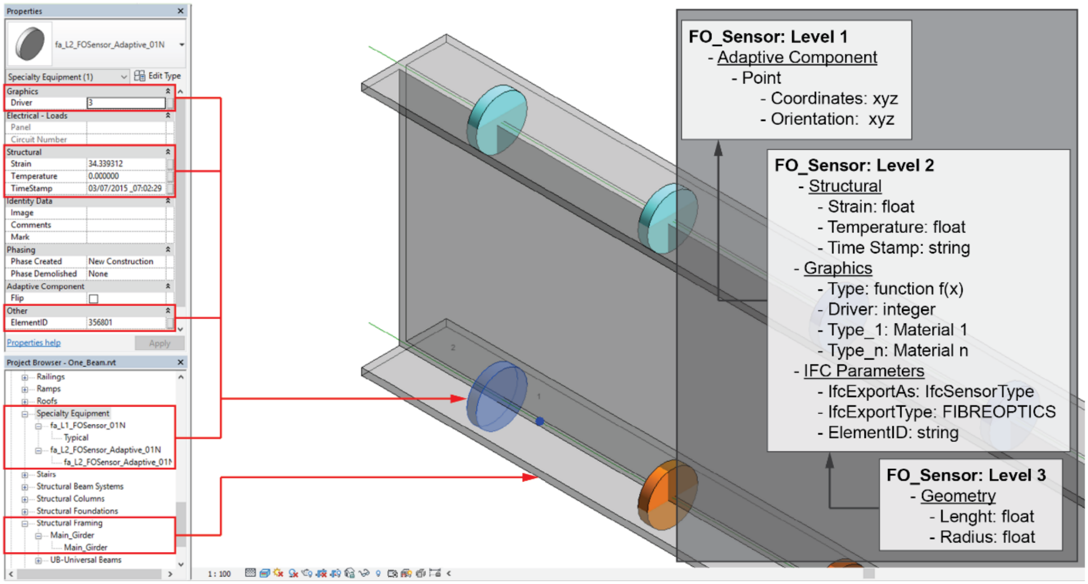

Figure 1 Parametric and semantically-rich BIM element used to model the sensors. The material (colour) of the sensors changes with different strain values

The FO_Sensor consists of three BIM elements nested into three levels as shown in Figure 1. At the lowest level, Level 3, the FO_Sensor defines the geometry of the sensor. In this case, a cylinder has been used to represent the sensor. The parameters defined at this level are the length and the radius of the cylinder. At Level 2, two categories of parameters are defined: (i) structural, in which the values for strain, temperature, and the time stamp are recorded; (ii) graphics, in this category the material-change capability is implemented. First, a list of element types ($Type_1$, $Type_2$, … $Type_n$) with their corresponding materials (Mat_1, Mat_2, … Mat_n) are defined. The variable selector *s* stores the type of the selected element type and the function TypeDef assigns the corresponding material to the selected element type. The value for the selector variable will be dynamically assigned by the (graphical) script based on the sensor data loaded from the external files; (iii) IFC Parameters, in which the ID of the BIM element, the object type and the enumerated type are defined. These parameters enable the BIM elements to be exported to the IFC 4 specification. Lastly, at Level 1, the position and orientation of the FO_Sensor are defined by a set of coordinates. These values will also be populated dynamically by the (graphical) script.

Note that because the FO_Sensor has been created by nesting BIM elements, modifications to its parameters and capabilities can be readily carried out by changing each nested BIM element. This will not affect the parameters and capabilities of the other BIM elements. For example, if a different or more complex geometry is desired, a different BIM element can be linked instead of FO_Sensor: Level 3; and all the other capabilities will remain functional. Therefore, this approach facilitates easy modifications and can be used to describe any type of sensor by defining the required attributes and dependencies.

The (graphical) script has been developed to using the visual programming plugin Dynamo for Autodesk Revit. Figure 2 presents a diagram of the (graphical) script. Note that this diagram is not an exhaustive representation and it is presented to give an overview of the developed script. Many of the nodes, represented as grey rectangles in Figure 2, are “nested nodes”. They are a collection of nodes grouped together; and others are “python nodes”, which are graphical representations of traditional text-based code implemented using the programming language Python.

The (graphical) script works as follows: (1) the file path for the external data files is selected, in which the strain values and time stamps are stored. In this case, an Excel file is used for each structural element. In this case, each of the main girders has a file with two sheets that contain the strain values for the sensors located along the top and bottom girder flanges. All the data in all the files is compiled into a single list and the number of required sensor cables and sensors per cable are inferred from the data. The number of cables corresponds to the number of sheets of each file and the number of sensors per cable corresponds to the number of strain values per each time stamp.

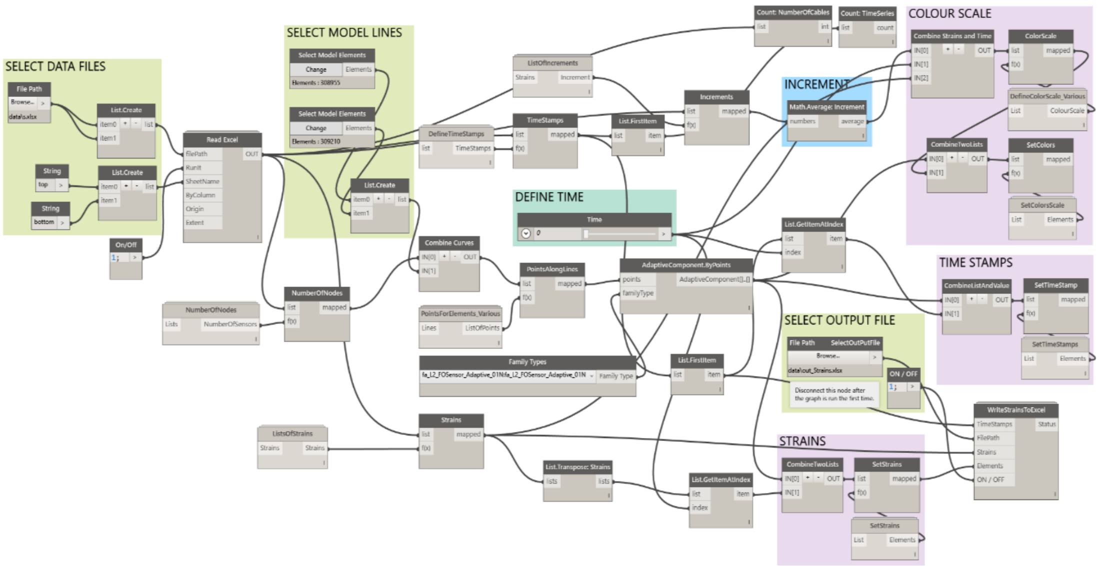

Figure 2 Diagram of the (graphical) script developed using Dynamo to automatically model the sensor system

(2) The BIM element to be used, in this case FO_Sensor: Level 3, and the lines along which the sensors will be populated are selected. Note that the order in which the files are selected in the previous step and the order in which the lines are selected should correspond. The script combines the lines that correspond to a single cable into a polyline; then, it generates points at equidistant locations along the polyline and creates an instance of the BIM element at the generated points. Note that the distance in-between sensors is predefined in the script by the user. (3) The corresponding values for strain and time stamps are assigned to each sensor instance. (4) A colour scale is defined to match a colour to a given strain value. It is defined specifically for the uploaded data i.e. the scale will automatically adapt to varying sets of data. This is done as follows: the number of steps S in the scale is defined by the number of material types defined in the FO_Sensor: Level 2. Then, the increment I of each step is defined as:

$$I = 0.5\left(\frac{\varepsilon_{\max}}{0.5S} + \frac{\varepsilon_{\min}}{0.5S}\right) \qquad \textit{Equation 1}$$

Where ε_{max} and ε_{min} are the maximum and minimum strain values in the data set. Then, the appropriate materials are selected. A material is a combination of texture images and attributes (colour, reflectivity, opacity, etc.) that define the appearance of an element in a 3D environment. Each material has a predefined tag (Mat_1, Mat_2, … Mat_n). A selector variable s for each sensor instance will determine the correct material depending on its strain value ε as follows:

$$\left\{\begin{array}{ll} & \vdots \\ 2I < \varepsilon \leq 3I & \rightarrow s = 1 \rightarrow \mathrm{Mat}_1 \\ I < \varepsilon \leq 2I & \rightarrow s = 2 \rightarrow \mathrm{Mat}_2 \\ -I < \varepsilon \leq I & \rightarrow s = 3 \rightarrow \mathrm{Mat}_3 \\ -2I < \varepsilon \leq -I & \rightarrow s = 4 \rightarrow \mathrm{Mat}_4 \\ -3I < \varepsilon \leq -2I & \rightarrow s = 5 \rightarrow \mathrm{Mat}_5 \\ & \vdots \end{array}\right\}$$ *Equation 2*

For example, if $\varepsilon = 2.5I$ (first row in equation 2), then $s = 1$, and Mat_1 is selected for that sensor instance. Note that negative strain values represent compression and positive represent tension. Lastly, (5) an output file is generated, in which each sensor instance is related to its corresponding element ID, strain, time stamp, and colour scale.

The result is a semantically-rich BIM model which has been augmented with sensor data that represents the state and performance of the constructed asset. It can be interacted with in a dynamic manner and new sensor data can be readily imported as it becomes available. Note that this approach can be applied to any new or existing structure by defining the dependencies between structural characteristics of the structure and the monitoring data.

The next step is to visualise the newly added data dynamically to support decision-making –this will be explained in the next section. The (graphical) script allows the user to choose what strain values to visualise in the time series. However, as explained before the visualisation capabilities of BIM authoring tools (e.g. Revit, ArchiCAD, etc.) for time series data is limited. Therefore, a dynamic BIM viewer was developed to overcome these limitations.

The data-driven and dynamic BIM environment

A dynamic BIM viewer has been developed using the game engine Unity, which was selected because of its cross-platform capabilities, extensive documentation, and free licenses for non-commercial applications. The dynamic BIM viewer visualises animations of varying strains in structural elements due to changing loads. The variation in strain is represented by changing the colour of sections of the structural elements according to a colour scale (see Figure 3).

Additionally, stresses and bending moments are calculated using the acquired strains. Stresses, σ calculated along the structural elements at the sensor locations using, $\sigma = \varepsilon E$ where, ε the strain and E is the Young's modulus. The moment, M due to bending stresses is obtained as follows: $M = \kappa EI$ where κ is the curvature and I is the moment of inertia of the section of the structural element. The curvature, κ is computed as follows: $\kappa = (\varepsilon_{top} + \varepsilon_{bot})/d$, where ε_{top} is the strain at the top of the section, ε_{bot} is the strain at the bottom of the section, and d is the distance between the two strain readings. A percentage of utilisation, U that gives an indication of the load capacity of the structural elements can be calculated as $U = P_{MAX}/P_{DESIGN}$ where P_{DESIGN} represents some design value or structural capacity parameter of a particular structural element and P_{MAX} is the maximum value of the corresponding structural parameter due to mechanical loads obtained from the sensor readings.

Figure 3 presents the graphical user interface (GUI) of the dynamic BIM viewer. The label (1) in Figure 3 is the viewport in which the semantically-rich BIM models are visualised and the animations are displayed. A compass, located in the left top corner indicates the North direction thus allowing to identify different structural elements (e.g. east main girder). In this case, a BIM model of the steel railway bridge used in the case study is presented in Figure 3, in which selected BIM elements are displayed. Changing colours due to changing strains of the top and bottom flanges of the west and east main girders are displayed. Label (2) identifies the controls to initiate, pause, and control the speed of the animation. This section also displays the time step of the animation. Label (3) identifies the section where the results are displayed: maximum strain, maximum stress, design moment, current moment, and utilisation percentage. A progress bar provides a graphical representation of the utilisation percentage as well. Label (4) identifies the section where the colour scale is displayed. Note that the colour scale is dynamically generated based on the data as described above. Label (5) displays a graph in which the strain values of a pair of sensors located on the top and bottom flanges are displayed. The intensity of the colours of the plotted points increases as the animation progresses to indicate changing strains due to the change in loading. Located at the bottom of the graph is a timeline slider that controls the time step of the animation in real time. Label (6) identifies the dynamic stress diagram, which at every time step of the animation plots the estimated bending stress of the beam at a location of a pair of sensors. In this case, there are 20 sensor locations for 20 sensor pairs (one along the top flange and another one along the bottom flange). The strain readings for corresponding top and bottom sensor pairs are used to calculate the stresses and plot the stress diagram. The sensor location to be used to plot the stress diagram can be selected. Finally, label (7) identifies the graph in which the changing strain readings for all the sensors in the bottom and top flanges are dynamically plotted for the selected main girder. Note that all the monitoring data is normalised and scaled to plot the different graphs and diagrams presented in the dynamic BIM viewer.

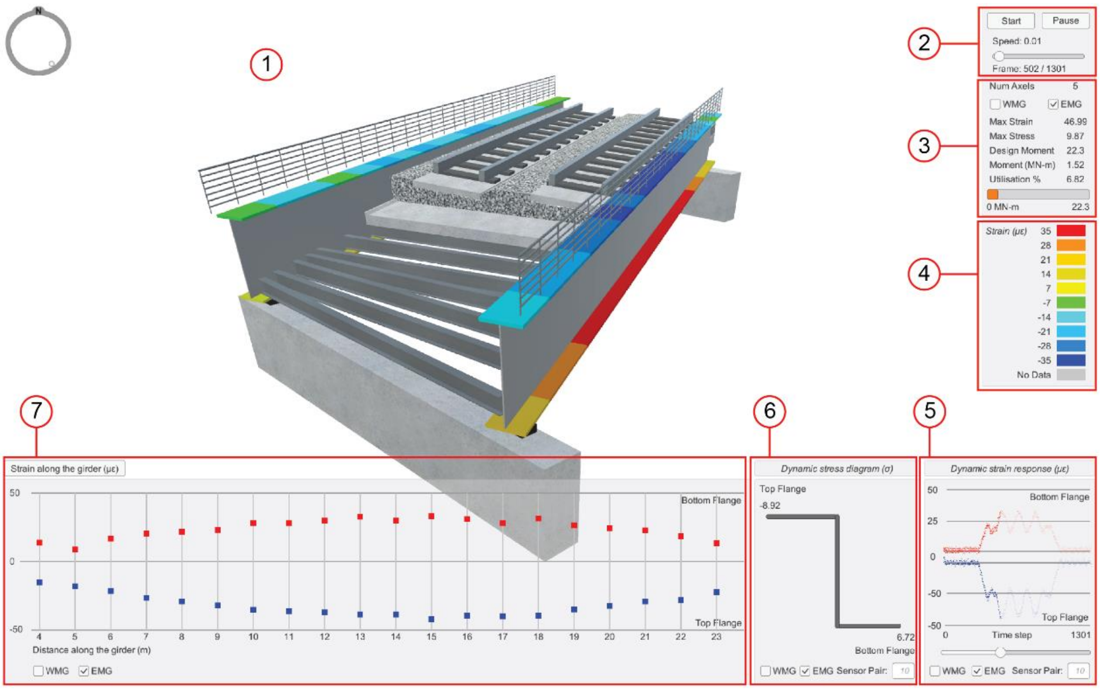

Figure 3. Graphical User Interface of the Dynamic BIM viewer.

The dynamic BIM viewer is a user-friendly tool that allows to communicate key parameters of the structural performance of a built asset in a dynamic and interactive manner. It provides different stakeholders (e.g. owners, operators, contractors, authorities, etc.) with a platform to take informed decisions based on data acquired by monitoring systems. It also facilitates data interpretation and analysis by automatically calculating key performance parameters and generating useful dynamic plots. Note that the proposed approach does not intends to completely replace traditional workflows usually followed by experts. The idea is that the proposed approach would complement and make more efficient traditional processes as is exemplified in the case study presented in the next section. For example, it can reduce time by automating repetitive tasks, particularly for long-term monitoring projects, by allowing to invest time in analysing data rather than in organising, pre-processing and visualising it.

Case Study

In order to illustrate the capabilities of the proposed data-driven and dynamic BIM environment, a real-world bridge monitoring case study is presented. Completed in April 2016, a new 26.8 metre steel-composite railway bridge was constructed near Stafford, UK (Figure 4). The bridge was instrumented during its construction with a permanent network of fibre-optic sensors (FOS). Over 120 individual strain FOS were installed on the main structural elements including the two main girders, several cross-beams, at one transverse stiffener, and at several transverse locations in the concrete deck slab to create a 'self-sensing' bridge. The primary objectives of this monitoring study were to investigate fundamental structural response under passing trains, evaluate sensor network robustness, and to develop tools for more intuitive data visualisation, interpretation and management.

Figure 4. Completed self-sensing railway bridge (west elevation).

The monitoring system

Fibre optic sensing technology based on Bragg gratings (fibre Bragg gratings or FBGs) was chosen for this monitoring study as it provides high accuracy, data acquisition rates up to 250 Hz, resilience to corrosion, and multiplexing ability for reducing the number of cables and interrogator channels. Bragg gratings are periodic alterations of the refractive index of the optical fibre core. Each Bragg grating is tuned to reflect light at a specific wavelength (i.e. the Bragg wavelength, λ_B). When a fibre optic cable is strained, the Bragg wavelength shifts. In order to measure strain at multiple points along the length of fibre optic cable, the shift in the Bragg wavelength (within the FBG sensing region) is measured for each individually tuned Bragg grating. Figure 5 depicts the principle of FBG strain sensor operation.

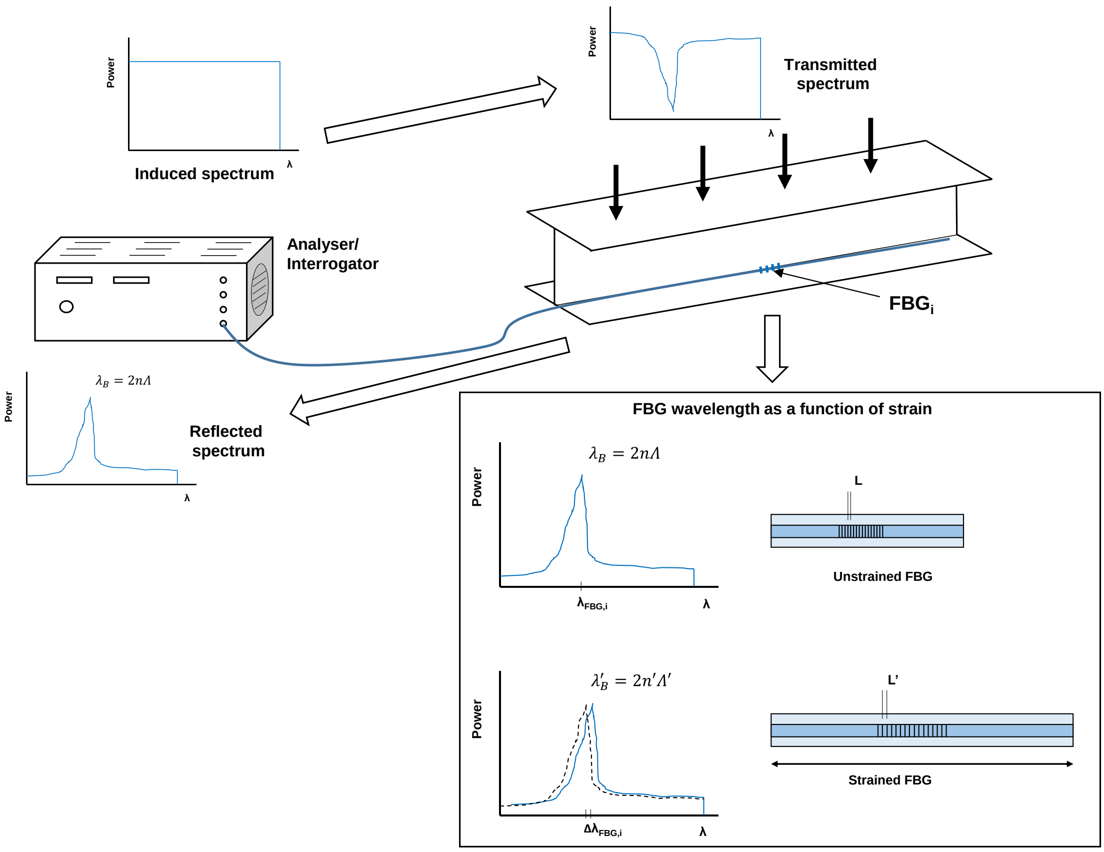

Figure 5. Principle of fibre Bragg grating sensor operation

To provide adequate resilience during their installation and in-service operation, the FBGs used in this research were fabricated with a glass-fibre reinforced coating. FBGs were spaced at one metre centres and had a strain measurement resolution of +/- 5 micro-strain (με). A Micron Optics sm130 optical interrogator was used in combination with a Micron Optics sm041 16-channel multiplexer in order to simultaneously measure all 250+ FBGs at an acquisition rate of 250 Hz. The sensor topology, bridge dimensions and further details are presented in Figure 6.

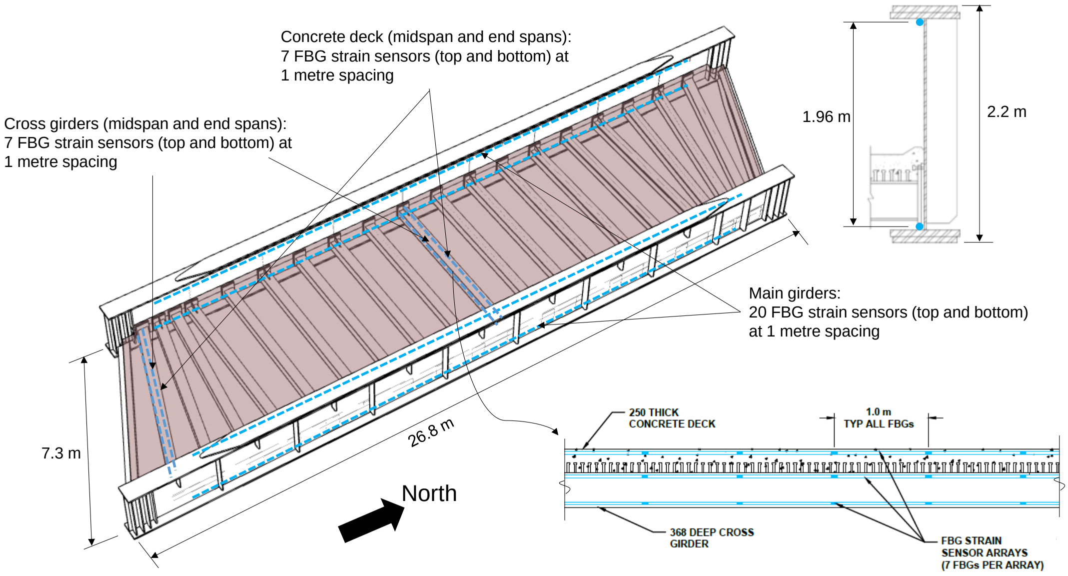

Figure 6. Bridge superstructure geometry and sensor layout

Data processing and analysis

After the monitoring data was collected, the raw data files were itemised, logged and stored (along with relevant meta-data) using a hyperlinked spreadsheet which represented the data management system. In order to interface with the dynamic BIM environment, the raw data acquired from the FOS had to then be pre-processed. The raw data collected using the FBG analyser was output in the form of wavelengths (measured in nanometres). In order to convert to strain, Eq. (3) was used.

$$\Delta\varepsilon = \frac{1}{k_\varepsilon}\left[\left(\frac{\lambda_t - \lambda_0}{\lambda_0}\right)_S\right] \qquad \textit{Equation 3}$$

Where,

$\Delta\varepsilon$ = change in strain between time t and initial baseline at time t_0.

$[(\lambda_t - \lambda_0)/\lambda_0]_S$ = change in relative wavelength of strain sensor

λ_t = wavelength at a particular time, t.

λ_0 = initial (baseline) wavelength at time t_0.

k_ε = photoelastic coefficient (gauge factor) for the strain sensor

A primary assumption when processing the FBG strain data during the passage of a train was that temperature-induced strains were negligible during this short period. Furthermore, the baseline strain is taken approximately 10 seconds before the train passes over the bridge.

After converting to strain, the data was further post-processed in the form of filtering and converting data files into a variety of different file formats (e.g. xlsx). At this stage in the data processing workflow, the data was then imported in the dynamic BIM environment for further processing and visualisation. Figure 7 presents the monitoring data work flow and its interface with the proposed BIM approach to data management.

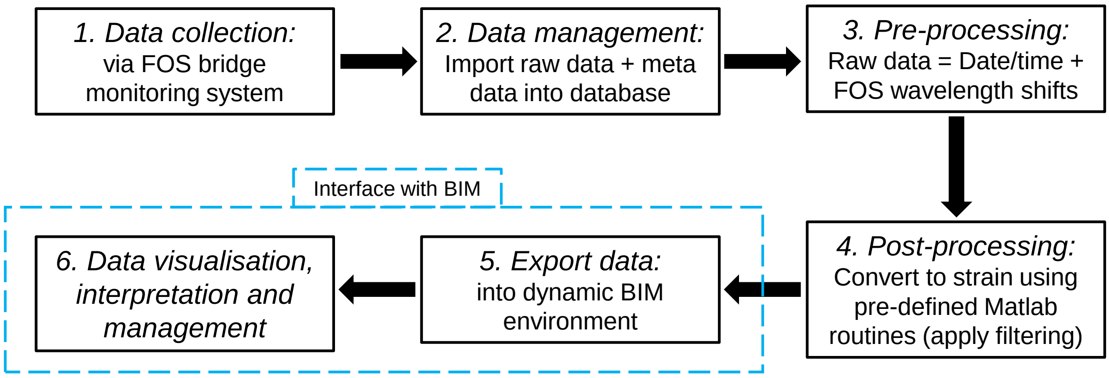

Figure 7. Monitoring data workflow and interface with dynamic BIM environment

Performance threshold for structural assessment

A critical task in any structural health monitoring project is to establish acceptable definitions of performance criteria. For this project, the sensors were installed during the construction stages and were therefore able to capture the entire loading history of the bridge. This included all the permanent or dead loads (DL) from installation of the concrete composite deck, the railway ballast, sleepers, rails and services. In the current study and for the purposes of demonstrating the integration of structural assessment within the dynamic BIM environment, only the performance of the main girders under live loading (LL) were considered. The main girders' bending capacity ($M_{b,Rd}$) was governed by lateral stability of the top (compression) flange and was calculated using the Eurocode design equations (BSI 2005, 2006) presented in Table 1. For the purposes of calculating the capacity of the main girders, it was assumed that the longitudinally-connected reinforced concrete deck did not contribute to the bending capacity (i.e. no composite action was assumed).

Table 1. Calculation of maximum bending moment capacity

Strain (LL)	Stress (LL)	Maximum Moment (LL)	Moment capacity of main girders according to Eurocode
From processed FOS live load data	$\sigma_{LL} = \varepsilon_{LL} E$	$M_{LL} = \kappa EI$ Where, $\kappa = \frac{\lvert\varepsilon_{top}\rvert + \lvert\varepsilon_{bot}\rvert}{d}$	$M_{b,Rd} = \chi_{LT} W_{el,y} f_y \gamma_{M1}$ Where, $W_{el,y}$ = elastic modulus of compression flange γ_{M1} = partial factor for steel members $\chi_{LT} = \frac{1}{\phi_{LT} + \sqrt{\phi_{LT}^2 - \lambda_{LT}^{-2}}} \leq 1.0$ $\phi_{LT} = 0.5\left[1 + \alpha_{LT}(\bar{\lambda}_{LT} - 0.2) + \lambda_{LT}^{-2}\right]$ α_{LT} = imperfection factor $\bar{\lambda}_{LT} = \sqrt{\frac{A_{eff} f_y}{N_{crit}}}$ N_{crit} = critical elastic buckling load of compression flange

Based on previous data collected by the authors, an estimate of the maximum dead load moments induced in the main girders was determined using the FOS results. For the purposes of assessing the performance of the girders under live loading only, the FOS results must be compared with the girder moment capacity ($M_{b,Rd}$) minus the previously calculated dead load moments carried by the girders ($M_{DL,FOS}$). Therefore, the design moment capacity under live loading ($M_{DES,LL}$) is calculated using Eq. (4).

$$M_{DES,LL} = M_{b,Rd} - M_{DL,FOS} \qquad \textit{Equation 4}$$

Corresponding maximum strains and stresses can also be calculated based on the design moment capacity and can be used to establish performance thresholds for structural health monitoring. It must be noted that in the long-term, performance criteria may have to be adjusted. For example, once longer-term monitoring data has been collected, the fatigue stress ranges for several main components may also be evaluated and compared against a separate set of established performance criteria. Note that these performance criteria are also assigned as attributes of the main girders' BIM elements. The dynamic BIM viewer is then capable of displaying the threshold percentages (i.e. FOS measured/threshold value) in real time for the main girders during the passage of a train.

Data visualisation and interpretation

Traditionally, based on the data analysis techniques described above, the dynamic strain data for each main girder during the passage of a train can be visualised through a series of plots. As an example, Figure 8 represents the strain captured for the main girders (midspan sensors) during the passage of a 4-car passenger train. From this plot, the separate and adjacent sets of bogies can be identified and the relative load sharing between the west and east main girders clearly indicates that the east main girder carries the majority of the loading from which one may infer that the train was travelling along the eastern track (in this case in the northbound direction).

In addition, Figure 8 highlights four time steps corresponding to a time just before the train passes over the bridge (time step 138), at the instant the locomotive (first car) passes over the girder (time step 378), at the instant when the second set of bogies passes over the girder (time step 504), and at the instant where the middle bogies (middle of train) passes over the bridge (time step 684). Note that at time step 504 the maximum load effects on the bridge were recorded. Data from these four time steps will be referenced in subsequent discussions and visualisations of the monitoring data. Spatially-distributed strain plots across the main girder length are also valuable for assessing the girders' structural performance (refer to Figure 9). These strain distributions depict the increasing levels of recorded strain measured at the critical time steps. A malfunctioning sensor was also identified along the bottom flange of the east main girder at approximately 4.7 metres from the girder's south end. Stress distributions along the girder cross sections (at midspan) may also be derived by multiplying the recorded strains by the modulus of elasticity of steel, 210 GPa, and presented in similar plots such as Figure 10. It was assumed that the stress distributions are linear across the cross-section. As would be expected, prior to the train passing over the bridge, the stresses are nearly zero (time step 138) and they reach a maximum when the second set of bogies passes over the midspan of the bridge girders (time step 504).

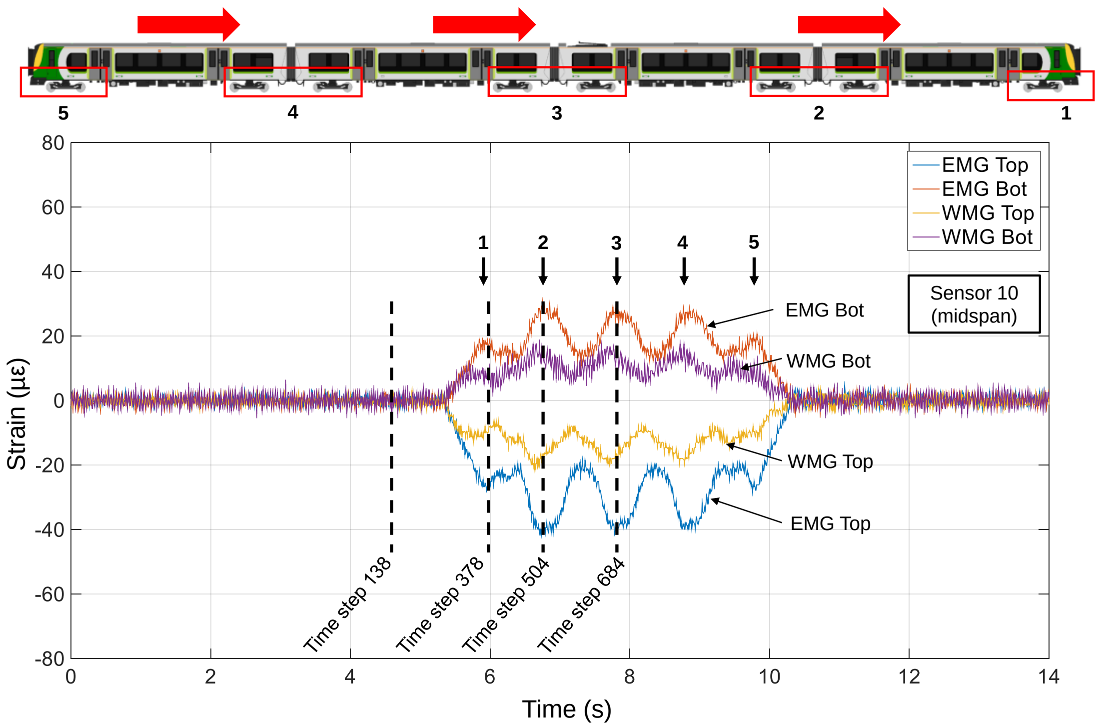

Figure 8. Dynamic strain response of main girders due to passenger trains

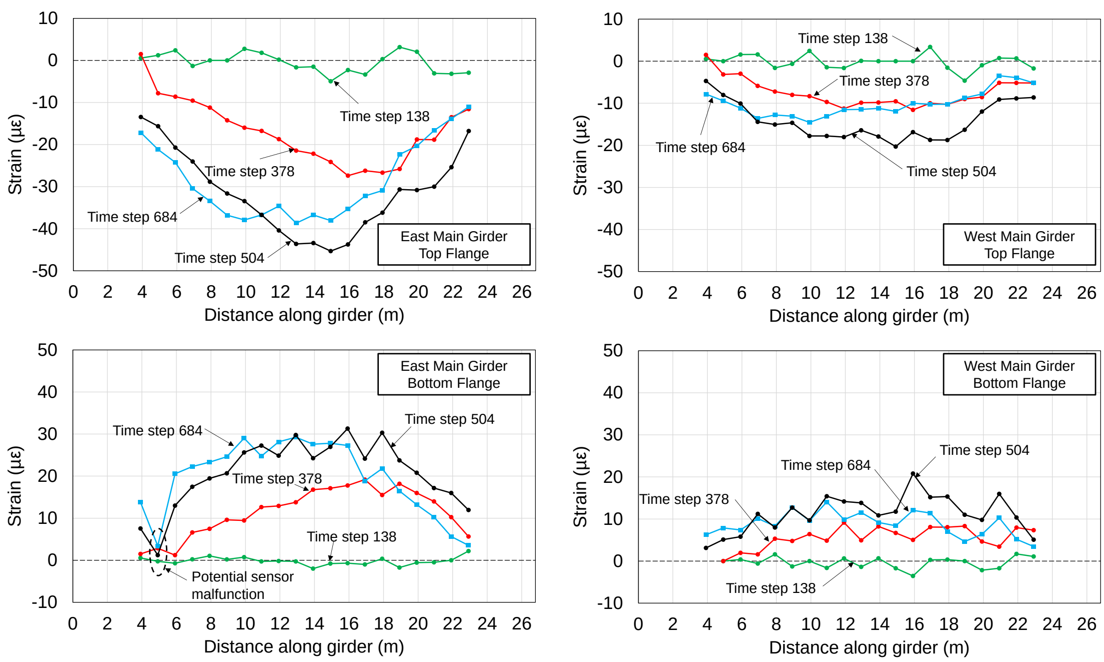

Figure 9. Spatially distributed strains along the main girders

Another primary structural property is the moment distribution and corresponding maximum moment acting on the girders under live loading. These measured maximum moments can then be compared with the performance threshold, $M_{DES,LL}$ described previously in order to assess the percentage utilisation of each girder. Using the formulae provided in Table 1 and Eq. (4), $M_{DES,LL}$ = 22330 kN-m. The corresponding moments calculated based on the recorded FOS strain data and the percentage utilisation of each girder are presented in Figure 11. The main girders were found to experience very low utilisation percentages under live loading conditions. This response is expected for smaller passenger trains of this type as the bridge was originally designed to carry very heavily loaded freight trains travelling at high speeds. In addition, the recorded data clearly highlights the high factors of safety inherent in such bridge designs under normal operating conditions. In terms of load distribution, these plots show that the moment-share ratio between the east and west main girders is 2.1:1. The plots also reveal that the maximum bending moments do not necessarily occur at the midspan of a simply-supported girder for a given time step. Cantero and Karoumi (2016) studied this effect numerically and attributed this discrepancy to the relative energy contents of the higher modes of vibration induced by the moving loads. While they primarily evaluated that the difference was greatest when considering vibrations, they also found that significant differences did exist when comparing bending moments.

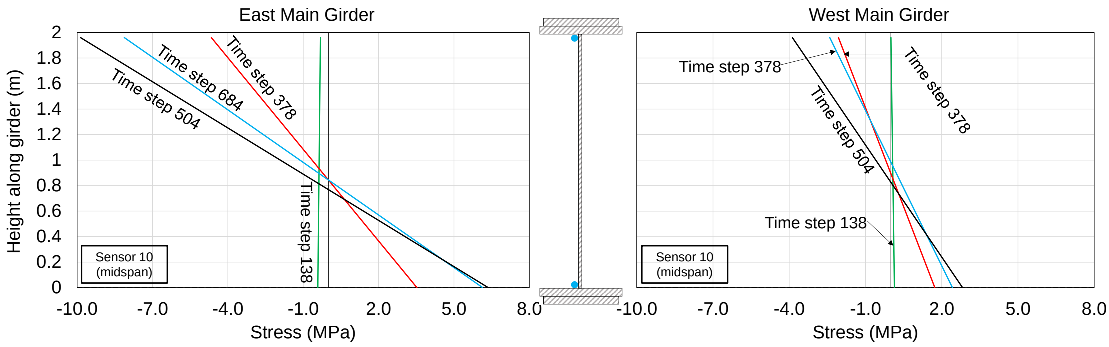

Figure 10. Stress distributions along the main girder cross-sections

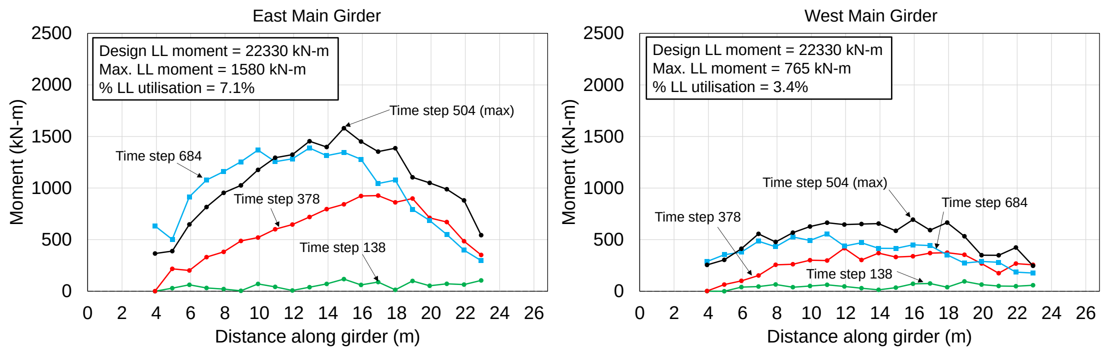

Figure 11. Moment distributions along the main girders

All of the information provided within these several plots can be displayed directly within the dynamic BIM environment with the added advantage of displaying the information continuously and in an interactive manner. Figure 12 presents an alternative visualisation for the distributed strain along the east main girder (EMG) in a discrete (point-based) manner for time steps 138, 378, 504, and 684. This figure uses the IFC-compliant models generated by the (graphical) script. Figure 13 and Figure 14 present visualisation of key performance parameters of the EMG as presented by the dynamic BIM viewer for time steps 138, 378, 504, and 684. Based on these visualisations, the non-midspan maximum bending moment observation is clearly displayed graphically. Figure 13 and Figure 14 also display the real-time strain distributions along the cross sections and dynamic stress diagrams. It is also possible to detect the malfunctioning sensor on the bottom flange of the east main girder (see Figure 14). In this way, the BIM viewer can also be used to assess the long-term durability of the monitoring system itself. Finally, the dynamic BIM viewer can calculate the maximum bending moment in the main girders and provide the percentage utilisation of each girder based on the $M_{DES,LL}$ attribute associated with each girder. The percentage of utilisation is presented both numerically and graphically using a progress bar (see Figure 13 and Figure 14).

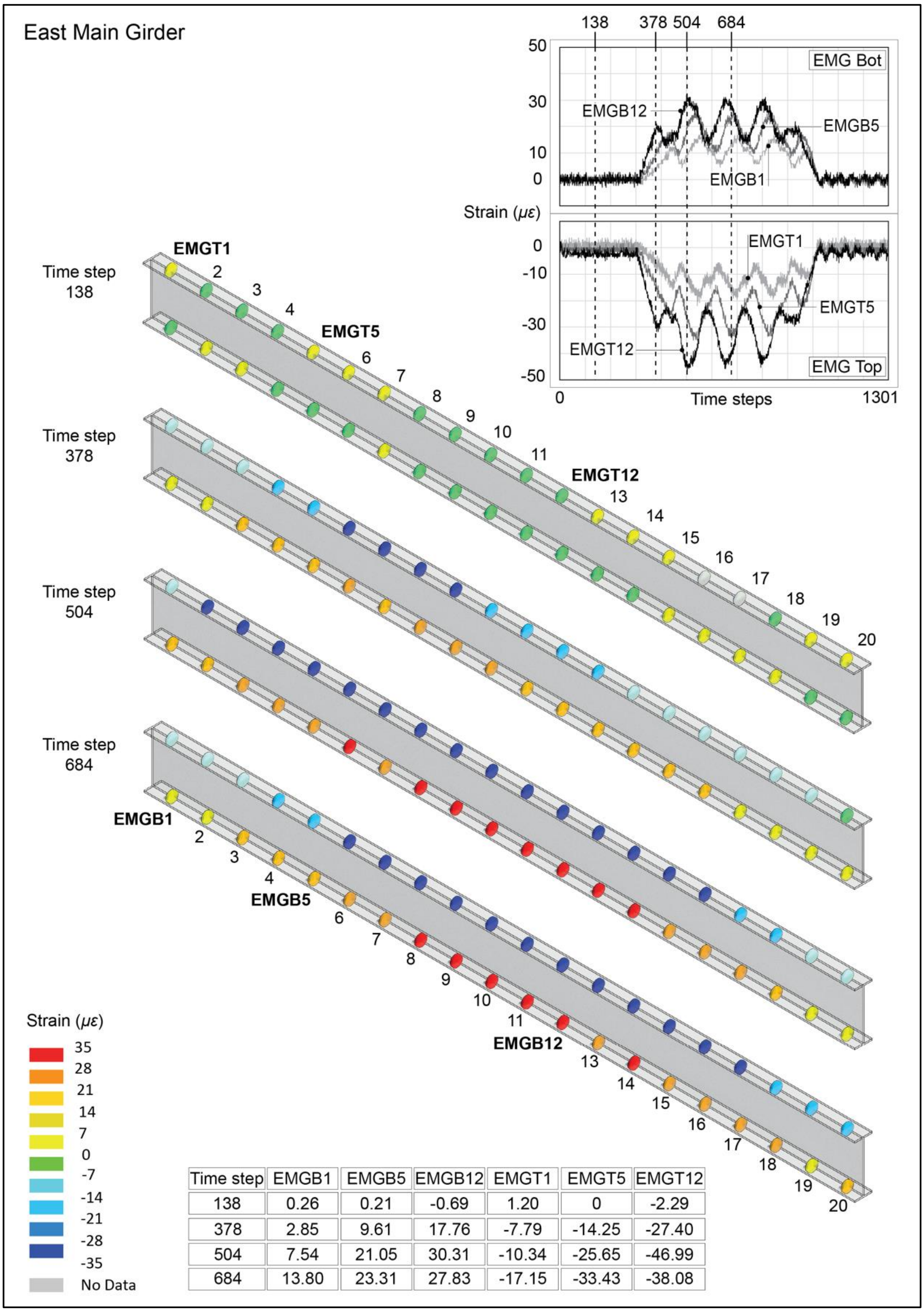

Figure 12. East main girder (EMG), discrete strain visualisations generated by the (graphical) script for time steps 138, 378, 504, and 684. The BIM elements include monitoring data.

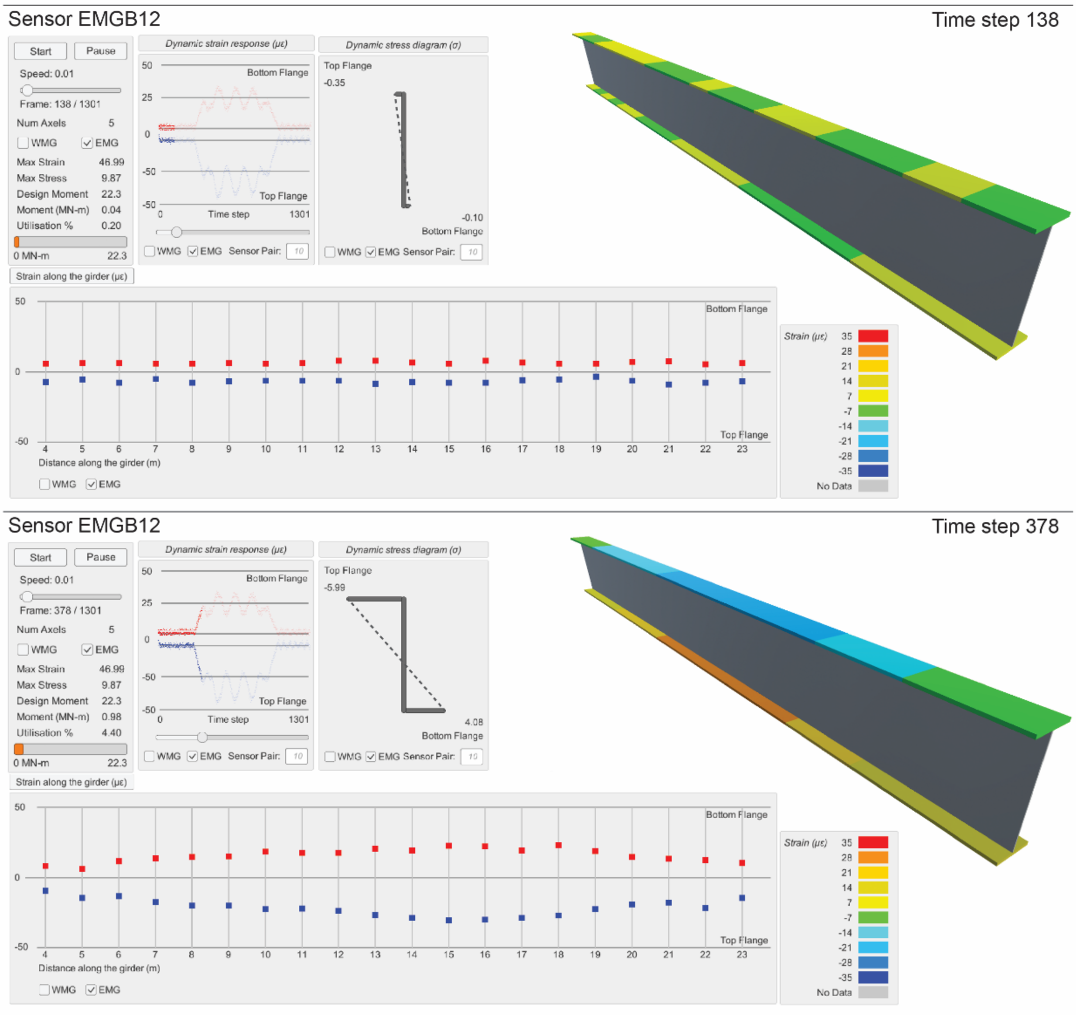

Figure 13. East main girder (EMG), distributed strain visualisations from dynamic BIM viewer (time steps 138 and 378).

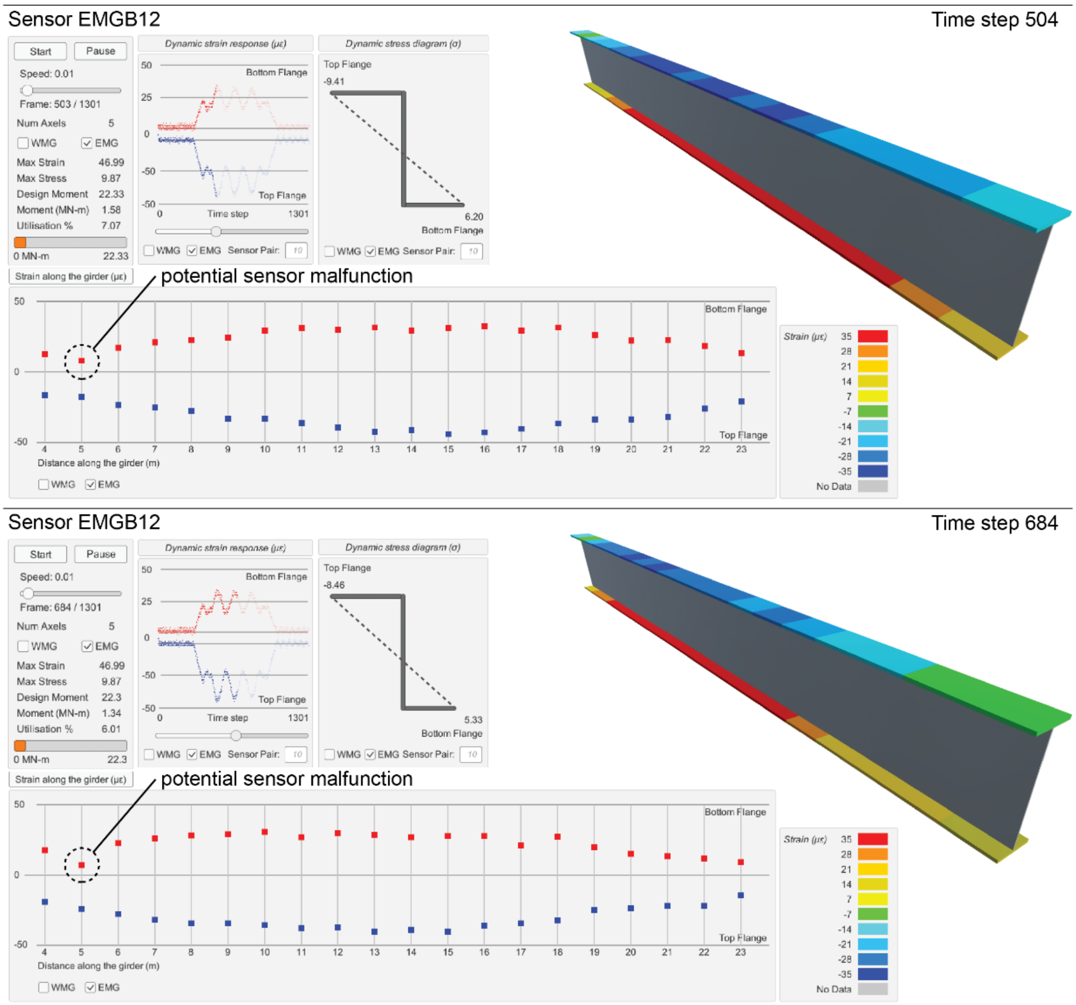

Figure 14. East main girder (EMG), distributed strain visualisations from dynamic BIM viewer (time steps 504 and 684).

Discussion

Considerations for interoperability and database capabilities

The BIM approach presented in this project generates IFC4 compliant models. However, the dynamic BIM viewer cannot directly use IFC models. In this case, the models were converted to the proprietary file format FBX (Filmbox), which is commonly used for videogame development. Besides geometry and material capabilities (common in various 3D file formats), it also includes animation, physic dynamics, and deformation capabilities; all of which are very useful to develop dynamic BIM environments. Therefore, further research efforts are required to devise solutions that enable robust exchange of models from various data formats that encompass all the required capabilities. Furthermore, data standards that are capable to describe models parametrically are needed as well. In the case of bridges, a parametric extension to the IFC standard has been developed (Ji et al. 2011), but the extension only allows to parametrically alter the geometry of the bridge. Monitoring data is not handled in a parametric manner as is required to implement solutions such as the presented in this paper. Semantic web technologies have been increasingly used to enable communications in fragmented, heterogeneous, multinational business environments. This has led to the development of ifcOWL a sematic web technology that allows to encode IFC files in the W3C Ontology Web Language (OWL) (Beetz et al. 2008). ifcOWL has proven to be very efficient to handle many types of data related to built assets (Pauwels and Terkaj 2016); but, it is not the best solution to describe geometrical data. Lastly, the presented approach still relies in part on accompanying data files. A direct link between a federated BIM model and monitoring data stored in a database system has not been fully achieved yet. Furthermore, a seamless workflow to automatically record, process, integrate and analyse monitoring data is not in place yet (see Figure 7). The major reason for this the lack of standard data models and standard processes for exchange of data as has been identified in literature (Davila Delgado et al. 2015; Gerrish et al. 2015; Smarsly and Tauscher 2015). On the whole, interoperability remains a big challenge for the implementation of BIM and novel data-driven technologies.

Considerations for long-term asset management and decision making

Standard asset management practice for infrastructure assets relies very heavily on manual inspection. The problems of manual inspection are well known and well documented (Middleton 2014). The BIM approach presented in this paper will enable asset managers and designers to use the monitoring data –generated during the infrastructure asset operations– to support their decisions. This will ensure a systematic and reproducible workflow avoiding the subjectivity and low reliability of current manual inspections. One of the primary advantages of interfacing a monitoring system with BIM resides in the long-term management of data. Using advanced data mining techniques, critical knowledge can be extracted from the collected data to inform operations, maintenance and repair decisions. For example, valuable information such as changes with time in the percentage utilisation of critical structural elements can be stored and assessed thereby allowing an asset manager to decide whether an asset is operating at sufficient levels of safety, whether a more detailed inspection should be undertaken, or whether immediate intervention is required. A summary of this decision-making framework, which is applicable across all stages of an assets' life (i.e. construction, in-service and at end of life) is presented in Figure 15. Note that this is a very different approach compared to the current practice and hence it will take some time before any significant changes in practice are realised.

Additionally, potential modifications can be easily implemented. For example, if future upgrades, repairs, alterations to the original structure, or changes in monitoring methods are undertaken, the BIM model along with the sensor data can be readily updated. Specifically to the case study presented in this paper, it was assumed that the temperature change during the passage of a train was negligible. However, for longer term monitoring this assumption is not valid. Therefore, the temperature of each monitored structural element must also be recorded over time and the strains reported should be temperature-compensated. Further details of this compensation process are reported in Butler et al. (2016).

Other considerations for undertaking a long-term monitoring study that interfaces with BIM is data storage and data collection frequency. Adequate provisions must be made to ensure that sufficient capacity exists within the database system and the federated BIM model. The frequency of both data collection and data import into the BIM environment must also be considered. As part of the authors' future work, autonomous, continuous, and real-time post-processing and updating of the SHM-BIM interface is envisioned.

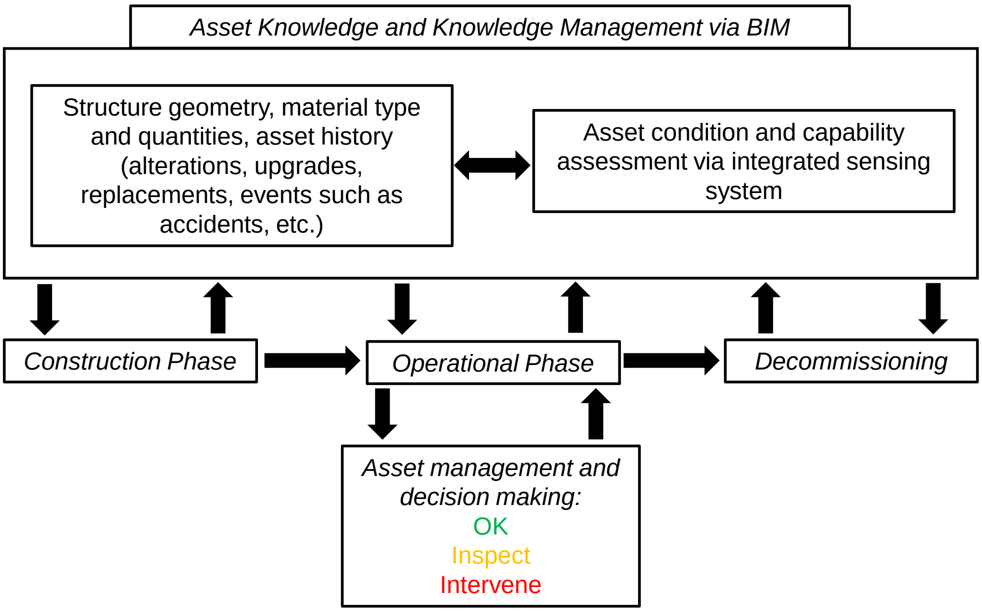

Figure 15. BIM-based long-term asset management and decision-making framework

Additional capabilities

As initially discussed, data modelling, visualisation, and simulation have been identified as key aspects to support decision-making during the built asset's life cycle (Leite et al. 2016). A reasonable next step for this research study would be to integrate simulation capabilities, predictive models, and optimisation techniques. The presented BIM approach provides a platform on which to use the acquired monitoring data to leverage Big Data and novel Machine Learning methods such as Artificial Neural Networks (ANNs) – a resurgent and prominent method for predictive modelling. There a several potential applications of these methods. As an example, the acquired data could be used to validate finite element models generated during design and to amend finite element models for future designs. In addition, predictive models could be developed and included in the dynamic BIM viewer to visualise changes in performance due to degradation and increasing traffic. For example, ANNs have been used to aid in the design of water harvesting structures (Chandwani et al. 2016) and to predict risks for building maintenance (de Silva et al. 2013). Optimisation models can also be used to leverage the acquired monitoring data to devise more efficient design solutions, such as using generative and genetic algorithms to predict structural design solutions given limited data (Davila Delgado and Hofmeyer 2013; Hofmeyer and Davila Delgado 2015, 2013); and using ANNs to generate optimum designs of bridge decks (Srinivas and Ramanjaneyulu 2007). Lastly, machine learning methods can leverage monitoring data for performing damage detection in infrastructure assets (Mehrjoo et al. 2008). These additional capabilities, when interfaced with a dynamic BIM environment will widen the usability of the installed SHM systems and increase the value of the acquired monitoring data.

Conclusions

The prevalent digital revolution has influenced every aspect of life. However, the AEC sector is lagging behind in leveraging the use of new data-driven technologies to support decision-making. The main obstacles preventing the uptake of these new technologies include: (i) the lack of BIM approaches that provide the required capabilities, (ii) the fragmented nature of the AEC sector, and (iii) non-existent real-life use case examples that demonstrate the potential benefits. This study addresses these limitations by developing a data-driven and dynamic BIM approach to leverage structural monitoring data for decision-making. The project addressed obstacle (i) by developing an approach that automatically generates parametric and semantically-rich BIM models of structural monitoring systems and that enables the visualisation of the monitoring data in a 3D environment in a dynamic and interactive manner. It addressed obstacle (ii) by enabling the generation of BIM models that can be exported to the IFC4 specification thus facilitating data exchange among stakeholders. This is achieved due to the previously developed approach to model structural monitoring systems (Davila Delgado et al. 2016, 2017). Lastly, it addressed obstacle (iii) by presenting a real-life case study in which potential benefits are demonstrated. The case study validates the presented approach and it represents the first time where a BIM-based data management and condition monitoring system has been implemented on a real structure.

The case study presented a bridge monitoring system, which utilised a pervasive network of fibre-optic based strain sensors, to illustrate what is possible within a data-driven and dynamic BIM environment. It demonstrated that the key structural performance parameters such as live load moment and the percentage utilisation of the main bridge girders could be dynamically displayed using the developed dynamic BIM viewer. The two main girders were assessed to be performing well-within their design capacity highlighting the inherent factors of safety present within the bridge design. In addition, using the dynamic BIM viewer interface a malfunctioning sensor could be clearly identified, a moment-share ratio between east and west main girders of 2.1:1 was found, and the maximum bending moments in the main girder due to the passing trains were shown to occur slightly away from the midspan.

Interfacing sensing systems, which have been integrated during construction, with a BIM environment capable of importing, visualising, and managing the associated long-term monitoring data, creates a powerful data-driven asset management tool for asset owners and operators. By incorporating BIM provisions during the operational phase of an asset, significant reductions in costs could be realised through the reduction of tactile and visual inspections and maintenance; and the dynamic BIM interface enables a more accurate interpretation of the asset's structural performance leading to more informed decision-making.

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References

Akinade, O., Oyedele, L., Bilal, M., Ajayi, S., Owolabi, H., Alaka, H., and Bello, S. (2015). "Waste minimisation through deconstruction: A BIM based Deconstructability Assessment Score (BIM-DAS)." *Resour. Conserv. Recycl.*, 105, 167–176.

Autodesk. (2002). *Building Information Modeling, White Paper*.

Becerik-Gerber, B., Jazizadeh, F., Li, N., and Calis, G. (2012). "Application Areas and Data Requirements for BIM-Enabled Facilities Management." *J. Constr. Eng. Manag.*, American Society of Civil Engineers, 138(3), 431–442.

Beetz, J., van Leeuwen, J., and de Vries, B. (2008). "IfcOWL: A case of transforming EXPRESS schemas into ontologies." *Artif. Intell. Eng. Des. Anal. Manuf.*, Cambridge University Press, 23(1), 89.

Bilal, M., Oyedele, L. O., Qadir, J., Munir, K., Ajayi, S. O., Akinade, O. O., Owolabi, H. A., Alaka, H. A., and Pasha, M. (2016). "Big Data in the construction industry: A review of present status, opportunities, and future trends." *Adv. Eng. Informatics*, 30(3), 500–521.

Boeykens, S. (2011). “Using 3D Design Software , BIM and Game Engines for Architectural Historical Reconstruction.” *Proc. 14th Int. CAAD Futur. Conf.*, P. Leclercq, A. Heylighen, and G. Martin, eds., Les Editions de l’Universite de Liege, Liege, Belgium, 493–509.

Botts, M., and Robin, A. (2014). “OGC SensorML: Model and XML Encoding Standard.” Open Geospatial Consortium, MA, USA.

Butler, L., Gibbons, N., Middleton, C., and Elshafie, M. (2016). “Integrated fibre-optic sensor networks as tools for monitoring strain development in bridges during construction.” *19th Congr. IABSE Proc.*, International Association of Bridge and Structural Engineering, Stockholm, 1767–1775.

Cantero, D., and Karoumi, R. (2016). “Numerical evaluation of the mid-span assumption in the calculation of total load effects in railway bridges.” *Eng. Struct.*, 107, 1–8.

Chandwani, V., Gupta, N. K., Nagar, R., Agrawal, V., and Jethoo, A. S. (2016). “Artificial neural networks aided conceptual stage design of water harvesting structures.” *Perspect. Sci.*, 8, 151–155.

Chen, J., Bulbul, T., Taylor, J., and Olgun, G. (2014). “A Case Study of Embedding Real-time Infrastructure Sensor Data to BIM.” *Constr. Res. Congr. 2014*, ASCE, 269–278.

Davila Delgado, J. M., de Battista, N., Brilakis, I., and Middleton, C. (2016). “Design and data modelling of fibre optic systems to monitor reinforced concrete structural elements.” *ASCE, Constr. Res. Congr.*, ASCE, San Juan, Puerto Rico, 2291–2301.

Davila Delgado, J. M., Brilakis, I., and Middleton, C. R. (2015). “Open data model standards for structural performance monitoring of infrastructure assets.” *CIB W78 Conf. 2015*, J. Beetz, ed., TU Eindhoven, Eindhoven, The Netherlands, 1–10.

Davila Delgado, J. M., Butler, L. J., Gibbons, N., Brilakis, I., Elshafie, M. Z. E. B., and Middleton, C. (2017). “Management of structural monitoring data of bridges using BIM.” *Proc. Inst. Civ. Eng. - Bridg. Eng.*, Thomas Telford Ltd, 170(3), 204–2018.

Davila Delgado, J. M., and Hofmeyer, H. (2013). “Automated generation of structural solutions based on spatial designs.” *Autom. Constr.*, Elsevier B.V., 35(November), 528–541.

de Silva, N., Ranasinghe, M., and de Silva, C. R. (2013). “Use of ANNs in complex risk analysis applications.” *Built Environ. Proj. Asset Manag.*, Emerald Group Publishing Limited, 3(1), 123–140.

Dossick, C. S., and Neff, G. (2010). “Organizational Divisions in BIM-Enabled Commercial Construction.” *J. Constr. Eng. Manag.*, ASCE, 136(4), 459–467.

Eastman, C., Teicholz, P., Sacks, R., and Liston, K. (2011). *BIM Handbook: A Guide to Building Information Modeling for Owners, Managers, Designers, Engineers and Contractors*. Wiley.

Farrar, C. R., and Worden, K. (2007). “An introduction to structural health monitoring.” *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.*, 365(1851), 303–315.

Ferrari, P., Silva, N., and Lima, E. (2010). “Building Information Modeling and Interoperability with Environmental Simulation Systems.” *Innov. Adv. Comput. Sci. Eng.*, T. Sobh, ed., Springer Netherlands, Dordrecht, 579–583.

Gerrish, T., Ruikar, K., Cook, M. J., Johnson, M., and Phillip, M. (2015). “Attributing in-use building performance data to an as-built building information model for lifecycle building performance management.” *Proc. 32nd CIB W78 Conf.*, J. Beetz, ed., CIB, 1–11.

Giel, B. K., and Issa, R. R. A. (2013). “Return on Investment Analysis of Using Building Information Modeling in Construction.” *J. Comput. Civ. Eng.*, 27(5), 511–521.

Gu, N., and London, K. (2010). “Understanding and facilitating BIM adoption in the AEC industry.” *Autom. Constr.*, Elsevier B.V., 19(8), 988–999.

Hashem, I. A. T., Yaqoob, I., Anuar, N. B., Mokhtar, S., Gani, A., and Ullah Khan, S. (2015). “The rise of ‘big data’ on cloud computing: Review and open research issues.” *Inf. Syst.*, 47, 98–115.

Haug, A., Haug, A., Zachariassen, F., and Liempd, D. van. (2011). “The costs of poor data quality.” *J. Ind. Eng. Manag.*, 4(2), 168–193.

Hofmeyer, H., and Davila Delgado, J. M. J. M. (2015). “Coevolutionary and genetic algorithm based building spatial and structural design.” *Artif. Intell. Eng. Des. Anal. Manuf.*, Cambridge University Press, 29(4), 351–370.

Hofmeyer, H., and Davila Delgado, J. M. M. (2013). “Automated design studies: Topology versus One-Step Evolutionary Structural Optimisation.” *Adv. Eng. Informatics*, 27(4), 427–443.

Indraprastha, A., and Shinozaki, M. (2009). “The Investigation on Using Unity3D Game Engine in Urban Design Study.” *ITB J. Inf. Commun. Technol.*, 3(1), 1–18.

Ji, Y., Borrmann, A., and Obergrieβer, M. (2011). “Toward the Exchange of Parametric Bridge Models Using a Neutral Data Format.” *Comput. Civ. Eng.*, American Society of Civil Engineers, Reston, VA, 528–535.

Kota, S., Haberl, J. S., Clayton, M. J., and Yan, W. (2014). “Building Information Modeling (BIM)-based daylighting simulation and analysis.” *Energy Build.*, 81, 391–403.

Kumar, S., Hedrick, M., Wiacek, C., and Messner, J. I. (2011). “Developing an experienced-based design review application for healthcare facilities using a 3d game engine.” *J. Inf. Technol. Constr.*, 6, 85–104.

Lavalle, S., Lesser, E., Shockley, R., Hopkins, M. S., and Kruschwitz, N. (2011). “Big data: analytics and the path from insights to value.” *MIT Sloan Manag. Rev.*, 2(52), 21–32.

Leite, F., Cho, Y., Behzadan, A. H., Lee, S., Choe, S., Fang, Y., Akhavian, R., and Hwang, S. (2016). “Visualization, Information Modeling, and Simulation: Grand Challenges in the Construction Industry.” *J. Comput. Civ. Eng.*, 30(6), 4016035.

Lin, K.-Y., Son, J. W., and Rojas, E. M. (2011). “A pilot study of a 3D game environment for construction safety education.” *J. nformation Technol. Constr.*, Royal Institute of Technology, 5, 69–84.

Liu, R., and R.A. Issa, R. (2014). “Design for maintenance accessibility using BIM tools.” *Facilities*, (S. Lavy, ed.), Emerald Group Publishing Limited , 32(3/4), 153–159.

Liu, X., and Akinci, B. (2009). “Requirements and Evaluation of Standards for Integration of Sensor Data with Building Information Models.” *Comput. Civ. Eng.*, American Society of Civil Engineers, 95–104.

Martínez-Rojas, M., Marín, N., and Vila, M. A. (2016). “The Role of Information Technologies to Address Data Handling in Construction Project Management.” *J. Comput. Civ. Eng.*, 30(4), 4015064.

Mehrjoo, M., Khaji, N., Moharrami, H., and Bahreininejad, A. (2008). “Damage detection of truss bridge joints using Artificial Neural Networks.” *Expert Syst. Appl.*, 35(3), 1122–1131.

Miao, Q., Zhu, F., Lv, Y., Cheng, C., Chen, C., and Qiu, X. (2011). “A Game-Engine-Based Platform for Modeling and Computing Artificial Transportation Systems.” *IEEE Trans. Intell. Transp. Syst.*, 12(2), 343–353.

Middleton, C. R. (2004). “Bridge Management and Assessment in the UK.” *Proceedings of Austroads 5th Bridge Conference*, Hobart, Australia, 1-16.

Mousa, M., Luo, X., and McCabe, B. (2016). “Utilizing BIM and Carbon Estimating Methods for Meaningful Data Representation.” *Procedia Eng.*, 145, 1242–1249.

Pauwels, P. (2014). “Supporting Decision-Making in the Building Life-Cycle Using Linked Building Data.” *Buildings*, 4(3), 549–579.

Pauwels, P., and Terkaj, W. (2016). “EXPRESS to OWL for construction industry: Towards a recommendable and usable ifcOWL ontology.” *Autom. Constr.*, 63, 100–133.

Pipino, L. L., Wang, R. Y., and Funk, J. D. (2006). *Journey to Data Quality*. MIT Press.

Rio, J., Ferreira, B., and Poças Martins, J. (2013). “Expansion of IFC model with structural sensors.” *Inf. la Construcción*, 65(530), 219–228.

Shiratuddin, M. F., and Thabet, W. (2002). “Virtual office walkthrough using a 3D game engine.” *Int. J. Des. Comput.*, University of Sydney, 4.

Shiratuddin, M. F., and Thabet, W. (2011). “Utilizing a 3D game engine to develop a virtual design review system.” *J. Inf. Technol. Constr.*, 16, 39–68.

Smarsly, K., and Tauscher, E. (2015). “IFC-based monitoring information modeling for data management in structural health monitoring.” *20 Int. Conf. Appl. Comput. Sci. Math. Archit. Civ. Eng.*, (K. Gurlebeck and T. Lahmer, eds.), Bauhaus-University Weimar, Weimar, (July), 200–206.

Srinivas, V., and Ramanjaneyulu, K. (2007). “An integrated approach for optimum design of bridge decks using genetic algorithms and artificial neural networks.” *Adv. Eng. Softw.*, 38(7), 475–487.

Wang, X., Dunston, P. S., Proctor, R., Hou, L., So, J. C. Y., Wang, X., Dunston, P. S., Proctor, R., Hou, L., and So, J. C. Y. (2011). “Reflections On Using A Game Engine To Develop A Virtual Training System For Construction Excavator Operators.” *Proc. 28th ISARC* , IAARC, Seoul, Korea, 631–636.

Zhiliang, M., Zhenhua, W., Wu, S., and Zhe, L. (2011). “Application and extension of the IFC standard in construction cost estimating for tendering in China.” *Autom. Constr.*, Elsevier B.V., 20(2), 196–204