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Digital twin enabled structural integrity management: Critical review and framework development

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Abstract

This paper presents a critical review of literature on the emerging technology known as digital twin and its application in structural integrity management for marine structures. The review defines digital twin in relation to structural integrity management as a virtual representation of a physical structure that mirrors the same structural conditions in real time. Twinning is a dynamic process that involves reducing the discrepancy between the virtual representation and physical structure, which is achieved with the aid of monitored data. Regarding the state-of-the-art concerning marine structure applications, all require the creation of a finite element model to represent the physical structure. Several practical schemes for physical to virtual interconnection have been proposed, but few researchers have concentrated on virtual to physical feedback. In addition, most works have focused only on assessing the current states of structures. To address this, a digital twin-based monitoring framework is proposed and three key enabling technologies, namely model updating, real-time simulation, and data-driven forecasting are demonstrated using a numerical case study. Such technologies enable structural diagnostics, as well as prognostics, to support decision making such as inspection/maintenance planning. Based on the case study, the opportunities and associated challenges of digital twin are discussed. For instance, to fully exploit the potential of digital twin, challenges related to monitoring systems such as standardisation, enhanced redundancy for long-term application, and monitored data quality assurance need to be addressed. Further, because digital twin can avail a vast amount of data, a dedicated data mining capability should also be incorporated.

Keywords

Digitalisation, digital twin, structural integrity management, structural health monitoring, condition assessment

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Introduction

Background and research context

Operating in a harsh ocean environment, marine structures such as ships, ocean energy structures and so on can experience different undesired damages, for example, fatigue crack and corrosion.[1] These degrade structural integrity and affect the serviceability of structures if the damage accumulates to a critical threshold. To manage this, structural integrity management, an ongoing life-cycle process that ensures the continued fitness-for-purpose of marine structures, is essential.[2] This process usually consists of four phases: data – evaluation –strategy – programme. Traditionally, the structural integrity data of marine structures is obtained through offshore inspection. Most offshore inspection are conducted periodically by a trained surveyor, relying on principally visual inspection, supported by local thickness measurement and non-destructive evaluation (NDE) techniques in the areas of interest. This traditional approach can, however, be limited by the low accessibility of certain critical structural details and unexpected bad weather which causes delay in inspection. In addition, the periodic inspection does not provide information on the real-time condition of target structures and potentially overlooks some forms of structural damages. Moreover, the offshore survey may pose health and safety risks to the surveyors and lead to a considerable increase in the life-cycle cost.

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Consequently, a wide spectrum of efforts has been aimed at installing various sensing units on board to remotely and continuously monitor the structural condition. The monitored data are input to dedicated condition assessment modules to assess the health of the structures. This can assist the management of lifetime structural integrity and possibly to demonstrate the case for life extension.[3] This is known as structural health monitoring. In the recent years, there is an emerging technology known as digital twin. In the same way as conventional structural health monitoring, this technology is reliant on a dedicated monitoring system and condition assessment module. However, it differs from the conventional structural health monitoring in that a computer-based model (digital model) of the target structure is also required. This model is usually created and utilised during the initial design phase but is revitalised by the digital twin concept.[4]

Historical developments

The concept of twinning an in-service asset may originate from the NASA's Apollo programme where an identical space vehicle, that is, physical twin rather than a digital twin, was built to allow mirroring the conditions of the in-service space vehicle.[5] This offered engineers opportunities to test and assess the recovery strategy on earth, prior to providing instruction to the crew. Regarding digital twin, it is generally recognised that the initial concept was introduced by Michael Grieves during the executive product life-cycle management (PLM) courses at University of Michigan.[6] At that time, the concept was known as 'mirrored spaces model'[7] and later referred to as 'information mirroring model'.[8] The concept was expanded by Grieves,[9] whereupon the term 'digital twin' was introduced. However, the basic concept that has largely remained since its inception in 2002 is that a digital informational construct about a physical system could be created as an entity in its own right. This digital information would be a 'twin' of the information that was embedded within the physical system itself and is linked with that system throughout its entire life-cycle. At its optimum, any information that can be obtained from inspecting a physical manufactured product can be acquired from its Digital Twin.[10] Parrott and Warshaw further elaborates the five enabling components of a Digital Twin system: sensor, data, integration, analytics, digital twin and actuators.[11] A physical-digital-physical loop is formed by these components and comprises the cornerstone of a digital twin system.

Aims and objectives

Different initiatives have been undertaken to apply digital twin in different sectors, such as manufacturing,[12] health care,[13] green life science,[14] fashion design[15] and so on. This paper focuses on the structural integrity management in particular for marine structures and presents a critical review that answers the following questions: How is digital twin defined in relation to structural integrity management? What are the recent developments of digital twin concerning its application in marine structures and structural integrity management? What are the opportunities and challenges? The first question aims to clarify the expected functionality of digital twin in the context of structural integrity management. Exploring the second question will unveil the current progress and answering the third question provides guidance in terms of future development. Additionally, a digital twin-enabled structural integrity management framework is proposed and key technologies within the framework are illustrated using a numerical example. This will assist the discussion of opportunities and challenges associated with digital twin and its future development.

Paper layout

The remaining part of this paper is structured as follows: Section 2 will deal with the definition of digital twin by consolidating the different concepts given in the literature. Thereafter, the recent developments and applications of digital twin for marine structure integrity management are reviewed and discussed in Section 3. As part the proposals for future development, an integrated digital twin-based framework for structural integrity management is introduced in Section 4, in which the key enabling technologies are demonstrated using illustrative numerical examples. With reference to these examples, Section 5 further discusses the opportunities of digital twin approach and the existing challenges in order to fully realise its potential. Finally, concluding remarks are provided in Section 6.

Definition of digital twin

Digital twin has been an active research area in the recent years. Various definitions are proposed to clarify the underlying concept of digital twin. A comprehensive review on the definition of digital twin in several academic publications was given by Liu et al.[16] They concluded that digital twin is a digital entity that reflects physical entity's behavioural rule and updates continually throughout the entire life-cycle. However, the authors recognised that this conclusion is rather general and ambiguous. This is largely because digital twin is not a specific technology, but a concept that can be implemented with a number of different advanced technologies (e.g. data-related technology, high-fidelity modelling technology, model-based simulation technology) and differs in different life-cycle phases (design phase, manufacturing phase, service phase, retire phase).

Wagg et al.[17] introduced the capability hierarchy of digital twin, which includes five different levels: supervision (Level 1), operation (Level 2), simulation (Level 3), learning (Level 4) and management (Level 5). Supervision is the most basic level and refers to the continuous monitoring of an asset or process. Building upon this, an interactive capability to inform and to support the operational decision making is required, that is, Level 2 – operation. The next level of sophistication is the simulation using digital twin. This enhances the previous two capabilities by adding a function to simulate the physical twin using numerical models and data. A graphical representation for visualising the physical twin is desired to support design and operational decisions. Extending the simulation by digital twin are two more levels within the capability hierarchy, namely learning and management. These are the current aspirations of digital twin. The former refers to an intelligent ability to learn from data so that supporting the decision making and scenario planning (i.e. prognostics, forecasting). Additionally, the learning capability minimises the discrepancy between simulation model and physical structure based on monitored data (i.e. model updating). Management refers to the automation of the digital twin. With all the aforementioned capabilities included, the digital twin system also needs to be able to perform all forms of decision making and asset management with minimal human intervention. This aspect of the capability is perhaps more relevant to artificial intelligence.

A consolidated and generalised definition of digital twin was proposed by VanDerHorn and Mahadevan.[18] This conceptualises it as a virtual representation of a physical system (and its associated environment and processes) that is updated through the exchange of information between the physical and virtual systems. The physical system, physical environment and the physical process constitutes the physical reality. These components all have their counterparts in the virtual world. Information is interconnected in a physical to virtual and virtual to physical manner. The former primarily refers to the means by which collected and/or interpreted information is used in physical reality to update the virtual representation. The latter indicates the means by which an action is informed by findings in the virtual representation and undertaken to influence the physical reality. The implementation of digital twin includes specifying the intended outcomes, scoping the digital twin, creating the virtual representation and establishing the interconnection scheme. A measurable and quantifiable outcome should be defined for the digital twin to be developed, which enables realistic bounding of the digital twin and allows for the value proposition to be explicitly defined; in other words, how much improvement can be achieved with respect to the expected outcome. In terms of scoping of the digital twin, it is important to define the modelling portion of the physical reality and set the boundary between the physical system and physical environment. The other requirement is to specify the level of abstraction, which means collecting the physical system states that are to be modelled and maintained. This will also determine the fidelity of the computational model used for creating the virtual representation. With regard to the latter, the two principal aspects are the development of data model for both current and historical system states and the implementation of relevant computational models. Visualisation is another important consideration as this demonstrates the value of digital twin to the organisational leadership and non-domain experts. Regarding the physical to virtual data connection, this is largely focused on sensor technology; however, offline data such as maintenance record, logbook, subject matter expert opinion should be considered during the implementation of digital twin. The virtual to physical data connection can be achieved through providing feedback from the virtual representation to a control actuator in the physical reality. This may correspond to the level 5 digital twin concept introduced by Wagg et al.[17]– autonomous management. Alternatively, a human-in-the-loop approach can be used, in which the information or insights from digital twin are adopted to support the decision-making of relevant actions. A digital twin can also be distinguished from digital model or simulation approach by two qualifiers: the virtual representation that represents a single instance of a physical system, and the data/information which is used to update the states of the virtual representation over time.

In the context of structural integrity management, a hypothetical scenario was described by Tuegel et al.[19] to introduce the digital twin as a structural model that was ultra-realistic in geometric and material details. This structural model was tightly coupled to an as-built computational fluid dynamics model providing environmental load conditions. Simulation could be performed on the coupled model to forecast the structural response. This design-point-based simulation, however, may deviate from reality due to the unplanned usage or payloads and structural degradation etc. In view of this, an accompany digital twin was required, which was linked to the dedicated sensing system deployed on the physical asset. The sensing system provided condition data of the physical asset such as deflection, strain, acceleration and so on. These become the basis on which to periodically update the structural model so that reflecting the physical asset.

Erikstad[20] defined digital twin as a digital model capable of rendering state and behaviour of a unique real asset in (close to) real time. The core characteristics include: (1) identity; (2) representation; (3) state; (4) behaviour; (5) context. Identify refers to the uniqueness of physical asset to which digital twin connects. Representation refers to the computer model that captures the essential physical manifestation. This may also correspond to the virtual system concept introduced in VanDerHorn and Mahadevan.[18] State and behaviour reflect the condition and response of the physical asset, and information on both will be provided in real time. These are the characteristics that demarcates digital twin from a conventional computer model as it can inform the physical asset as to what is happening but a simulation model can only infer what could happen to the prototype product.[21] Additionally, context describes the external environment in which the asset operates.

Kim et al.[22] indicated that any definition of digital twin should reflect three key characteristics and also the technical qualifiers of digital twin: trinity form, real-time and state representation. Digital twin is of a trinity form, consisting of physical object, virtual object and a data connection. The three components within this basic configuration interacts in real-time (However, offline information exchange is possible). Additionally, the geometrical, structural and behavioural states of the digital twin must be represented.

Examination of the above research makes it clear that digital twin is the counterpart of physical structures in a digital world. It mirrors the same responses and conditions of the physical structures in real time (i.e. structural configuration, detailed scantling, material property, macro and micro degradation) and is able to predict the same structural response and damage under a given future scenario. Twinning is a process of reducing the uncertainty between the physical structures and its digital counterpart. This is achieved by updating the digital counterpart using real-time monitoring data which effectively removes the modelling assumptions. The insights obtained from digital twin will then provide feedback to optimise the physical world operation. Figure 1 summarises the key features of digital twin for the five-level capability hierarchy defined by Wagg et al.,[17] including the modelling of virtual representation and the two-way interconnection between the physical and virtual domains.

However, as discussed in Erikstad,[23] there is no universal acceptance for these features being required, or even sufficient. Digital twin is multifaceted and may vary substantially between each case in which it is used. It constitutes an 'opportunity maker' rather than an end product by acting as a live, rich data source, beyond what can be offered by point-based sensor configurations and what is directly observable. The opportunities could be numerous and may be diverse depending on specific application. The remainder of this paper will discuss the opportunities it presents with respect to structural integrity management through demonstrating the key enabling analysis methods.

During the literature survey, a highly relevant research topic, model-based structural health monitoring, has drawn the attention of the present authors. Although a computer-based analytical/numerical model is required in both cases, there are fundamental differences between the two methods, attributing to the way by which the measurements are utilised and structural conditions are predicted. Concerning model-based structural health monitoring, the goal is to infer an analytical model directly from the observed response data, which is usually posed as an inverse problem: given some observed response from a potentially damaged structural system, due to some external action, determine an analytical model of the structural system which accurately captures this observed response.[24] The successful discovery of this analytical model then provides direct insight into the physical condition of the system such as damage identification and localisation.[25] This can be achieved using a structural model updating approach as illustrated by Refs.[26–29] On the contrary, the key objective of digital twin is to develop a virtual replicate with an emphasis on obtaining the responses of the entire structures including unmonitored locations. This enables the integrity engineers to evaluate the health condition of unmonitored yet structurally critical components directly using the virtually monitored response. Solving an inverse problem using the modal decomposition and expansion technique, which translates the monitored responses to the responses at um-monitored locations, is one of the solutions to achieve aforementioned objective. Alternatively, measurements of real-time external actions (i.e. wave conditions) can be taken and input to the analytical/numerical model to enable all-over response simulation, as presented by Refs.[30–32] In general, the techniques developed within the field of model-based structural health monitoring are highly beneficial for the realisation of digital twin; however, the latter arguably represents a difference paradigm for structural integrity monitoring and assessment.

Recent developments regarding marine structures

Overview

This section reviews the state-of-the-art practical implementation of digital twin-based structural integrity management regarding marine structures. Due to the rapid development of computational power, the use of high-fidelity digital models (e.g. finite element model) has become increasingly prevalent for marine structural design and assessment. These models are usually employed in combination with code-based assumptions regarding the environmental conditions required to evaluate the structural performance during the entire life cycle. This provides a quantitative basis on which to approve the structural design. Glaessgen and Stargel[33] argued that this approach may fail to support the development of next generation of structures, which are likely to encounter unforeseen scenarios. Thus, there is a need to integrate the on-board sensor measurement with high-fidelity physical models so that a real-time and continuous health management system can be developed, namely digital twin. A recent project call from the Ship Structures Committee (SSC) may provide an exemplar expectation of digital twin system in association with structural integrity management.[34] According to the proposed scope of the project, a digital twin system should be able to utilise monitoring data in combination with finite element analysis to support fatigue damage accumulation estimates and evaluate the likelihood of exceeding damage threshold. The

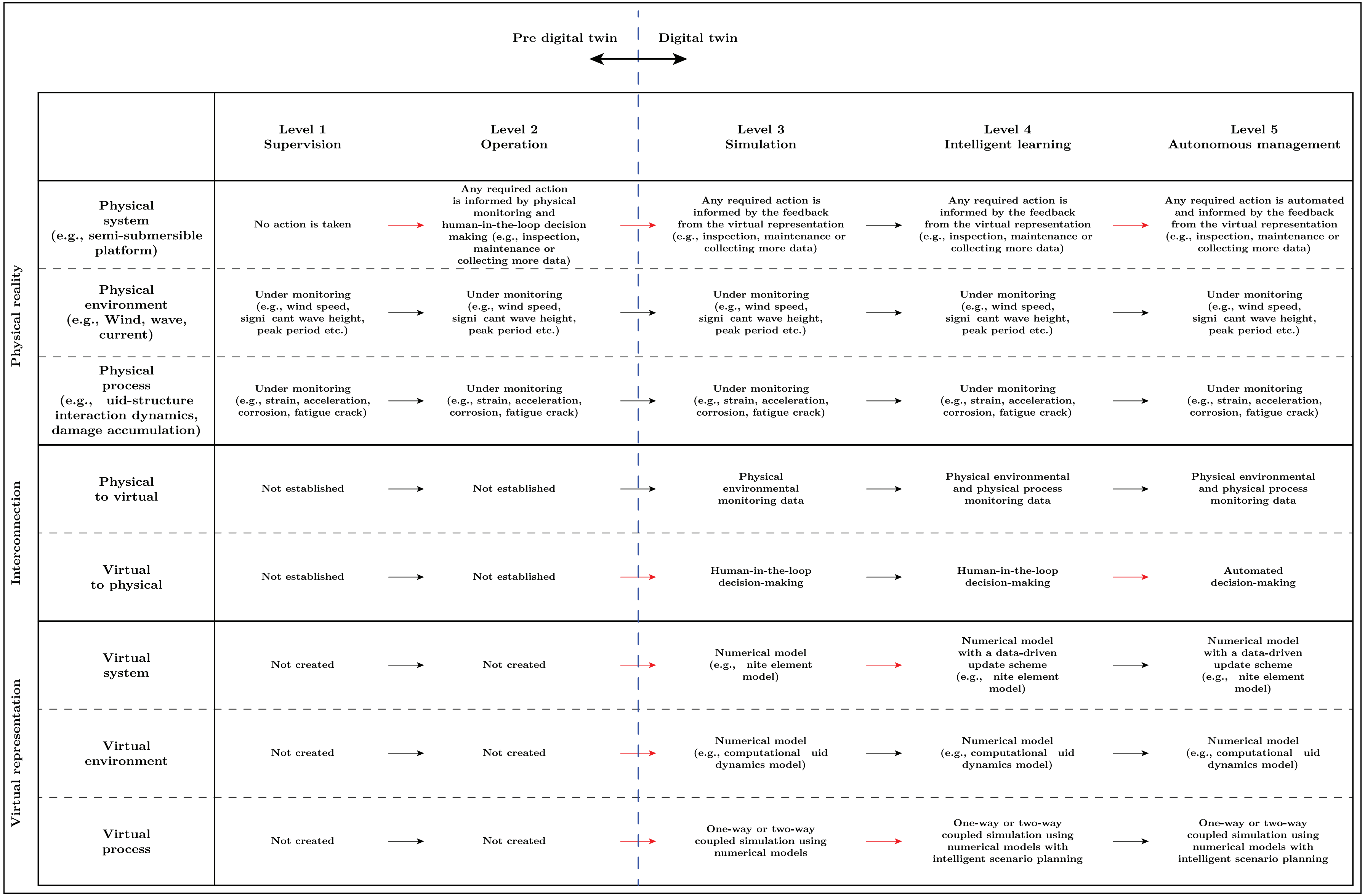

Figure 1. Key features of digital twin.

Table 1. Summary of the recent developments of digital twin for marine structures.

References	Physical to virtual	Virtual to physical	Virtual system	Virtual environment	Virtual process	Digital twin level
Thompson[30]	Operational profile update	Human-in-the-loop intervention	Finite element model	Potential flow-based frequency domain hydrodynamics	Hydro-structural simulation; SN-based fatigue	Level 3
Thompson[31]	Operational profile update by wave hindcast	Not report	Finite element model	Potential flow-based frequency domain hydrodynamics	Hydro-structural simulation; SN-based fatigue	Level 3
Hageman and Thompson[32]	Operational profile update by wave hindcast or motion	Not reported	Finite element model	Potential flow-based frequency domain hydrodynamics	Hydro-structural simulation; SN-based fatigue	Level 3
Aarsnes et al.[35]	Operational profile update by AIS and wave hindcast	Not reported	Finite element model	Potential flow-based frequency domain hydrodynamics	Hydro-structural simulation; SN-based fatigue	Level 3
Hulkkonen et al.[36]	Operational profile update by AIS and wave hindcast	Not reported	Finite element model	Potential flow-based frequency domain hydrodynamics	Hydro-structural simulation; SN-based fatigue	Level 3
Sugimura et al.[37]	Operational profile update by wave radar	Human-in-the-loop intervention	Finite element model	Potential flow-based frequency domain hydrodynamics	Hydro-structural simulation; SN-based fatigue	Level 4
Sireta and Storhaug[38]	Direct structural monitoring by strain gauge	Not reported	Finite element model	Not required	Modal decomposition and expansion; SN-based fatigue	Level 3
Henkel et al.[39]	Direct structural monitoring by accelerometer	Not reported	Finite element model	Not required	Modal decomposition and expansion; SN-based fatigue	Level 3
Augustyn et al.[40]	Direct structural monitoring by accelerometer	Not reported	Updated finite element model	Not required	Modal decomposition and expansion; SN-based fatigue	Level 4
Augustyn et al.[41]	Direct structural monitoring by accelerometer	Not reported	Updated finite element model	Not required	Modal decomposition and expansion; SN-based fatigue	Level 4
Boutrot et al.[42]	Periodic thickness measurement	Not reported	Finite element model	Potential flow-based frequency domain hydrodynamics	Hydro-structural simulation; SN-based fatigue	Level 3

developed system shall be performed in near-real time and account for the uncertainty inherent in the process. The above scope of work suggests that, in terms of functionality, a digital twin system should possess the capability of diagnostics and prognostics for the performance of any structural component of interest; for example, cumulative fatigue damage and remaining life forecast. These assessments must be performed in near-real time, providing up-to-date information about the health condition of structures. Although this project call was only concluded recently, and technical developments from this project have not been published yet, several relevant research are identified from a literature survey as summarised in Table 1. In generally, the main research activity within this theme is to develop a practical scheme for integrating monitoring data with the numerical model of physical structures. Broadly speaking, two kinds of digital twin are reported, which are based on different fatigue damage assessment methodologies namely spectral-based and time-domain approaches. The following sections will present the different digital twin developments making using of these two fatigue assessment methods respectively. Additionally, a number of research are conducted aiming to develop a more accurate numerical model through finite element updating techniques. Research on this subject will also be introduced in the following.

Physical to virtual domains connection approach

Spectral-based approach. Within this spectral-based approach, in essence, the developed digital twin systems attempt to evaluate the short-term wave spectrum by processing the monitoring data. This short-term sea state can be combined with the stress Response Amplitude Operator (RAO) obtained from a 3D finite element model to obtain the stress spectrum of structural details of interest. Fatigue damage accumulation can then be completed using relevant damage models such as the S-N curve.

Thompson[30] proposed a framework to assess the fatigue of marine structural component using digital twin approach to increase awareness of structural condition and limit maintenance costs. In the proposed framework, virtual monitoring is enabled by a finite element numerical twin which is driven by the real-time update of the operational profile (e.g. wave spectrum). Aarsnes et al.[35] described a digital product prototype which combines the structural and hydrodynamic design models with specific encountered wave information that matches the Automatic Identification System (AIS) and global wave hindcast data. This allows a real-time evaluation of structural integrity concerning fatigue, and therefore provides a useful basis for inspection and maintenance planning. To examine the validity of using wave hindcast data for virtual monitoring, Thompson[31] compared the calculated stress spectra based on wave hindcast data with those derived from the full-scale strain gauge measurement. This comparison was made with reference to the root-mean-square stress and mean stress zero-crossing frequency. Positive results were obtained, which suggests virtual hull monitoring using wave hindcasts can be used for calculation of stress spectra with an acceptable degree of accuracy. However, it was also acknowledged that the sea trial was performed in a relatively short duration. Thus, it was unknown whether the encouraging results were representative of a wide range of operational conditions. Hageman and Thompson[32] continued to explore the use of hindcast wave data for virtual monitoring of structural integrity. Spectral fatigue assessments were conducted using publicly available wave hindcast data. A comparison was made with the fatigue accumulation estimation by direct onboard strain measurement. The authors concluded that the calculated fatigue damage based on hindcast data was generally acceptable in a mild sea state and exhibited reasonable agreement with that evaluated based on direct strain measurement. However, the hindcast wave data-based prediction was underestimated, causing unacceptable deviation with respect to that based on strain measurement. Further developments of hindcast models may overcome this, but based upon the available models, the effect of random errors, spectral wave distribution, and directional spreading on fatigue damage were assessed. Monte-Carlo simulation revealed that the random error in hindcast data had only a negligible effect on the fatigue damage estimation. Although the spectral wave distribution and direction are not provided by the hindcast model, the choice of spectral shape and wave spreading information significantly influenced the estimation of fatigue accumulation. The case study showed that using a Brettschneider spectrum led to a 70% higher fatigue accumulation than when using a Gaussian spectrum. Introducing wave spreading to calculations reduced the fatigue accumulation estimates by 25% compared with a long-crested wave condition. In addition to the use of wave hindcast data, Hageman and Thompson[32] attempted to utilise the motion data of a floater to retrieve the wave condition, following the method introduced in.[43] An artificial neutral network (ANN) was developed to predict the wave characteristics (significant wave height, peak period and main direction) using input from a time series of six degree of freedom motions. The training data included both full-scale measurement and 10,000 sea-keeping numerical simulations. In comparison with the adoption of hindcast wave data in a spectral fatigue analysis, the use of motion data-derived wave statistics exhibited varying agreement with respect to the fatigue damage estimated by direct strain measurement. In higher sea states, the motion data set yielded marginally improved agreement with the strain measurements than the hindcast-based calculation. Nevertheless, in mild conditions, stress was significantly overestimated. The aforementioned methods are reliant on the 'wave buoy analogy', and serve as an alternative to the sea state estimation using wave radar etc. A concise account of techniques for the sea state estimation using the 'wave buoy analogy' concept can be found in.[44] Hulkkonen et al.[36] introduced a digital twin approach for monitoring the structural integrity. The proposed method was built upon the existing computing capability of NAPA software which was combined with the Automatic Identification System (AIS) messages and wave nowcast data from WAVEWATCH III (WW3) model of National Centre for Environmental Prediction (NCEP). NAPA is an integrated hydro-structural analysis platform. In the proposed digital twin approach, it provides the stress RAO of structural details of interest. This was combined with the wave spectrum evaluated by the AIS message and the corresponding wave nowcast data to obtain the stress spectrum and perform the fatigue damage estimation using appropriate S-N curve and Miner rule.

Although the virtual monitoring for all structural details of interest can be realised by a numerical twin (i.e. finite element model) with real-time environmental load input, as reviewed above, a discrepancy between the predicted and monitored stress response could exist. Specifically, the predicted stress spectrum and that evaluated by spectral analysis of monitored stress series as examined by Hageman and Thompson.[32] To this end, a Bayesian approach was introduced by Sugimura et al.[37] In the developed approach, the short-term wave spectrum is generated every 20 min by processing the wave radar measurement. The short-term wave spectrum is adopted in combination with the stress Response Amplitude Operator (RAO) at the structural details of interest to obtain the stress spectrum. The correlation factor is derived by comparing the available measured stress spectrum and the corresponding predicted stress spectrum, accounting for the uncertainty caused by the inadequacy of the finite element model and the wave data.

Time-domain approach. In addition to the above approach are studies focusing on a time-domain solution. However, time-domain simulation is usually computationally demanding.[45] Hence, the use of reduced-order model was suggested by Leng et al.[46] Alternatively, interpretation and extrapolation of real-time structural strain from a network of on-board sensors has been extensively applied. For instance, Sireta and Storhaug[38] formulated a modal approach to reconstruct the structural response based on measurements from a few strain gauges. In addition to the use of the modal principle,[47] this method is able to select the required structural modes and to optimise the strain gauge layout. Through numerical validation, the proposed method demonstrates sufficiently high practicality to be incorporated into a time-domain digital twin framework for estimating the cumulative fatigue damage of offshore structures. Henkel et al.[39] adopted the modal decomposition and expansion method to extrapolate the measured response to locations of interests. As a proof of concept, the modal decomposition and expansion (MDE) method was applied on an offshore wind turbine with jacket substructure. The estimated time history was checked in both time domain and frequency domain and subsequently fatigue damage. Outcomes revealed that the MED method was suitable for reproducing the stress history at leg K-joint, whereas the prediction of stress history at brace X-joint was unsatisfactory. The latter was attributed to the neglect of local mode shapes. In addition, this method was shown to be less accurate in severe sea states. The MDE method can be regarded as a physics-based approach for the reconstruction of strain/displacement field. For the same purpose, a data-driven approach was introduced by Refs.[48,49] based on the radial basis function which was shown to be both accurate and efficient.

To verify the direct use of structural strain measurement for fatigue damage evaluation, Magoga et al.[50] performed a comparison between the fatigue life predicted based on direct strain measurement and measured fatigue life. The estimation of the former was based on the stress spectrum derived by on-board strain measurement proximal to the structural detail of interest. The latter was evaluated using maintenance data of vessels of a similar class, in which fatigue life was defined as the time from commissioning to the detection of the first crack. The rationale for measuring the fatigue life from fleet maintenance data is that the presence or absence of cracks in a structural detail of a particular vessel is viewed as a indicator of the corresponding fatigue life. This rationale is reflected in the International Association of Classification Societies description of 'damage experience', or the number, extent, location, and frequency of cracks related to the fleet, as the main source of information for maintenance planning. The case study of an aluminium high-speed craft demonstrated good agreement between the predicted fatigue life and the measured fatigue life. This is partly attributable to the rationality underpinning the linear summation rule for damage accumulation and the adopted S-N curve, but mostly the direct use of strain gauge measurement in fatigue analysis.

Finite element model updating

As inferred from the SSC project scope and the foregoing reviewed literature, the numerical twin of a structure, usually in the form of a 3D finite element model, plays a crucial role in the overall digital twin framework in terms of virtual domain modelling. The use of finite element method for representing the physical structural system was reported in all the literature reviewed in this paper, such as Refs.[30–32,35,37] The accuracy of this numerical model in terms of representing the physical assets will dictate the credibility of any diagnostics and prognostics made with respect to structural integrity. Whilst finite element modelling has been widely applied in marine structures, there is inevitably a discrepancy between the design specification and actual configuration, such as wall thickness of tubular structures. In view of finite element model updating, Augustyn et al.[40] developed an updating scheme by finding the best match between the eigenfrequencies predicted by finite element model and the as-installed modal properties measured by accelerometers. The application of the proposed scheme to the jacket substructure of an offshore wind turbine showed an error reduction from 30% to 1%. To further reduce the uncertainty in modelling, a calibration of the wave loads was implemented by the same author using wave radar so that the static response to wave load could be accurately estimated.[41] These techniques were incorporated into the digital twin framework for offshore wind structures, as discussed in Refs.[51,52]

In addition to the improvement of numerical modelling, it is equally important to account for the time-variant degradation of physical assets, such as corrosion wastage. Therefore, the finite element model developed during the initial design of the structure must be updated periodically. In this respect, Boutrot et al.[42] discussed a methodology based on 3D digital twin for the engineering reassessment of ageing offshore units from the viewpoint of life extension. The digital twin, in the form of a 3D finite element model, was periodically and automatically updated with critical inspection data on corrosion wastage. Engineering reassessment concerning corrosion and fatigue was performed on the updated model using a rule-based environment load calculation.

Remarks on recent developments

Overall, with respect to digital twin-based structural integrity monitoring and management for marine structures, most recent developments require the creation of a finite element model for the considered structure. This digital model is used in combination with data

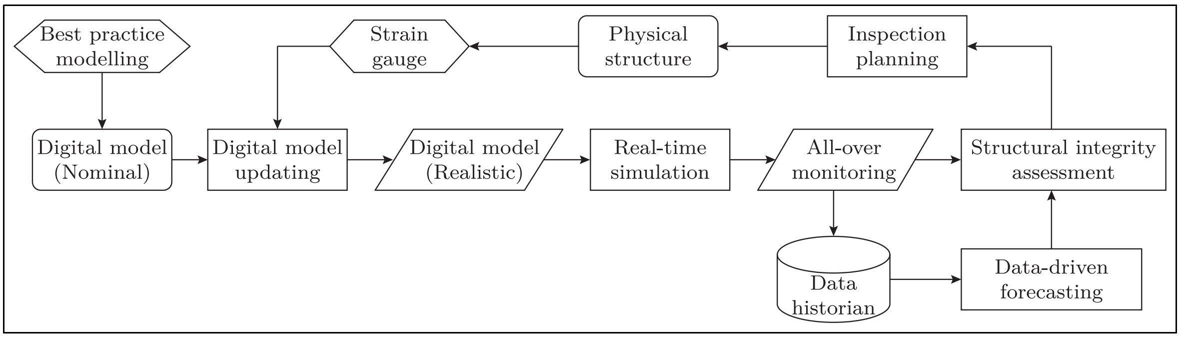

Figure 2. Digital twin-enabled structural integrity management framework.

and information collected from the sensing units of short-term wave characteristics and structural strain. Specifically, the short-term wave spectrum is combined with the pre-calculated stress RAO using a series of finite element analyses to determine the stress spectrum of the structural details of interest and subsequently evaluate fatigue using spectral-based approach. Consideration may also be given to assessing the uncertainty of the predicted stress spectrum, in which a comparison between the predicted and monitored stress spectrum can be made and the incorporation of prediction uncertainty facilitated. In addition to direct measurement of wave characteristics, an alternative solution is to use wave hindcast data. Aside from a spectral-based fatigue evaluation principle, the time-domain philosophy is feasible when the structural strain measurement is used directly for fatigue damage prediction. In this alternative approach, the key step is to convert the measurement to unmonitored yet critical structural locations of interest. In this regard, modal decomposition and expansion theory appears to be a commonly used method.

In either case, the stress life approach (S-N curve) combined with linear summation rule is still the most common strategy for fatigue damage evaluation in the foregoing reviewed works. Explicitly predicting the crack growth has also been investigated, such as Refs.[53,54]; however it seems that relatively few attempts have been made to apply this to full-scale structures. Additionally, most of the papers focused on current structural state evaluation (diagnostics), but very little attention has been given to structural performance prognostics. In addition, in terms of data interconnection between the physical and virtual space, a practical scheme of physical to virtual data transfer has been established. However, virtual to physical feedback, the digital twin informed decision-making process, is absent in the literature. Furthermore, although a number of studies related to digital twin have been proposed in the literature, most are limited to a conceptual level, while some are only concerned with sub-system development. An integrated framework to enable the creation and application of digital twin appears to be lacking.

Digital twin enabled SIM framework

Overview

Based upon the works reviewed, this section proposes an integrated digital twin-based framework for structural integrity management (SIM). The basis is an interconnection between the physical domain (i.e. physical structure in real world) and the digital/virtual domain (computer-based model), in which the link is the monitoring data. The three key enabling technologies are model updating, real-time simulation and data-driven forecasting. These allow physical-to-virtual connection to be performed in an effective and accurate manner, from which a replicate of the physical asset/structure is developed. This framework is based on a time-domain fatigue evaluation approach as outlined in previous section. An overview is shown in Figure 2. A digital model (analytical or numerical) of the physical structure is developed based on best practice. However, it is considered a nominal model as the modelling is based on nominal specification. Therefore, a model updating technique is required to update the modelling specification in order to derive a realistic model, in which case the digital model can be regarded as a 'digital twin'. This corresponds to the building phase of digital twin, including its maintenance, where the monitored data coming from the physical environment facilitates the creation of a virtual base with equivalent characteristics in terms of behaviour.[55] The real-time simulation is aimed at virtually monitoring the structural response all over the structure, which overcomes the limitation of physical monitoring. Data-driven forecasting is relevant as a vast amount of data can be obtained through digital twin. Utilisation of these data to assist long-term performance prediction also needs to be considered. Subsequently, the information related to structural integrity such as cumulative damage offers decision-making support regarding the planning of inspection/maintenance or other remedial actions to be implemented in a timely fashion. This will then close the loop of the interconnection between physical domain and digital domain. The following section presents the underlying theory of relevant model updating, real-time simulation and data-driven forecasting approaches. Thereafter, this framework will be demonstrated using a numerical example, which facilitates subsequent discussion of the opportunities and associated challenges of digital twin.

Model updating

The objective of model updating is to minimise the discrepancy in the modal property (e.g. natural frequency) measured from physical structures and those predicted by digital twin based on nominal design specification at the first instance:

$$\delta \mathbf{z}_{n\times 1}\begin{Bmatrix} \omega_1 - \omega_{DT(1)} \\ \omega_2 - \omega_{DT(2)} \\ \vdots \\ \omega_n - \omega_{DT(n)} \end{Bmatrix} \tag{1}$$

where ω_n is the natural frequency measured from the physical structures and $\omega_{DT(n)}$ is the natural frequency predicted by digital twin. A sensitive-based model updating technique, which iteratively updates the nominal parameters through the following relationship, can be employed:

$$\delta \mathbf{z}^i_{n\times 1} = \mathbf{S}^i_{n\times m}\boldsymbol{\theta}^i_{m\times 1} \tag{2}$$

where $\delta\,\theta^i_{m\times 1} = \{\delta\theta^i_1, \delta\theta^i_2, \cdots, \delta\theta^i_m\}^T$ is the perturbation in the parameters after i iteration, $\delta \mathbf{z}^i_{n\times 1} = \{\delta z^i_1, \delta z^i_2, \cdots, \delta z^i_n\}^T$ is the error in the natural frequency, and $\mathbf{S}^i_{n\times m}$ is the sensitivity matrix with each entry being the first derivative of the modal property with respect to the parameters, evaluated at the current estimate of the parameter (equation (3)).

$$\mathbf{S}^i_{n\times m} = \begin{bmatrix} S^i_{11} & S^i_{12} & \cdots & S^i_{1m} \\ S^i_{21} & S^i_{22} & \cdots & S^i_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ S^i_{n1} & S^i_{n2} & \cdots & S^i_{nm} \end{bmatrix} \tag{3}$$

For instance, S^i_{nm} refers to the first derivative of the natural frequency $\omega_{DT(n)}$ with respect to the parameter θ_m when $\theta_m = \theta^i_m$. Note that $\omega_{DT(n)} = \omega^i_{DT(n)}$ in this case and is predicted by the digital model with parameters $\theta^i_{m\times 1}$:

$$\omega^i_{DT(n)} = f_{DT}(\theta^i_1, \theta^i_2, \cdots, \theta^i_m) \tag{4}$$

A central difference method may be adopted to numerically approximate the first derivative as follows:

$$S^i_{nm} = \frac{\omega^{i(+)}_{DT(n)} - \omega^{i(-)}_{DT(n)}}{2\epsilon} \tag{5}$$

Assuming that the number of measurements exceeds the number of parameters to be updated, a least square solution can be obtained for the unknown parameter perturbation:

$$\delta\theta_{m\times 1} = [\mathbf{S}^T_{n\times m}\cdot \mathbf{S}_{n\times m}]^{-1}\mathbf{S}^T_{n\times m}\delta \mathbf{z}^i_{n\times 1} \tag{6}$$

The parameters can then be updated using the perturbation estimate until convergence is achieved.

Real-time simulation

Real-time simulation is aimed to virtually monitor the structural response all over the asset, which overcomes the limitation of physical monitoring. To achieve this, the physically monitored can be combined with the digital model via a modal decomposition and expansion theory. It is assumed that the dynamics of a structure can be decomposed into an infinite number of mode shapes with different modal amplitudes:

$$\mathbf{u}(x,t) = \boldsymbol{\Phi}(x)\mathbf{Q}(t) \tag{7}$$

where $\mathbf{u}(x,t)$ is the dynamic structural response vector as a function of the spatial and temporal coordinates, $\boldsymbol{\Phi}(x) \in \mathbb{R}^\infty$ is the mode shape matrix and $\mathbf{Q}(t) \in \mathbb{R}^\infty$ is the time-varying modal amplitude vector. Let us consider the structural response of a finite number of discrete locations within the structure and partition the response into physically monitored responses and responses to be converted (i.e. virtually monitored):

$$\mathbf{u}(t) = \begin{Bmatrix} \mathbf{u}_m(t) \\ \mathbf{u}_c(t) \end{Bmatrix} = \begin{Bmatrix} \boldsymbol{\phi}_m \\ \boldsymbol{\phi}_c \end{Bmatrix}\mathbf{q}(t) \tag{8}$$

Using a least-square approach, the modal amplitude, that is, $q(t)$, can be estimated as follow:

$$\tilde{\mathbf{q}}(t) = (\boldsymbol{\phi}^T_m\boldsymbol{\phi}_m)^{-1}\boldsymbol{\phi}^T_m\mathbf{u}_m(t) \tag{9}$$

The converted response (virtually monitored response) is then estimated using:

$$\tilde{\mathbf{u}}_c(t) = \boldsymbol{\phi}_c\tilde{\mathbf{q}}(t) \tag{10}$$

There is an inevitable discrepancy between the virtually monitored response and the actual response of the physical structure. To quantify the discrepancy, four uncertainty indicators may be relevant, namely the time response assurance criterion (TRAC), coefficient of determination (CoD), bias (b) and coefficient of variation (CoV). The TRAC is defined by the following expression:

$$\mathrm{TRAC} = \frac{(\mathbf{u}^T\tilde{\mathbf{u}})^2}{(\mathbf{u}^T\mathbf{u})(\tilde{\mathbf{u}}^T\tilde{\mathbf{u}})} \in [0,1] \tag{11}$$

where $\mathbf{u}$ denotes the actual response and $\tilde{\mathbf{u}}$ denotes the virtually monitored response. TRAC is a measure of the temporal correlation between the monitored and converted data with TRAC = 1 indicating a perfect correlation and TRAC = 0 implying no correlation. Further, because TRAC does not account for the amplitudes of the signals, the CoD is introduced to capture the potential amplitude errors:

$$\text{CoD} = 1 - \frac{E[(\mathbf{u} - \tilde{\mathbf{u}})^2]}{Var[\mathbf{u}]} \in [-\infty, 1] \tag{12}$$

where $E[\cdot]$ denotes the expectation operator and $Var[\cdot]$ denotes the variance operator. Two matrices (b and CoV) are introduced to evaluate the amplitude range uncertainty. The bias is defined as the expected value of the cumulative amplitude range ratios of the time series:

$$b = E\left[\frac{\Delta\mathbf{u}}{\Delta\tilde{\mathbf{u}}}\right] \tag{13}$$

where $\Delta\mathbf{u} \in \mathbb{N}^m$ is the cumulative rainflow count over actual response time series, $\Delta\tilde{\mathbf{u}} \in \mathbb{N}^m$ is the cumulative rainflow count over actual response time series. m is the number of rainflow count bins. The coefficient of variation (CoV) is defined as the standard deviation of the cumulative amplitude range ratios for all rainflow count bins normalised to the bias:

$$\text{CoV} = \frac{\sqrt{Var\left[\frac{\Delta\mathbf{u}}{\Delta\tilde{\mathbf{u}}}\right]}}{b} \tag{14}$$

Data-driven forecasting

Forecasting the structural response (e.g. stress) and possible damage (e.g. fatigue) to support the verification of structural design adequacy and long-term planning of inspections have long been an integral component of the design of engineering structures. However, forecasting at an initial design stage can only be performed based on certain assumptions, such as long-term stress range distribution. These design assumptions are usually derived from the historical data of structures with a similar configuration and operational profile. Digital twin offers an opportunity to utilise the actual response of the structure to improve the applicability of analytical assumptions for specific case. With respect to digital twin-enabled integrity management, a key objective is to evaluate the fatigue damage accumulation of critical structural details. To achieve this, Bayesian inference is arguably one of the most suitable methods.

In Bayesian approach, the parameter to be estimated (θ) is treated as a random variable and is described by a prior distribution based on prior knowledge, denoted as $f'(\theta)$. New information obtained from the digital twin-based monitoring can be used to formulate the likelihood function:

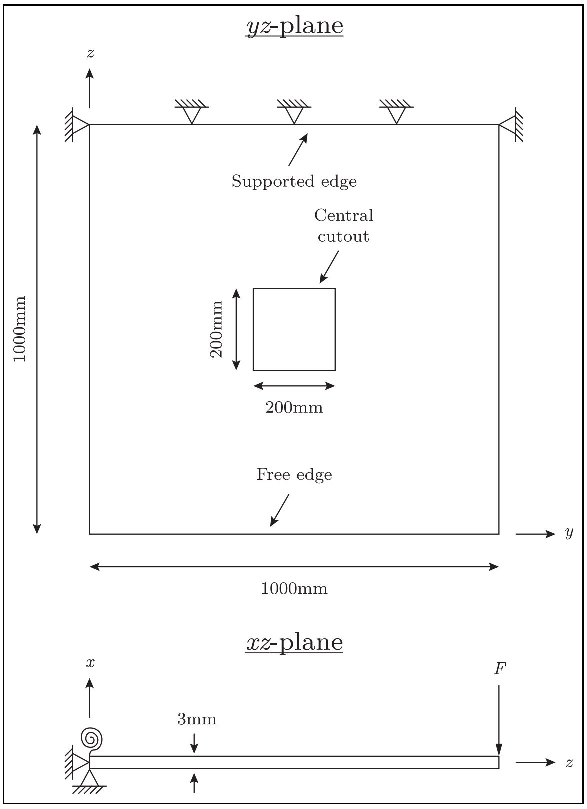

Figure 3. Schematics of the case study cantilever plate.

$$L(\theta) = \prod_{i=1}^{n} f_X(x_i|\theta) \tag{15}$$

According to the Bayesian theorem, the posterior distribution is proportional to the product of the likelihood function and the prior distribution:

$$f''(\theta) \propto L(\theta) f'(\theta) \tag{16}$$

A Markov Chain Monte Carlo can be employed to approximate the posterior distribution in case analysis solution is difficult to obtain.

Illustrative example

An illustrative example is presented to demonstrate the key features of the proposed digital twin framework, namely model updating, real-time simulation, and data-driven forecasting. A cantilever plate with a central cut-out subjected to a wave force at its free edge is considered (Figure 3). The central cut-out leads to a stress concentration in an area closed to the cut-out corner, which is therefore regarded as a fatigue-prone area with high criticality in relation to structural integrity.

The objective is to monitor this fatigue-prone area and ultimately assess its remaining life to support

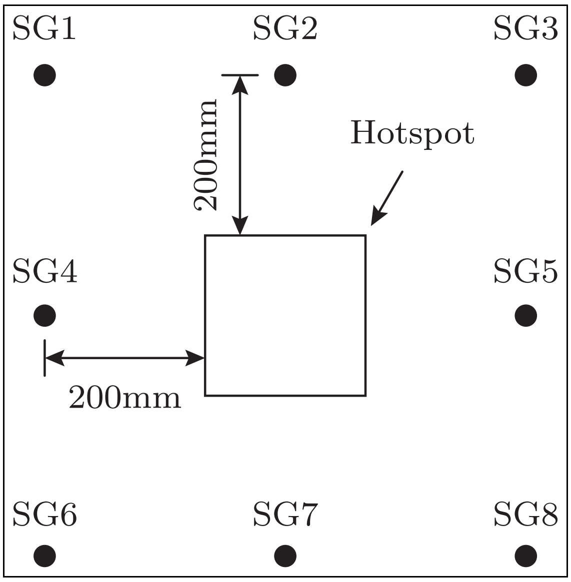

Figure 4. Strain gauge placement.

decision making with respect to inspection planning or other interventions. However, monitoring cannot be conducted proximal to this hotspot and thus measurements taken from other locations are required. Although this numerical example may appear to be trivial, it is sufficiently representative of a real-world scenario where the accessibility to a damage-prone critical location is limited. Thus, physical monitoring can only be performed at locations with better accessibility that are likely to be less structurally prominent. For now, it can help demonstrate the key features of the developed digital twin framework in a tractable manner. The monitored response will be obtained via a dynamic finite element analysis performed using a 'simulated physical model'. After completing the finite element simulation, the time histories of the responses at eight locations will be acquired (see Figure 4). These data represent the measurements from physical strain gauges. Strictly speaking they should be denoted as 'simulated monitored data'. However, to avoid confusion, the term 'monitored data' will be used hereafter.

For the present illustrative example, two finite element models will be developed, a 'simulated physical model' which provides the monitored data and a digital model which shall be used in conjunction with the monitored data. Both model is developed using four-node shell elements with the same mesh density (25 mm × 25 mm). The 'simulated physical model' is developed based on the actual geometric dimension, material property and boundary condition specified in Table 2, while the digital model is developed based on the nominal specification.

For illustrative purposes, the actual and nominal specifications only differ in plate thickness, elastic modulus, and rotational stiffness around the y-axis. A model updating technique will be applied to update these specifications in order to minimise the difference between the first-order natural frequencies predicted by the 'simulated physical model' and the updated digital model. The natural frequencies of the first eight modes of the cantilever plate are summarised in Table 3.

To obtain the monitored data, a dynamic finite element simulation is conducted in which a varied amplitude concentrated force along the x-axis is applied to the cantilever plate, approximating an irregular wave force. Assuming a JONSWAP wave spectrum, an irregular wave with significant wave height of 0.5 m and peak period of 2.5 s is considered. The 20-min time series of the wave elevation (η) is depicted in Figure 5. The concentrated force is estimated based on a simple static assumption, which can be given as a function of the wave elevation:

$$F = \begin{cases} 0.5\rho g b \eta^2 & \text{if } \eta > 0 \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

First, model updating is demonstrated. The iteration history of model updating is plotted in Figure 6. Following equation (6), model updating is conducted

Table 2. A summary of geometric dimension, material property and boundary condition of the cantilever plate.

Parameter	Symbol	Actual	Nominal	Unit
Length of plate	a	1000	1000	mm
Width of plate	b	1000	1000	mm
Thickness of plate	t	4.5	3	mm
Length of central cutout	d_1	200	200	mm
Width of central cutout	d_2	200	200	mm
Elastic modulus	E	200,000	200,000	MPa
Poisson's ratio	ν	0.3	0.3	-
Translational stiffness along x-axis	k_x	∞	∞	N/mm
Translational stiffness along y-axis	k_y	∞	∞	N/mm
Translational stiffness along z-axis	k_z	∞	∞	N/mm
Rotational stiffness along x-axis	k_{rx}	0	0	Nmm/rad
Rotational stiffness along y-axis	k_{ry}	40,500	30,000	Nmm/rad
Rotational stiffness along z-axis	k_{rz}	0	0	Nmm/rad

Table 3. A summary of the natural frequencies predicted by the 'simulated physical model' and the nominal digital model.

Parameter	Symbol	Actual	Nominal	Unit
First-order natural frequency	w_1	0.34	0.31	rad/s
Second-order natural frequency	w_2	1.47	1.02	rad/s
Third-order natural frequency	w_3	3.28	2.32	rad/s
Fourth-order natural frequency	w_4	5.45	3.65	rad/s
Fifth-order natural frequency	w_5	5.58	3.83	rad/s
Sixth-order natural frequency	w_6	10.56	7.17	rad/s
Seventh-order natural frequency	w_7	10.87	7.36	rad/s
Eighth-order natural frequency	w_8	12.84	8.68	rad/s

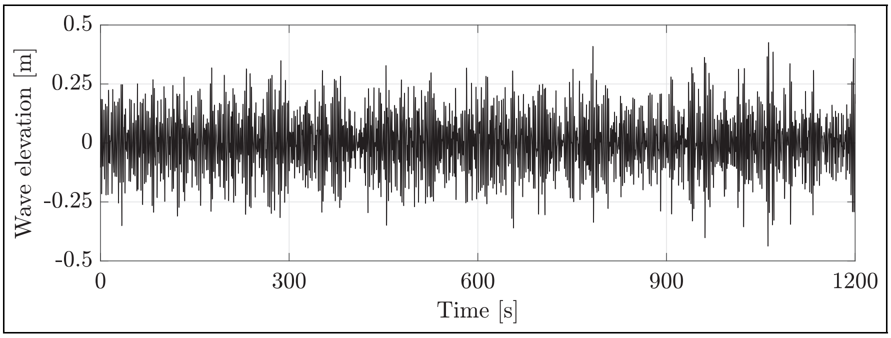

Figure 5. Wave elevation.

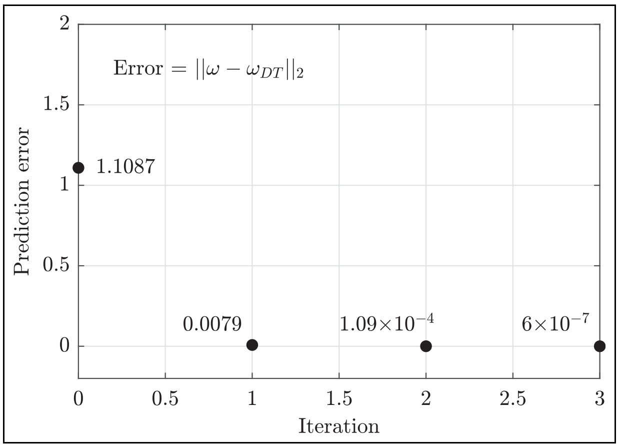

Figure 6. Model updating results.

for the nominal digital model. As shown in Figure 6, convergence of the prediction error (second norm of equation (1)) is achieved in three iterations and the error nearly approaches zero.

To obtain the first eight eigen-modes of the cantilever plate, eigenvalue analysis is performed using the updated digital model (Figure 7).

The time history of the converted stress response of the hotspot location is compared with the actual response in Figure 8. The effect of the number of monitoring units and the different combinations of monitored data are studied. Different combinations of mode shapes and the monitored data are available. To demonstrate its effect, example results are obtained using all strain gauge data and seven mode shapes (eight combinations are possible). The comparison is presented in Figure 9 in terms of the four uncertainty indicators (e.g. TRAC, CoD, bias, CoV).

This shows that without the inclusion of 1st or 4th mode shape, a worst correlation can be observed in the TRAC, CoD and amplitude range bias between the actual and the converted time series signals. However, a small variation of the amplitude range is also observed. A worst correlation in terms of TRAC and CoD can also be found when excluding the 6th mode shape, but the performance indicators related to the amplitude range (i.e. bias and CoV) are almost identical to the reference case. The above comparisons may demonstrate the negative effect of excluding structurally significant mode shapes in the dynamic response conversion, that is, a converted response with less correlation with the actual response. Nevertheless, it is not always necessary to include as many mode shapes as possible. For instance, the comparison between the reference case and case 7 in Figure 9 reveals that an improved correlation is achieved by removing the 7th mode shape from the conversion matrix. This is attributable to the fact that a high-order mode shape could potentially add noise to the time-series signal. It is clear that a number of mode shapes are insignificant regarding the structural responses of this case study model under the present load case (2nd, 5th and 8th). Based on these insights, a reduced set of mode shapes (1st, 3rd, 4th and 6th) is considered to investigate the effect of different combinations of strain gauges. Similarly, to demonstrate this effect, example results are obtained via the

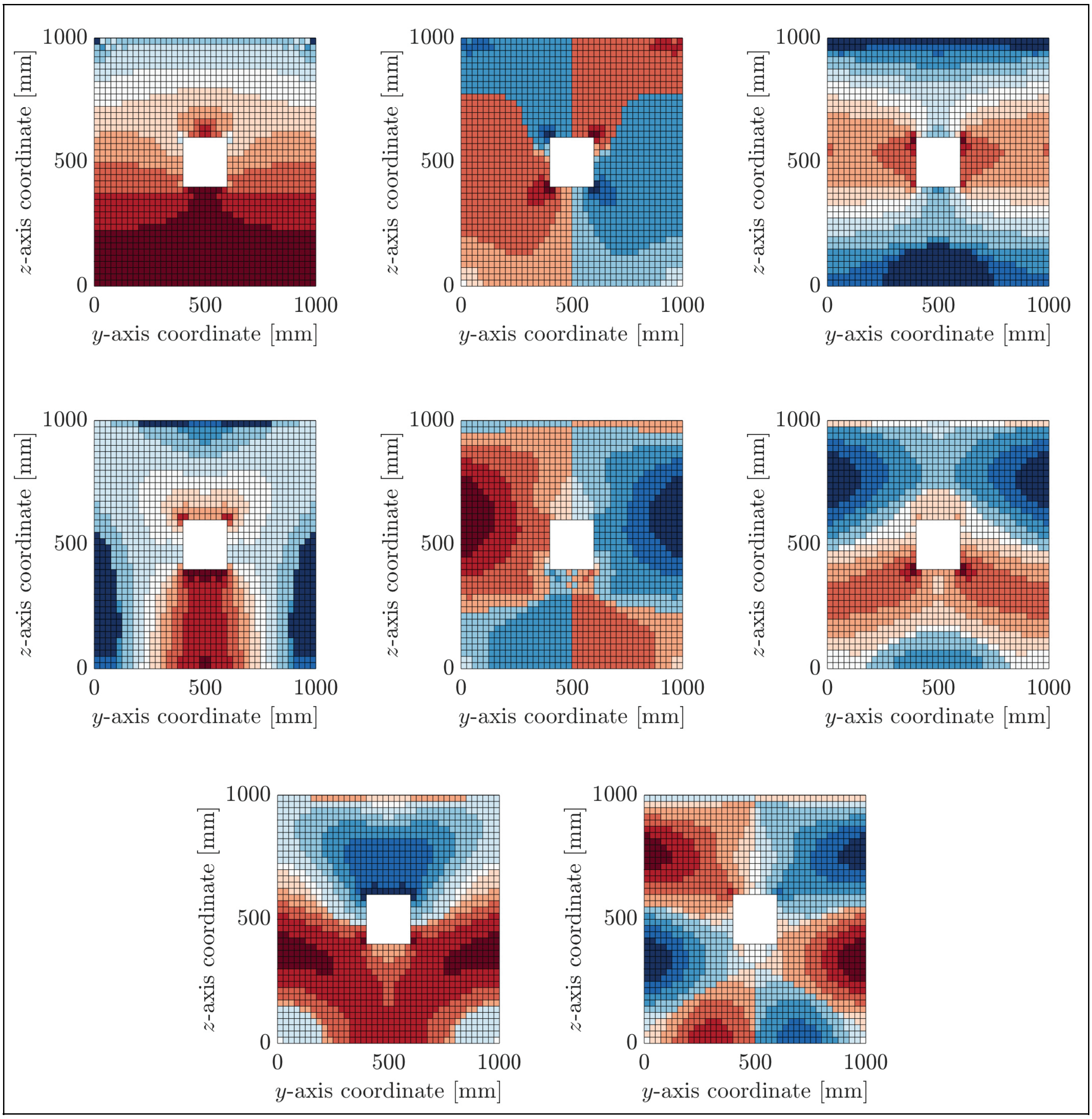

Figure 7. Maximum principal stress distribution at the different eigen-modes: (a) 1st mode, (b) 2nd mode, (c) 3rd mode, (d) 4th mode, (e) 5th mode, (f) 6th mode, (g) 7th mode and (h) 8th mode.

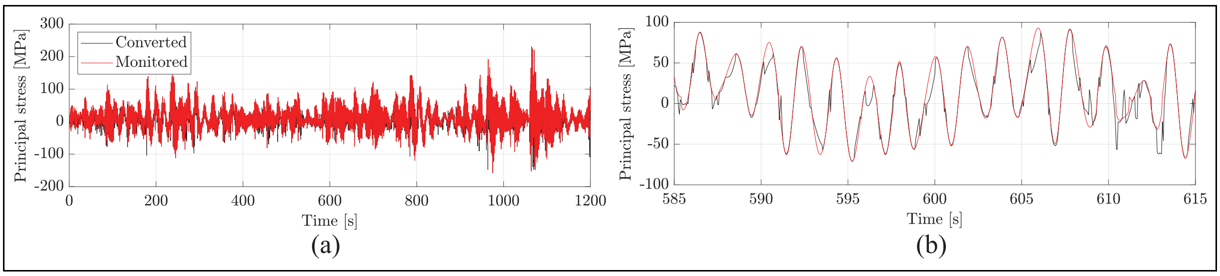

Figure 8. Comparison of the virtual and physical monitoring: (a) overview of time series comparison and (b) highlight of time series comparison.

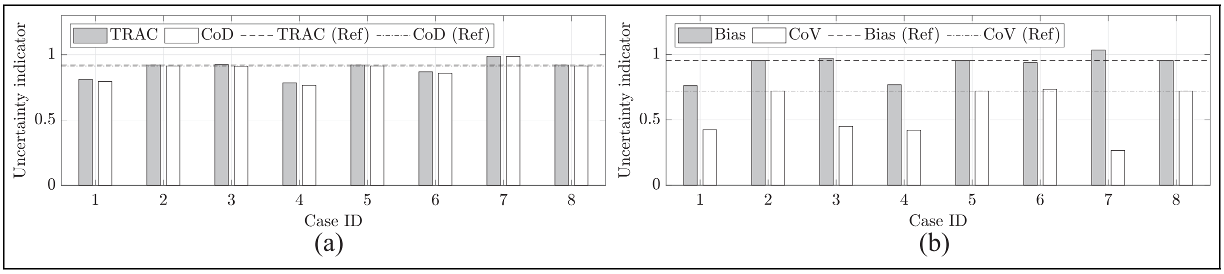

Figure 9. Comparison of uncertainty indicators – Load case 1 (Case 1: w/t 1st mode shape; Case 2: w/t 2nd mode shape; Case 3: w/t 3rd mode shape; Case 4: w/t 4th mode shape; Case 5: w/t 5th mode shape; Case 6: w/t 6th mode shape; Case 7: w/t 7th mode shape; Case 8: w/t 8th mode shape. Note: All strain gauges results are adopted: (a) TRAC and CoD and (b) Bias and CoV.

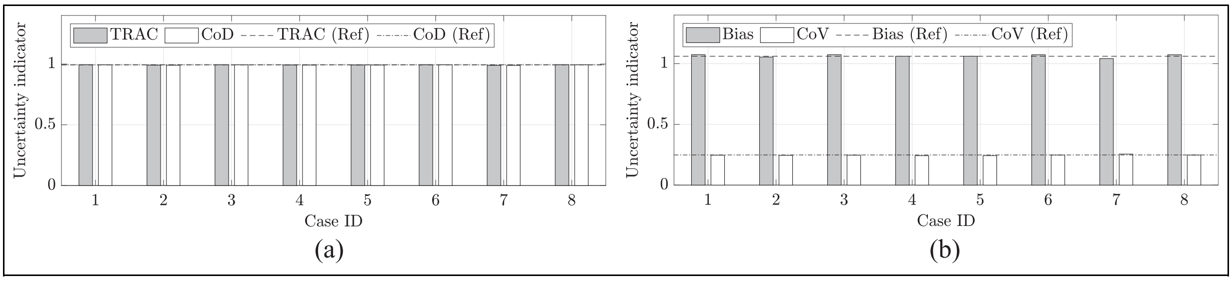

Figure 10. Comparison of uncertainty indicators (Case 1: w/t SG1; Case 2: w/t SG2; Case 3: w/t SG3; Case 4: w/t SG4; Case 5: w/t SG5; Case 6: w/t SG6; Case 7: w/t SG7; Case 8: w/t SG8. Note: 1st, 3rd, 4th and 6th are adopted: (a) TRAC and CoD and (b) Bias and CoV.

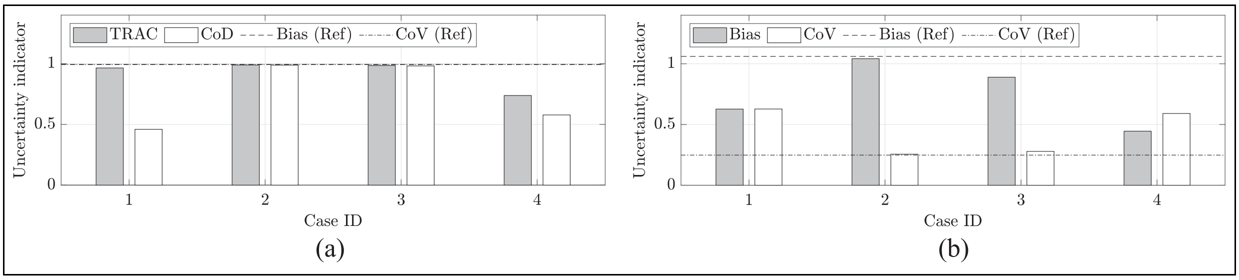

Figure 11. Comparison of uncertainty indicators (Case 1: SG1 + SG2 + SG3 + SG4; Case 2: SG1 + SG2 + SG4 + SG6; Case 3: SG1 + SG3 + SG4 + SG6; Case 4: SG4 + SG6 + SG7 + SG8. Note: 1st,3rd,4th and 6th are adopted: (a) TRAC and CoD and (b) Bias and CoV.

reduced set of mode shapes and seven strain gauge data (eight combinations are possible). As depicted in Figure 10, all uncertainty indicators (e.g. TRAC, CoD, bias, CoV) remain almost unchanged in all cases, demonstrating the insignificance of removing one strain gauge data from the conversion.

With this preliminary observation, a further analysis is performed using the reduced set of mode shapes and only four strain gauge data, which is the minimum data required by equation (10). As presented in Figure 11, a near identical performance with respect to the reference case is achieved when adopting data of SG1, SG2, SG4 and SG6. However, significantly inaccurate conversion may be obtained in other cases. This demonstrates the importance of selecting an appropriate combination of strain gauge data. Overall, the selection of mode shapes and strain gauge data can be addressed as an optimisation problem, in which the optimal set of mode shapes and strain gauge data need to be selected with the aid of an optimisation algorithm.

As the monitored data accumulates, a data historian can be developed and used in conjunction with the Bayesian inference to enhance the long-term prediction of structural performance. In the context of the structural integrity management, this typically involves an update of the long-term stress range distribution. Conventionally, a Weibull distribution is used to approximate the long-term stress range distribution of marine structures, and the distribution parameters are determined empirically, which may lead to a deviation

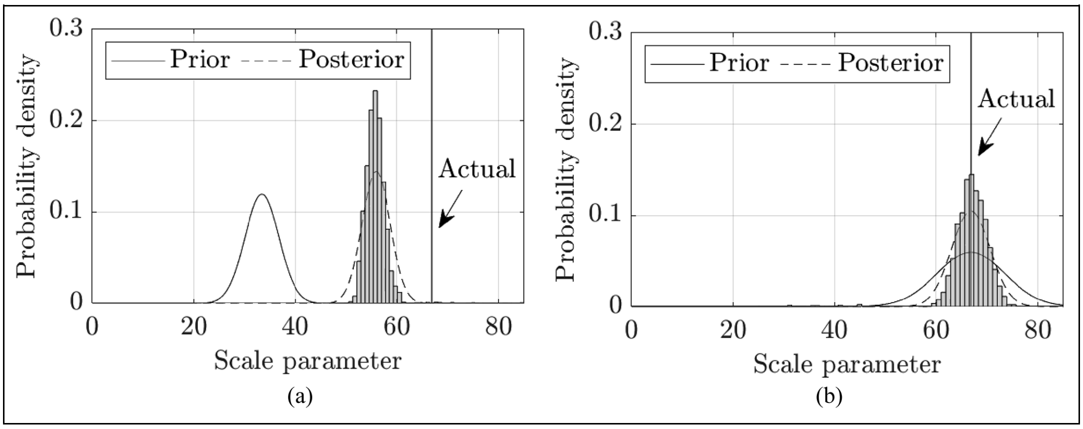

Figure 12. Effect of monitored data on the parameters estimations: (a) $\mu = 66.8$ and $\sigma = 0.1\mu$ and (b) $\mu = 33.4$ and $\sigma = 0.1\mu$.

from reality. Based on the simulation presented in Figure 8 and applying Marko-Chain Monte Carlo simulation, the posterior distributions of the scale parameter of Weibull distribution with different prior assumptions are depicted in Figure 12.

Applying a Weibull fit to the obtained simulation data gives a scale parameter of 66.8, illustrated as 'actual' in the plots for comparison. In both cases, the scale parameter is assumed to be normally distributed with different mean values and a 10% coefficient of variation (i.e. prior distribution). Figure 12(a) depicts the scenario with significant deviation between the prior assumption and the observation, and Figure 12(b) displays the scenario in which the prior assumption is closely correlated with the observation. In the former case (Figure 12(a)), it is clear that a more accurate (closer to observation) evaluation of the parameter of interest is obtained. It should be noted that this is highly dependent on the sample numbers. If the updated scale parameter is considered in a fatigue analysis using deterministic closed-form solution presented in Ref.[56] that incorporates D-curve, a remaining fatigue life of 1 year is obtained. By contrast, a remaining fatigue life of 9 years is estimated. The overestimation of the fatigue life suggests an inadequacy of the initial design proposal; hence proper reinforcement may be required. There is also a possibility that the fatigue life is underestimated by the designer, in which case a case of life extension may be demonstrated. In the latter case (Figure 12(b)), the standard deviation of the posterior distribution is much smaller than the prior distribution, which may have an implication in the fatigue reliability analysis (an improved safety index). However, just 20 min monitored data is arguably limited with respect to the typical fatigue life of marine structures (20–25 years). More data is required for better prediction, thus the present analysis only serves as a demonstration of how monitored data may be utilised within integrity assessment and management. As no real database is available for this research, numerical simulation is performed to generate the response data. For this reason, a 20 min simulation is carried out for the sake of reducing computational efforts. In real-world application, as the database develops, a more accurate model of stress-range distribution can be derived.

Discussions

With reference to the illustrative example presented, this section discusses opportunities presented in structural integrity management as a result of digital twin technology. Additionally, it outlines the associated challenges that need to be addressed.

Opportunities

Benefits for structural integrity management. Digital twin is an ideal tool with which to support structural integrity management. The virtual monitoring capability (e.g. real-time simulation) combined with condition assessment algorithm provides a useful method for monitoring the current states of structures in operation, an approach known as structural integrity diagnostics. Additionally, the availability of vast (virtual) monitored data stimulates data-driven forecasting (i.e. structural integrity prognostics) which can inform risk-based inspection/maintenance planning. Modern risk-based inspection (RBI) techniques are already in use across the maritime industry, enabling an optimised inspection programme that focuses resources on the most critical areas and makes the most efficient use of the resources available to perform condition assessment. A key aspect of a successful RBI programme is the accurate and timely recording of the asset condition, which ensures this information can be used effectively to make decisions as to how to utilise the available maintenance resources. An accurate digital condition model, or 'digital twin' is the ideal means of recording and maintaining the asset condition data that supports a well-executed RBI plan.[57] The diagnostics and prognostics of structural health conditions can also be performed by a relatively well-established technology – structural health monitoring. However, with respect to the latter, the digital twin approach can provide information on structural conditions at all locations (all-over monitoring). Conversely, conventional structural health monitoring only collects structural condition data at a selection of locations. Although both global and local condition assessments may be performed, such monitoring cannot evaluate the conditions at unmonitored locations and thus may overlook potential damage.[20,46] The all-over monitoring of digital twin makes it possible to perform a comprehensive health condition diagnostics and prognostics in different structural hierarchies, including unmonitored locations (see Figure 8) and may thereby improve the prediction of unknown failures. Additionally, the use of a digital model allows users to verify the sensing units, which may greatly reduce systematic errors of measurement. Further, decision makers can make use of the digital twin to assess the impacts of their decisions through computational experimentation of different scenarios.[55] All these opportunities may collectively contribute to the 'digital class' and 'smart certification' concept where the compliance of marine structure is demonstrated remotely and continuously.[58]

Implications on structural design. Whilst the emphasis of this paper is on digital twin-based structural integrity management, an improved strategy for integrity management could also have an impact on structural design. For instance, reduced structural redundancy may be achieved. Reliability-based evaluation is the state-of-the-art approach for marine structural design. It can either follow a partial safety factor-based design format (i.e. load resistance factor design) or a failure probability-based design format.[59] The use of reliability analysis in structural design aims to accommodate the uncertainty in structural performance assessment caused by the inherent randomness of geometric dimensions and material properties (aleatoric uncertainty), and the inability of an engineering model to characterise physical phenomena (epistemic uncertainty). Accounting for uncertainty will inevitably lead to a degree of structural redundancy. The availability of real-time responses and health conditions of the target structure via the introduction of digital twin technology can substantially remove such uncertainty. Within the context of load resistance factor design, which is the most common approach in ordinary structural design, it would be reasonable to consider a relaxation of partial safety factors. As a result, unnecessary structural redundancy can be removed to create a more cost-effective structural design. Furthermore, the development of a digital twin system provides mitigation for a substandard design, which exists as a result of the financial or manufacturing infeasibility of a design proposal which fully complies with the prevailing codes and standards. An example of this kind would be the internally ring-stiffened tubular joint. Internal ring-stiffener is an effective way to increase the strength and stiffness of a tubular joint, which means the wall thickness of the tubular can be substantially reduced. As a result, it is viable in terms of cost and fabrication. However, various design codes require a stringer design factor of fatigue life for tubular joints with internal stiffeners. In the most extreme scenario where the tubular joint is regarded as structurally critical yet inaccessible for inspection, the design factor of fatigue life can as high as 10. The benefit gained from the internal stiffening is therefore outweighed by this conservative design requirement. Digital twin-based continuous monitoring and its diagnostic and prognostic capabilities increases the transparency of the consumed fatigue life. Preventive actions can be taken to avoid catastrophic failure. This becomes a mitigation measure for structures with substandard design.

Challenges

Whilst a number of academic and industrial developments in digital twin-based structural integrity management have been proposed, it is still too early to conclude that this technology is sufficiently mature to be introduced to the marine and offshore industry. There are several challenges outstanding and technological developments are required for a comprehensive realisation of digital twin.

Standardisation. One of the most relevant challenges is the standardisation of digital twin, which is extremely important for the interoperability and interconnection of digital twins of different assets.[60] It is expected that digital twins will be applied for different marine structures and assets, some of which might be heterogeneous in nature. To enable an efficient collaborative decision making, standardising the digital twin architecture and developing a framework for interfacing different digital twin is essential. Additionally, standardisation of monitoring units is also required[61] as this is the element underpinning digital twin technology. Many off-the-shelf sensors suitable for structural integrity monitoring are supplied in the market. However, different sensors would have different specifications such as measurement range, sampling rate, uncertainty tolerance and size etc. Currently, there is limited guidance on the specification of monitoring units applied to digital twin-based structural integrity management. Recommendations have been made on monitoring system specification for marine structures issued by DNV, ABS,[62] GL ClassNK; however these have not been introduced within the context of digital twin development. There is a need to standardise the specification of monitoring units, or at least recommend minimum requirement, such that all stakeholders could follow the norms and potentially accelerates the commercialisation of digital twin. In addition, standards and/or recommended practices of the monitoring device testing should be developed to assess the repeatability of measurement, uncertainty of measurement and durability of sensors in extreme environment.

Data quality assurance. Secondly, the monitored data need to be quality assured.[63,64] As reviewed in the foregoing sections, a digital twin-based integrity assessment and management is critically reliant on the monitored data. To ensure the quality of all subsequent condition assessments, an initial examination of data quality is required. For instance, Ibrion et al.[65] discussed lessons learnt from two recent accidents in the aviation industry (Boeing 737 MAX crashes in Indonesia and Ethiopia in 2018 and 2019), foremost of which is that the implementation of digital twin comes with its own risk. One of the challenges is related to the sensor data quality, which was cited as the primary cause of the Boeing 737 MAX accidents. As such, a digital twin system should be able to detect any anomaly in the monitored data and provide an alarm for users before moving to any decisional support. Moreover, consideration of monitoring system redundancy is highly recommended, especially when it comes to the long-term application of a digital twin system. Because the monitoring module is an underpinning element, any loss in the sensing unit may lead to the total shutdown of the system. Thus, it is essential to consider redundancy of the monitoring system. Finally, it will be beneficial to optimise the sensor network. This is particularly relevant to structural response monitoring using a strain gauge or accelerometer, as introduced by Sugimura et al.[37] and Augustyn et al.[40,41] To maximise the performance of modal decomposition and expansion while minimising the installation expenditure, techno-economical optimisation is needed to develop an optimal sensor network. Apart from technical and economic considerations, the placement of monitoring units should factor in the potential inference with other on-board activities.

Intelligent operation. As reviewed in previous sections, the state-of-the-art digital twin is generally categorised as a Level 3 functionality where monitoring data-informed simulation is performed to assist integrity management. Some implementations incorporate the model updating capability, which is also required at Level 4. However, the most appealing aspect of Level 4 digital twin is the fact that cognitive tasks such as deciding the workflow of digital twin can be performed with limited human intervention. Thus, to accomplish the advancement of digital twin from Level 3 to Level 4 (intelligent learning), dedicated data mining capabilities should be incorporated. For instance, cognitive tasks can be addressed with the aid of intelligent feedback to users. This is highly relevant to promoting a digital twin-based programme/software to non-specialist users.

Computational demand. The use of a digital twin approach in life-cycle management and structural longevity was discussed by the Structural Longevity Committee of ISSC.[66] It was argued that whilst the digital twin enables the monitoring and condition assessment at structural system level, its direct use still faces many challenges, mainly with respect to computation. Whilst one may not need to perform model update, simulation or forecasting within seconds or less because structural degradation due to fatigue would not be significantly different in such a short time frame, the outputs from digital twin must stay ahead of the actual operation; for example forecasting a 1 h future operation should be completed in 1 h or less, otherwise, the value of digital twin will be diminished. Thus, the direct use of physics-based algorithm may be challenged by the limited availability of computational power. While computation capability continues to improve, the development of data-driven surrogate could be a promising alternative.[67,68] Although the development of surrogate model can still be computationally demanding, it is computationally efficient and suitable for incorporation into a digital twin system once developed. Relevant study was conducted in Fang et al.[53] who developed a surrogate for finite element model based on Gaussian Process to enhance the efficiency for estimating stress intensity factor.

System validation. Last but not least, despite considering the application of advanced data manipulation approach such as deep learning models, the uncertainty of response/performance forecasting may remain high due to stochastic nature of various parameters of influence.[69] Further research on model validation is needed to improve the forecasting accuracy. In this respect, it is important to classify the forecasting objectives. As introduced in Ref.[69] within the context of wind turbine, the output of forecasting can enable an efficient active control of the turbine, optimisation for power output, and maintenance scheduling and transmission stability. Different forecasting objectives implies differences in the forecasting time scales such as immediate forecasting lasting up to several minutes, short-term forecasting over the next 24–72 h, and long-term forecasting up to a week or more. The present paper demonstrates a Bayesian updating approach which is a statistical forecasting method relying on historical data with an update based on new observations. A dedicated validation campaign is necessary to assess the applicability of this approach, among others, in different forecasting objectives.

Concluding remarks

This paper presents a review of literature on the emerging technology known as digital twin and its application in structural integrity management for marine structures. The review defines digital twin as the counterpart of physical structures in a digital world, mirroring the same structural conditions as physical structures in real time such as structural configuration, scantling, material property, macro and micro degradation, and so on. This is achieved through continuous data transfer between the physical and digital systems. In essence, the development of digital twin is a process of reducing uncertainty and the use of real-time monitoring data effectively removes the modelling assumptions. Concerning the review of recent development and application in marine structure, it is found that there are two main digital twin approaches. Whilst both requires the creation of a finite element model, they mainly differ in the way structural fatigue load is assessed, that is, spectral-based approach versus time-domain approach. In terms of the damage model, S-N curve combined with linear summation rule is still the most common strategy for fatigue damage evaluation, even though the use of fracture mechanics has also been explored in some research but none of them have been applied to a full-scale structure in this context. Most research are dedicated to the development of physical-to-virtual connection, whereas the virtual-to-physical feedback, that is, the digital twin informed decision-making process, is absent in the literature. Furthermore, although a number of studies related to digital twin have been proposed in the literature, most are limited to a conceptual level, while some are only concerned with sub-system development. An integrated framework to enable the creation and application of digital twin appears to be lacking. Based on the review insights, a high-level framework is proposed in this work for digital twin-based structural integrity management. A numerical example is presented to illustrate the key enabling techniques, namely model updating, real-time simulation and data-driven forecasting. As illustrated by the numerical example, the use of digital twin offers considerable benefits to structural integrity management. Furthermore, it may also have an impact on the structural design.

In terms of the recommendation, standards and/or recommended practice for monitoring system should be developed such that all stakeholders can follow the norms and thereby benefits the commercialisation of digital twin. Meanwhile, it is recommended that data quality assurance, redundancy of the monitoring system and optimisation of the sensor network are taken into account during the monitoring system development. Dedicated data mining capability should be incorporated in the digital twin to accomplish the advancement from Level 3 to Level 4. For instance, it can assist addressing the cognitive tasks with the aid of intelligent feedback to the user. Moreover, the use of data-driven and machine learning algorithms to develop surrogate of physics-based methods will be particularly beneficial to tackle the challenges due to computational requirement.

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