Committee V.7: Structural Assessment During Operations

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Committee Mandate. Concern for the structural assessment of ship and offshore structures during operations, including unmanned operations. The focus shall be on methodologies translating monitoring and inspection data into operational and life-cycle management advice, with associated criteria for decision making. This shall include diagnosis and prognosis of structural health, prevention of structural degradation and failures, and structural renewal and reuse.

The research and development in passive, latent and active systems including their sensors and actuators shall be addressed. Special attention is to be given to structural digital twin technology and methods including reduced order analysis, inverse modelling, and AI technology application, combined with the use of monitoring systems and inspection data, to provide real-time advice for safe operation during the structural life-cycle.

Contributers

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W. Wu and J. Ding (Eds.): ISSC 2025, LNME, pp. 303–322, 2026.
https://doi.org/10.1007/978-981-95-2782-3_15

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1 Discussion

This report discusses the issue of structural safety assessment in ship during operations, however, there are many issues that require the committee to provide more detailed explanations or are worth further discussion.

1.1 *Issues in* Chapter 2

1.1.1 Section 2.1: Real-Time Processing

The last sentence of the second paragraph of Sect. 2.1 in the report mentions "For on-board operational guidance, data must be processed near or faster than real-time to inform operations whereas for maintenance, the data processing can occur over a much longer timescale", but for data processing, its main task is to process the data collected by the SHM system, then combining historical data with relevant algorithms to provide data support for structural safety assessment. Therefore, the fastest speed for data processing should be close to or same as real-time. However, "faster than real-time" in the report seems to be difficult.

If the authors want to mean that the data processing system will provide structural state information or decision supports based on estimation of future events calculated form historical monitoring data faster than real-time, then the statement could be rephrased.

1.1.2 Subsection 2.2.1: Applicability of Digital Twin Technology

The title of Subsect. 2.2.1 is "Digital Twins and Machine learning". However, the majority of this subsection mainly discussed the application of digital twin technology in structural monitoring and assessment. For machine learning, only its application in non-destructive testing was introduced at the end. Is it possible to also mention the applicability of machine learning in different application scenarios of structural health monitoring?

1.1.3 Subsection 2.2.1: Repeated Text

The third paragraph of page 7 in Subsect. 2.2.1 is highly similar to a previous paragraph. Compared to the last paragraph of Sect. 1.2, except for simplifying some terms, such as simplifying the digital twins to DT, and deleting the references, the rest content of these 2 paragraphs are completely the same.

1.1.4 Subsection 2.2.1: Damage Detection

The first sentence of the second last paragraph of Subsect. 2.2.1 of the report states that "…needs to be able to track damage evolution with sufficient temporal and spatial resolution ($\leq$ 10mm)." However, the author also mentioned in the report that existing monitoring systems and measurement technologies cannot meet this requirement, which is discussed by [30]. [2] mentioned that the accuracy of identifying structural damage depends on the density of sensors. Although it is possible to detect minor structural damage through sensors placed in high-density in some simple structure like a plate frame, it is impossible for large vessels due to the high costs. Regarding this, there are two discussions.

The first discussion is about the significance of detecting such high-precision damage. In the absence of the technology that can meet this requirement of tracking damage evolution, is there any conclusion or recommendation on what level of accuracy is meaningful for ship in operation?

The second discussion is that, due to the limited numbers of sensors, it is difficult to detect damage in the local structure with sufficient accuracy. It would be better to add a remark on the possible approaches for such purposes.

1.1.5 Subsection 2.2.2: Style and Typo

Style of citation and typo on Page 9: *"Tibaduiza Burgos et al."* should be "Burgos et al."

1.1.6 Section 2.2: Definitions of ML and AI

The conclusion of Sect. 2.2 states the major advances in ML and AI, which presents artificial intelligence and machine learning technologies in parallel. However, [19] mentioned that ML is a technology of AI. [15] also mentioned that the deep learning is a subset of AI technology. In this section, the differences or relationship between AI and ML are not mentioned, nor comparison of the merits of these two technologies for solving the problem of concern. The limitations of AI mentioned in 2.2.3 are also limitations of machine learning, such as the need for high-quality training datasets with high quantity. Therefore, it would be the best to introduce the relationship between ML and AI before listing machine learning separately.

1.1.7 Section 2.4: Definition of Virtual Hull Monitoring

The last paragraph of Sect. 2.4 mentions a technology named virtual detection. However, in the references cited in this paragraph, only [29] explicitly mentions the name "virtual hull monitoring". In that article, the author did not provide a clear definition of virtual hull monitoring, only stating that this method is a digital structural health monitoring approach that can be used to calculate the fatigue damage accumulated in a ship's hull.

In Subsect. 3.3.10 of this report, the author also mentioned another similar technology called "virtual sensing". The commonality between the two methods is that both of them can obtain structural responses that are difficult to obtain by using directly monitoring methods. Therefore, the differences of these two methods are interesting to be detailed comparison.

1.1.8 Section 2.5: Discussion About Effectiveness and Boredom

It is mentioned in the last paragraph of Page 15 the issue of information accessibility of the SHM system for the crews. The discussions by Whalstrom et al. (2015) are cited "a balance is needed to avoid information overload, but also boredom of the operator that may lead to the need for intervention being missed". According to the survey and study carried out by Veitch et al. (2022), the key issue here might not be the overload or boredom caused by information, but rather the effectiveness. The discussions could be summarized as that excessive information will lead to information overload when workers have to take care of several ships instead of just one, which result in a decrease in information effectiveness. However, the status of ships can be evaluated to workers after progressing and analyzing the monitoring data. For this, it seems that the boredom might be less of an issue, and only the most effective and intuitive information shall be given to the workers, while other information can be stored for subsequent analysis.

1.2 *Issues in* Chapter 3

1.2.1 Subsection 3.2.1: Style

In Subsect. 3.2.1, past tense is used in some paragraphs of Page 18, and present tense used in others.

1.2.2 Subsection 3.3.2: Corrosion Monitoring

In the first two paragraphs of Page 21, the author lists two articles on corrosion monitoring, i.e. [28] and [27]. These two articles research the application and reliability of optical fiber strain gauges in identifying structural corrosion or corrosion-induced thickness loss. However, in practical engineering, optical fiber strain gauges themselves can also experience such corrosion. In addition to the fiber brag grating structure, optical fiber gauges also have a steel protective shell, which can corrode during ship in operation and cause gauges failure. Figure 1 shows a photo of an optical fiber strain gauge taken during the maintenance of the SHM system of an ore carrier. It can be seen in Fig. 1 that the corrosion of optical fiber strain gauges may even exceed that of panels of ship hull in some cases. Meanwhile, other types of sensors, such as resistance strain gauges, clearly also have similar corrosion problems that are difficult to solve. If the sensors have corrosion problems, the sensor data might not be accurate enough for the identification of corrosion of ship structures.

Fig. 1. Corrosion of optical fiber strain gauges of a SHM system

1.2.3 Subsection 3.3.2: Various Types of Sensors

The authors provided a detailed classification of strain sensors in Subsect. 3.3.2. In this report, four different strain sensors are discussed notably: bondable or weldable foil gauges, fibre-optic sensors, strain rings, and short length LVDT type sensors. However, the SHM system includes other different kinds of sensors which used to monitor various parameters. For example, accelerometer and gyroscopes are widely discussed in Subsect. 3.3.3 and 3.3.4. [31] has summarized and categorized different types of sensors in the SHM system, including CMOS MEMS accelerometer. Due to the widespread application of accelerometer in the SHM system, the various types of accelerometers could also be mentioned, such as resistance accelerometers, fiber optic accelerometers, and MEMS accelerometers.

1.2.4 Subsection 3.3.2: Applicability of a Method in the Literature

In Subsect. 3.3.2, second last paragraph of Page 20: "The huge amount of strain data acquired by advanced sensors should be processed to evaluate the health status of the ship structures, allowing optimized scheduled maintenance interventions. For this aspect, Liu et al. (2023) presented a method for automatic interpretation of strain distributions measured from distributed fibre optic sensors for crack monitoring."

The structure used in the study by Liu et al. (2023) is a simple supported beam of very small dimensions, but for large and complex structures like ships, it would be difficult to apply the method. It would be better to include a comment on the limitation of that approach.

1.2.5 Subsection 3.3.3: Possible Applicability of a Method in the Literature

In Subsect. 3.3.3, the study by Sousa et al. (2022) is mentioned in the review of "Dynamic Response monitoring", and "a link was found between the loss of mass and the natural frequency of the plate." If possible, please add a remark on the scenarios where this method could possibly be applied.

1.2.6 Subsection 3.4.4: TinyML

The Tiny Machine Learning (TinyML) described in Subsect. 3.4.2 refers to "machine learning models on small, resource-constrained devices, such as microcontrollers or other embedded systems." Disabato (2023) further defined that the TinyML technology is used in Micro Controller unit (MCU), and defined memory of MCU as rarely exceed 1 Megabyte. For the SHM system, it is entirely possible to send the monitoring data in real-time to the computers deployed on the ship, and the machine learning algorithm can be implemented on the computer without any restrictions of power, memory, and energy of TinyML. It would be better for the committee to introduce the necessity and advantages of TinyML, as well as the possible application scenarios.

1.2.7 Subsection 3.4.3: Embedded Systems

The title of Subsect. 3.4.3 is "Embedded systems", and six references were cited. The core of an embedded system includes an embedded microprocessor and also the embedded software. For example, [17] defines an embedded system as "Embedded systems are information processing systems embedded into enclosing products." However, in the six references cited in this report, [26] embedded the sensor on the surface of the hydrofoil, [11] and [12] embedded sensors in the propeller blade, [4] embedded the sensors on the test piece of the offshore jacket structure, [18] and Riccioli et al. (2023b) embedded the sensor on the test piece of a plate. These studies only embedded sensors into the structure, but did not include embedded software packaged together with sensors. In other words, the systems in these cited violate the principle of software and hardware integration in embedded systems, nor the authors in these articles acknowledges that any part of their studies are related to embedded systems. Thus, if the definition of embedded system used here is different from what has been established, it's best to introduce the new definition in the report.

1.2.8 Subsection 3.3.4: Reconstruction of Sea State

In Subsect. 3.3.4, the study by [20] is mentioned, who proposed two methods for the reconstruction of the sea state using ship motion data.

Although it is concluded in the study by [20] that there was a strong agreement between the reconstructed sea states and direct observations. There are also studies in the literature, e.g. [21], suggesting that reconstruction of wave data from measured ship motion has some drawbacks. Is it possible to include in the report a remark on that?

1.2.9 Subsection 3.3.4: Applicability of a Method

In Subsect. 3.3.4, the method proposed by Le et al. (2022) is effective in the detection of early stage damage in wind turbine structures, but might not be a valid method for complex structures like offshore platforms. Since the authors of Le et al. (2022) did not validate the method for such structures in their paper, it's best to remove "the study highlights the adaptability of the technology to complex marine structures…" from the report.

1.2.10 Section 3.3: Applicability of Monitoring Techniques

In Subsect. 3.3.6 and Subsect. 3.3.7, acoustic emission monitoring and guided waves monitoring based studies are reviewed. It would be better to analyse the applicability of these techniques and their advantages and shortcomings according to the literature reviewed. Actually, this applies to most of the monitoring techniques reviewed in Sect. 3.3.

1.2.11 Subsection 3.4.1: A Discussion on Cloud Services

In the last paragraph of Subsect. 3.4.1, "Cloud services enable will (grammatical mistake?) play a significant role in future data sharing" —this may not be practically easy because the operators of the ships (offshore platforms) may not want to share the data with others as it will involve the issues of intellectual property, confidential information or other interests of concern, which is already happening.

1.2.12 Section 3.5: Data Fidelity and Reliability

In the concluding remarks (Sect. 3.5), data fidelity and reliability are mentioned, but no relevant studies are reviewed in the report.

1.3 *Issues in* Chapter 4

1.3.1 Chapter 4: Assessment of the Offshore Structures

Chapter 4 discusses the assessment of the offshore structures, which mainly include offshore wind turbines (OWTs), as well as subsea pipelines OWT support structures. However, there are also researches in the literature on other kinds of offshore structures that could be discussed in the report. For example, the offshore platform is a very important type of offshore structure, and researches on the offshore platforms have gradually increased in recent years. The author also mentioned the definition of ocean engineering structures in Sect. 4.5 [3] as oil rigs, platforms, wind turbines, and subsea installations, which proves the author's recognition that platforms belong to ocean engineering structures. However, there are only very few studies on platforms mentioned in the report, and in some chapters and sections they are not mentioned at all.

For example, Sect. 4.2 and Subsect. 4.3.2 describe corrosion mechanism and fatigue and fracture of offshore structures, but only discusses the research on offshore wind turbines (OWTs) and offshore wind farms (OWFs). It would better to include studies on other types of offshore platforms in the report. For instance, [9] proposed a fatigue crack growth prediction method for offshore platforms based on digital twin. [10] proposed a digital twin framework for real-time prediction of fatigue damage on semi-submersible platforms under long-term multi-sea conditions.

1.3.2 Subsection 4.3.2: The Accuracy of Methods with Different Levels of Coupling

In Subsect. 4.3.2 (the last paragraph of Page 34), review of the existing studies suggests that fully coupling simulations, decoupled methods, and decoupled methods are all accurate?

1.3.3 Subsection 4.3.2: A Typo

In the first paragraph of Page 35, "Studies investigating … are yet little…" should probably be "Studies investigating … are yet few…".

1.3.4 Subsection 4.4.4: Style of Citations

In Subsect. 4.4.4, the style of some of citations are different from that is used in the rest of the report. For instance, Nguyen Thanh and Nguyen Manh (2022), Singh and Singh (2023).

1.4 *Issues in* Chapter 5

1.4.1 Subsection 5.2.1: A Discussion on the Change in the Environment

In Subsect. 5.2.1, the author listed the changes in the environment like ice field, winds, and waves over the past few decades, with a focus on the changes in the Arctic routes and the changes in high-frequency extreme ocean wave events (Morim et al., 2021).

The wave environment has been widely used for the calculation of wave loads is the North Atlantic standard wave data Rec.34 by issued by the International Association of Classification Societies (IACS) in 1992, however, it has been found that the actual waves encountered by ships are different and IACS has released North Atlantic standard wave data (Rec.34 Rev.2) in 2022. This could be mentioned in the report (Fig. 2).

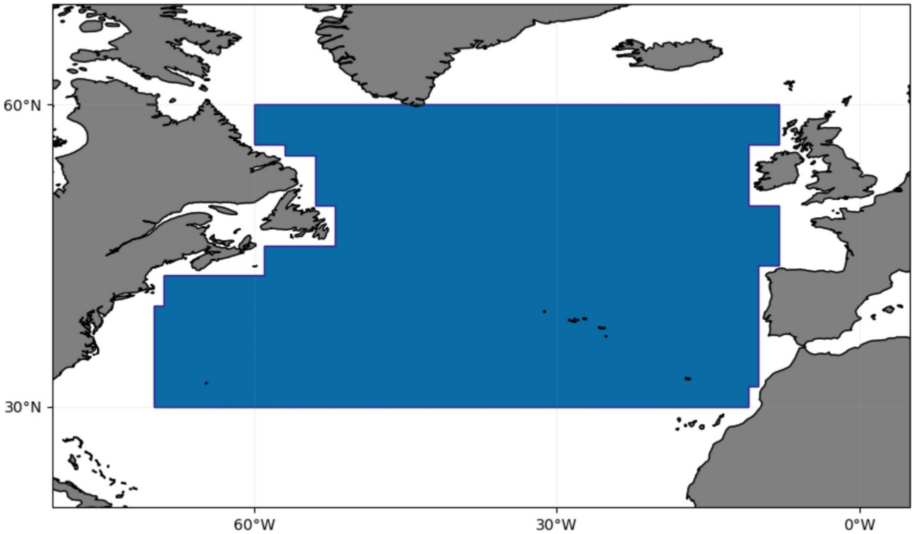

Fig. 2. Definition of the extent of the North Atlantic in Rec.34 Rev.2

1.4.2 Subsection 5.2.2: Inconsistent Acronyms

The author mentioned Hull Condition Monitoring Systems in the last paragraph of Subsect. 5.2.2 [1, 7], but the acronym of this system is inconsistent in this paragraph. HMS is used for the first mention, and HCMS is used for the second mention.

1.4.3 Section 5.4: Number of HMS Application to Commercial Vessels

Section 5.4 reviews the hull monitoring systems (HMS) applications. Only a single study is mentioned in the review of commercial vessels in Subsect. 5.4.1, which, compared to the relatively large number of military applications reviewed in Subsect. 5.4.2, is a very small number. There are many applications of HMS to commercial ships in many China, Norway, South Korea, and UK, etc.

1.4.4 Section 5.3: SHM Assisting Optimisation of the Design

In Sect. 5.3, it says "A structure health monitoring system allows to optimize the design, operation and/or maintenance…(Silva-Campillo et al., 2022)". At present, there are studies in the literature that demonstrate SHM is able to help optimize the operation and/or even the maintenance, but the optimisation of design using SHM is probably just a good will yet, and Silva-Campillo et al. (2022) did not provide any references to support this.

1.4.5 Subsection 5.5.3: Estimation of Spectrum and Sea-State Using Measured Ship Response

In Subsect. 5.5.3, in the first and second paragraphs of Page 59, studies of estimating wave spectrum and sea-state using measured ship response. This approach for estimating has known drawbacks, and the authors of the cited study (Chen et al., 2021) also stated the limitation in the future work section. It would be better to add a brief description of the limitation of the approach in the report.

2 Reply by committee

2.1 Reply to the Official Discusser Professor Xueqian Zhou

2.1.1 Introduction

The committee would like to thank Professor Xueqian Zhou for providing his time and expertise in reviewing the committee's report as Official Discusser. The following sections present the committee's response to the review in the order in which it was presented. Where typographical amendments were recorded, the committee was able to action these prior to publication of the report in Volume II of the [14] proceedings [14],therefore, no further response to these aspects has been included in this reply.

On several occasions the review includes comments on the practical applicability of techniques in real operations and structures, with recommendation to analyse the applicability of these techniques and their advantages and shortcomings. The committee appreciates these comments which point to a real gap in literature, which as yet does not provide a structured reasoning model to inform trustworthy lifecycle management advice for real-world applications.

2.1.2 Issues in Chapter 2: Condition, Performance, and Safety Assessment Techniques During Operations

Section 2.1: Real-Time Processing

The wording of the highlighted sentence was amended prior to publication to add parenthesis to the term "faster than real-time", and to include reference to predictive algorithms. If collecting data, processing the data and feeding back into the system, there will be a time delay to the reaction of the system. Such a delay to the system's response may be acceptable, but in some circumstances could influence the safety of the system, or lead to subsequent instability of the control system; for example, over correction on a steering control system that the system would subsequently need to respond to. Therefore, is the system achieving "real-time" control? To actually achieve real-time in a sensitive system, the processing needs to almost be faster than real-time, which is not possible in a linear system. However, through a predictive algorithm it may be possible to get ahead of the processing and control response. The committee would also like to highlight that the speed of processing should match the decision horizon demanded by the engineering application and not be termed "real time" for the sake of "real time".

Subsection 2.2.1: Applicability of Digital Twin Technology

As noted by the Official Discusser, the use of Machine Learning may be applied in structural health monitoring systems. For example, in an acoustic monitoring system, machine learning may be utilised to train the system on the baseline emissions from which changes may indicate development of a structural defect or crack. In reviewing publicly available literature, the committee has endeavoured to cover all considered aspects, but accept that additional literature may have been available in relation to application of machine learning.

Subsection 2.2.1: Repeated Text

The repetition of the noted paragraphs was noted in reviews of the report, but the context of the information was deemed relevant to the two sections and therefore retained and not cross-referenced.

Subsection 2.2.1: Damage Detection

In terms of tracking damage evolution in rotor blades, damages with a characteristic size of 1cm can already be significant, though depends on whether the damage is located in a critical region of the load carrying girder or in the secondary structure such as the lift generating shells. Even in the case of damage located in the secondary structure, a resolution of 1cm is required to track the effect on the performance reduction due to deformation of the aerodynamic surface – especially when the damage is sitting in vicinity of the leading edge. The lower bound is set by the resolution of the NDT applied to the blades after manufacturing to detect manufacturing defects which are also in the order of $>$ 1cm.

Sensing techniques including acoustic emissions and guided wave monitoring provide direct damage information. Additionally, damage detection can be enabled by multimodal sensor systems and data fusion. Virtual sensing and virtually-informed sensor placement shows promise in augmenting information from sparse sensor placement on assets.

Future approaches to increase the resolution and fidelity of damage detection foresee the integration of several different sensor types into one multimodal sensor system. In analogy to the human body, an enhanced understanding of the environment is provided by combining visual, acoustic and tactile information to form one holistic picture. This could be done by combining information from drone-based inspection (e.g. camera feeds from the visual and the IR spectrum) with acoustic emission sensors, strain gauges (e.g. fiber Bragg sensors embedded in the composite laminate), accelerometers and the SCADA feed from the turbine controller. The more frequent use of carbon fibre reinforced polymer composites due to the increasing stiffness and strength demands, offers novel approaches for damage detection inside the material as demonstrated by [16]. However, in order to enhance damage detection capabilities, it is necessary but not sufficient to develop novel sensing methods or to improve existing approaches. Future research effort must focus on how different sensor data formats can be bundled and integrated.

Section 2.2: Definitions of ML and AI

Machine Learning (ML) is a subset of Artificial Intelligence (AI), where the latter is an overarching umbrella term for a system capable of numerically solving fully coupled problems in a multidimensional parameter space. AI has the ability to learn from previous experiences and can adapt to changes in the problem formulation when seeking a solution. ML is a lower order building block of AI which is designed for a specific task typically related to a single sensor type such as thermal image recognition, recognizing patterns in datasets etc. While ML can make predictions, it doesn't on its own have the capability to process the consequences of the prediction on system level.

Section 2.4: Definition of Virtual Hull Monitoring

Virtual hull monitoring is a technique to calculate wave-induced ship responses without the need for onboard instrumentation. It segments the ship's track into short-term intervals (typically about an hour) to determine speed, heading, and position. Speed and heading combine with wave data, (usually extracted for the segment's location and time from meteorological model reanalysis) in spectral analyses to calculate the stress spectrum. This method is cost-effective due to the absence of direct hull sensors, but its accuracy depends on a chain of numerical models, making it sensitive to errors in any part of the modelling process.

Virtual sensing comprises the use of computational models, algorithms and indirect measurements to estimate physical quantities that are difficult, or expensive to measure directly on the structure. Virtual hull monitoring entails the use of virtual sensing, explicitly applied to monitoring the quantities of interest on a vessel hull.

Section 2.5: Discussion About Effectiveness and Boredom

The committee agree with the comments made. In the provision of information to workers in a remote control or remote monitoring setting, there will be a balance needed between useful information presented in an intuitive manner to which the operator may be able to respond, and information that is superfluous to normal operational controls but may be of use for analysis at a later time. The latter information may not need to be transmitted from the platform regularly, but stored and relayed (or collected) at a suitable opportunity. However, in the monitoring of a highly effective system, where operator input is infrequent, boredom may be a factor to consider.

2.1.3 Issues in Chapter 3: Inspection & Monitoring During Operations

Subsect. 3.3.2: Corrosion Monitoring

The committee agree with the comments made. The committee did not present information related to the degradation of sensors due to corrosion, though is an aspect that a future committee might consider to review when considering the reliability of SHM systems.

Subsect. 3.3.2: Various Types of Sensors

The Committee agree that the variety of acceleration type sensors may be extensive, for which a review of commercial accelerometers is provided by [8].

- Capacitive accelerometers, typically comprise a microelectromechanical system (MEMS) which measures changes in capacitance to detect motion from a small mass suspended on springs. Acceleration causes the mass to move, changing the distance between parallel capacitor plates and altering the capacitance. Capacitive accelerometers enable measurements of a DC response (such as static acceleration from gravity and reliable slow movements from wave-induced ship motion).
- Piezoresistive sensors use the principle where electrical resistivity of a material changes under mechanical stress. Acceleration-induced stress on the sensor material changes its resistance, which is then converted into an electrical signal. Similar to capacitive sensors, piezoresistive accelerometers can have a DC response, allowing them to measure static and dynamic acceleration.
- Piezoelectric accelerometers piezoelectric effect that the piezoelectric materials produce an electrical charge when they are subjected to stress or strain. Advantages of

these sensors include their high sensitivity, resistance to shock and high accuracy. These sensors do not measure DC responses (cannot detect gravity/ tilt) but are best suited for dynamic acceleration measurements and shock.

- Optical accelerometers function on a variety of transduction principles to convert a mass displacement into a change in optical characteristics. Optical fibre technology, in particular, the Fiber Bragg Grating (FBG) principle has become widely adopted. Bragg Gratings are interference filters written into optical fibres which only reflect a narrow spectral component of the induced light. In FBG accelerometers, an acceleration leads to a deformation of an optical fibre attached to a suspension beam which changes the reflection characteristic of the Bragg gratings. This change is detected by comparing the spectral component of the reflected light with the induced light.

Subsect. 3.3.2: Applicability of a Method in the Literature

The Official Discusser raises a valid point, and a need to consider the real application beyond the theoretical. Collectively, literature has not progressed to a level where the current value and practical implementation of some techniques are broken down in academic literature, though it is possible that application has progressed further in some spheres that publication is more limited, such as in military applications.

In relation to the referenced section of the Committee's report, in practice such techniques afford modern engineers with more accurate (not complete) information about the actual evolution of strain and fatigue in operation. It should be realised that this information is still dependent on intentional sensor placement where the spent resources are likely to deliver observations with practical value.

Subsect. 3.3.3: Possible Applicability of a Method in the Literature

The natural vibration frequency of a plate is a function of its mass and stiffness in terms of sectional inertia. Therefore, reduction in thickness due to corrosion will lead to a reduction in mass and/or a deduction in inertia. In many areas of a vessel, such as accommodation spaces, lagging is present for thermal and fire protection that prevents structural survey. Where corrosion is present in decks (for example due to a water leak), the issue may go undetected until corrosion has propagated through the plate and seepage is seen on the deckhead below. Monitoring of vibration response may allow early detection of such issues, minimising subsequent repairs if the cause can also be stopped.

Subsect. 3.4.4: TinyML

It is agreed that shipboard computers can run machine learning models without major hardware constraints. However, TinyML may still provide practical benefits for SHM in various scenarios. Local processing at the sensor can reduce transmission loads, enable faster anomaly detection, and support operation where connectivity is limited. It may also help address cabling challenges, since running wires through long distances and watertight bulkheads is technically demanding and costly. Potential example applications include acoustic emission nodes, where signals are sampled at MHz frequencies, and continuous vibration monitoring of machinery. In this way, TinyML can complement central computing and enhance overall monitoring efficiency.

Subsect. 3.4.3: Embedded Systems

The Committee agree that, by definition, an embedded system involves both embedded hardware (which may include transducers, cables, connectors, signal conditioning modules, pre-amplifiers, microprocessors, etc.) and embedded software integrated within a product. The research studies cited in Subsect. 3.4.3 [14] mainly address sensing elements embedded into maritime structures, reflecting the absence of fully developed embedded-system architectures in the current maritime literature. In recognition of the valuable remark, the following clarification is considered:

An embedded system, in its general sense, integrates embedded hardware components and embedded software within a product to enable data acquisition, processing, and/or transfer. However, in the current maritime SHM literature reviewed in this section, most studies focus on embedding sensing elements into structural components, without addressing the software–hardware integration that defines full embedded systems.

Subsect. 3.3.4: Reconstruction of Sea State

Nielson (2006) investigated a parametric method and non-parametric Bayesian method to estimate directional wave energy spectra from measured ship responses. In the parametric method, spectra are reconstructed as a sum of parameterised functions, while the Bayesian method estimates energy at discrete frequencies and relative headings. Both rely on linear spectral analysis. Results showed that both methods produced reasonable agreement with wave radar measurements. Despite the agreement, [21] cautioned that each method has limitations: the Parametric approach is computationally demanding due to nonlinear optimisation and can suffer from overlapping spectral peaks, though it ensures smooth results. The Bayesian method is more flexible, but its smoothness depends on the correct choice of hyperparameters. Overall, both methods perform comparably, but uncertainties in transfer functions remain unaccounted for in the provided estimations.

The Committee do not consider that [20] were as critical in the evaluation of their methods as Nielson (who conducted a much deeper study). In our opinion, Nielson also found an agreement between wave radar measurements and wave energy spectra which were calculated from ship-based measurements. However, Nielsen points to the limitations that accompany the use of transfer functions. Understanding of the limitation of the use of transfer functions relate to the assumption that the input-output relationship is linear, and time-invariant. Also, that the input-output relationship is sufficient to capture the output response (i.e. there could be an additional cause of the effect you are trying to predict, which is not captured.)

[20] estimated sea state conditions from ship motion data using a response amplitude operator (RAO) during the Antarctic Circumnavigation Expedition. They calculated the RAO with NEMOH and HydroSTAR models and compared the reconstructed sea states with wave energy spectrum measurements from the WaMoS-II marine radar. Their results demonstrated a strong agreement between the reconstructed sea states and direct observations. Historically, studies [21] concur that directional wave energy spectra can be calculated from ship-based measurements. However, these authors caution against uncertainties in transfer functions which relate ship responses to the estimated wave inputs (which may include measurement uncertainties, assumptions that the relationships are linear and time-invariant, and sufficient to capture the complete contribution of wave inputs to the resulting ship motion).

Subsect. 3.3.4: Applicability of a Method

In line with the comment provided, this section of the report was updated prior to publication in Volume II of the [14] proceedings [14], noting the potential adaptability of the technology.

Section 3.3: Applicability of Monitoring Techniques

In response to the Official Discusser's comment, the following additional information is provided. In relation to Sect. 3.3.6. Acoustic Emission (AE) monitoring is a technique used to detect and analyse transient elastic waves emitted by the rapid release of energy within a material or structure. This energy release typically occurs due to processes such as damage formation and growth. AE is highly applicable for detecting damage initiation and growth. Its advantages lie in high sensitivity and real-time capability, while challenges typically include countering the background noise, and complexities in source localization within ship structures.

In relation to Sect. 3.3.7 [14], Guided Waves are specific types of elastic waves that travel through a medium, such as a solid structure, in a constrained manner due to the free surfaces of thin-walled structures. These waves can travel over long distances with relatively low attenuation and are influenced by the structure geometry and material properties. Advantages of guided wave monitoring include efficient area coverage and damage quantification possibility, while limitations typically arise from sensitivity to boundary conditions, dispersion effects, and challenges in interpreting signals in complex geometries.

Subsection 3.4.1: A Discussion on Cloud Services

In the context of the subsection, sharing relates to the transmission of data and associated storage. "Sharing" to a cloud service does not necessarily mean the information is accessible to the cloud storage provider for use or exploitation, though is an aspect that should be considered in selecting an appropriate provider. However, by holding the data within a cloud service, the sharing in terms of distribution between stakeholders may be easier, and cheaper, to achieve. This may present opportunities for wider exploitation of the collected data. In this scenario, the committee agrees that confidentiality and Intellectual Property agreements will need to be in place to facilitate appropriate access and use of the data.

Section 3.5: Data Fidelity and Reliability

Whilst literature on the fidelity of sensors were not presented within Sect. 3 [14], the fidelity of data collected by sensors is noted at points throughout the section. For example, in reference to the micro-strain levels of strain gauges, natural frequency sensitivities of vibration monitors of noise levels of acoustic sensors. It is anticipated that through continued technological development, the sensitivity and associate reliability of such sensors will increase.

2.1.4 Issues in Chapter 4: Assessment of Offshore Structures

Chapter 4: Assessment of the Offshore Structures

The committee anticipate that the reviewer is correct that research and application of sensors to a wide variety of offshore structures has occurred in recent years. However, the identification of literature to present and discuss within the report has been challenging. In a previous comment in relation to cloud services, the Official Discusser notes the sensitivities around sharing data. It is hypothesised that similar concerns may limit the discussion of real-world application of SHM systems, which has potentially narrowed the committee's presentation of wider applications. It might be considered by a future committee to approach known SHM system developers to include views on application to different structures that otherwise may not be widely discussed in published literature.

Subsection 4.3.2: The Accuracy of Methods with Different Levels of Coupling

It is considered that all methods can accurately predict fatigue damage in offshore wind turbine (OWT) substructures. Naturally, higher fidelity methods are expected to yield more accurate results; however, they come with higher computational efforts. Thus, recent research has focus on lower fidelity modelling approaches to achieve reasonable accuracy while reducing computation times significantly. It is hard to estimate the differences in accuracy in general, but recent developments prove that smart modelling approaches can be useful to deal with ever increasing sizes of OWTs.

Subsection 4.4.4: Style of Citations

In line with the comment provided, this section of the report was updated prior to publication in Volume II of the [14] proceedings [14], noting the potential adaptability of the technology.

2.1.5 Issues in Chapter 5: Assessment of Ship Structures

Subsection 5.2.1: A Discussion on the Change in the Environment

The calculation of wave loads, on the one hand, corresponds to the topic of the section, but on the other hand, it is such a well-researched and studied topic that it has become a basic academic discipline. And when it comes to the development of new approaches to determining external forces, what comes to mind more is the possible changes in the nature of wind / wave phenomena themselves in the long term. That is why the subsection considered the results of research on climate change scenarios (Representative Concentration Pathways - RCP), and in particular, article (Morim et al., 2021) specifically mentions the possible significant asymmetry in changes in extreme wave events between the Northern and Southern Hemispheres by 2100 (RCP8.5). In this context, the reference to the unified IACS recommendations (Rec.34) on the Standard Wave Data in the North Atlantic is not an example or explanation for the research considered.

Subsection 5.2.2: Inconsistent Acronyms

In line with the comment provided, this section of the report was updated prior to publication in Volume II of the [14] proceedings [14], noting the potential adaptability of the technology.

Section 5.4: Number of HMS Application to Commercial Vessels

As discussed previously in this response, sensitivities around sharing data may be limiting publication of real-world application of SHM systems, which has potentially narrowed the committee's presentation of wider applications. Due to the representation of the committee, knowledge of articles related to Naval application may have led to a higher weighting of discussion in this area, though commercial vessels also have systems applied. Due to such commercial applications and expectation that their use will increase, Classification Societies are increasing guidance information for SHM, for example [1, 5] and [6]. It might be considered by a future committee to approach known SHM system developers to include views on application to different ships and the lessons learnt from such applications that otherwise may not be widely discussed in published literature.

Section 5.3: SHM Assisting Optimisation of the Design

In line with the comment provided, this section of the report was updated prior to publication in Volume II of the [14] proceedings [14], noting the potential adaptability of the technology, though full realisation may yet to be achieved in practice.

Subsection 5.5.3: Estimation of Spectrum and Sea-State Using Measured Ship Response

In line with the comment provided, this section of the report was updated prior to publication in Volume II of the [14] proceedings [14], noting the limitations of the approach.

2.1.6 Closure

The committee would like to thank Prof. Xueqian Zhou for his valuable and thoughtful comments, and for his time to fulfil the role of Official Discusser to [14] Committee V.7.

3 Reply to Written and Floor Discussions

3.1 Prof. Cesare Mario Rizzo

Question: After the Official Discusser pointed out about practical applications, I would like to add that also validation of new technologies is equally important. As an example, robots, drones, crawlers, etc. are barely accepted by Flag Administrations because of a lack of validation. A corresponding group is active at IMO dealing with such validation, whose goal is to develop guidelines for the issuance of a "Statement of Capabilities" of inspection technologies. This includes non-technical issues, e.g. legal, operational, etc. For instance, final decision is by human vs AI? Moreover, are these technologies more effective or at least equivalent to traditional ones/ Do they cost less? Are they faster? I would appreciate the committee's opinion on that? [[16, 26, 27, 28, 30]].

Committee's Response: The Committee would like to thank Prof. Rizzo for his question and for supplying the supporting references. Whilst the use of crawler robots and drones for survey was mentioned in the report, this was done so to highlight the technology, but was not explored in relation to the acceptance of the results by certifying authorities. Much of the report considered monitoring of structural performance and structural health from a perspective of informing on the presence of structural degradation or damage development to inform the operators. However, the subsequent use of the output information to inform Classification Societies and other certifying bodies as evidence as to the structural health of the platform was not explored by this committee. It is agreed that this is important where the outputs are to be used as evidence as to the structural condition for certification, and should be considered for inclusion in the future reporting of the committee.

3.2 Prof. Daniele Dessi

Question: In structural sensing, due to limited availability of sensors, optimizing the sensor positions can improve the quality and significance of experimental data: can you better highlight this aspect in the available literature and provide the Committee's view on this problem?

Committee's Response: The committee agree that determining the number of sensors, type of sensors and their placement is critical to ensuring results are suitable for interpretation or correlation with digital models. A strain gauge will measure the surface strain at a specific location; if applied to a ship for the purposes of determining global bending loads, then: how many are required? Is it acceptable to only assess in the midships region of peak bending? Are local bending loads important? etc. In acoustic emissions sensing, multiple sensors may be required to triangulate damage, but how many are required, and in what locations? Additionally, the positioning of sensors need to consider practical influences, such as movement of personnel, equipment or stores in areas where sensors are placed and the risk of damage to the sensors; such considerations may lead placement in less optimal positions for sensing, but where longevity of the sensor may be more assured.

The committee did not specifically review publications with the intention of taking a view on how best to optimise sensor locations, but is an approach that could be considered by the next committee.

3.3 Unknown Author #1

Question: How do you see the role of AI in helping to interpret results? For example, acoustic monitoring was installed on the Titan submersible, but they did not understand the results. Could AI plug this gap, or will it just encourage risk taking by people who do not understand what they are doing?

Committee's Response: The presence of a monitoring system does give the user more confidence, as there is information available about the operation of the asset. This may inspire non-founded confidence as the user expects a warning – and enough time to mitigate the risk – in a safety-critical situation. The role of AI is no different from any other tool at the disposal of engineers – it should be used in applications where this technique and its limitations suits the requirement of the engineering problem.

3.4 Unknown Author #2

Question: AI vs AI model vs AI Agent. Please ask someone from AI domain to do a review. Your text in the report for AI related sections (e.g. Section 2.2.3 [14]) and in terms of terminology being used. For example, AI takes the role of making automated decisions. AI is a very broad term, e.g. Machine Learning, AI, generic AI, Generative AI. In many sentences it seems you are referring to an AI agent.

Committee's Response: The Committee acknowledges non-specific use of terminology related to AI and ML. This links to comments of the Official Discusser where the Committee was urged to be clearer on the differentiation and intentional use of ML & AI. The Committee will take forward this point to include more precise definitions in future reports.

References

ABS. Advisory on Structural Health Monitoring: The application of sensor-based approaches. American Bureau of Shipping (ABS); 2020 (2020)

Anyfantis, K.N.: An abstract approach toward the structural digital twin of ship hulls: a numerical study applied to a box girder geometry. In Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment, **235**(3), 718–736 (2021). SAGE Publications

API. API-RP-2SIM. Structural integrity management of fixed offshore structures. First edit. American Petroleum Institute (API) Publishing Services (2014).

Borgelt J, Possekel J, Schaumann P, Dreger D, Ghafoori E (2024) Innovative test concept for evaluating fatigue degradation process of submerged grouted connections. Eng Struct 302:117335

BV. Hull Stress and Motion Monitoring MON-HULL; Part F, Chapter 5, Section 1; Bureau Veritas, France (2022)

DNV. Structural Health Monitoring by use of sensor data. DNV; report no. 2023–1241, Rev 1, 21/02/2024 (2024)

DNV. Class Guideline DNV-CG-0264: Autonomous and remotely operated ships; September 2021 (2021)

Elies S (2015). Performance Analysis of Commercial Accelerometers: A Parameter Review. Sensors and Transducers; Vol 193, Issue 10, October 2015, pp.179–190

Fang X, Wang H, Li W, Liu G, Cai B (2022) Fatigue crack growth prediction method for offshore platform based on digital twin. Ocean Eng 244:110320

Ge H, Wu B, Li X, Wei Q, Jiang Y (2024) Enhanced digital twin framework for real-time prediction of fatigue damage on semi-submersible platforms under long-term multi-sea conditions. Ocean Eng 314:119696

Hamada, R., et al.: Structural Health Monitoring of CFRP Propellers by Piezoelectric Line Sensors. In: Farhangdoust, S., Guemes, A., Chang, F.K., (eds.) Struct. Heal. Monit., Stanford: DEStech Publications, Inc., pp. 408–416 (2023)

Huijer, A.J., Kassapoglou, C., Pahlavan, L.: Acoustic emission monitoring of composite marine propellers in submerged conditions using embedded piezoelectric sensors. Smart Materials and Structures **33**(9), Article 095018 (2024)

IMO. Development of guidance on assessments and applications of remote surveys, ism code audits and isps code verifications. International Maritime Organization Sub Committee on implementation of IMO instruments (III 8/INF.2); 19th April 2022 (2022)

ISSC. Proceedings of the 22nd International Ship and Offshore Structures Congress, Volume 2. Eds. W Wu & J Ding. Springer Nature Singapore Pte Ltd; September 2025 (ISBN: 978–981–95–2785–4) (2025)

LeCun Y, Bengio Y, Hinton G (2015) Deep learning. Nature 521:436–444

Li Y, Sharif-Khodaei Z (2024) A novel damage detection method for carbon fibre reinforced polymer structures based on distributed strain measurements with fibre optical sensor. Mech Syst Signal Process 208:110954. https://doi.org/10.1016/j.ymssp.2023.110954

Liu Y, RenH (2023) Rapid acquisition method for structural strength evaluation stresses of the ship digital twin model. Ocean Eng 285(P1):115323

Marwedel, P.: Embedded System Design: Embedded Systems Foundations of Cyber-Physical Systems, and the Internet of Things, Springer Nature (2021)

Mieloszyk, M., Majewska, K., Ostachowicz, W.: Application of embedded fibre Bragg grating sensors for structural health monitoring of complex composite structures for marine applications. In Marine Structures (Vol. 76, p. 102903). Elsevier BV (2021)

Mitchell, T.: Machine learning. Published by McGraw-Hill, Maidenhead, U.K., International Student Edition. ISBN: 0-07-115467-1 (1997)

Nelli, F., et al.: Reconstructing sea-states in the Southern Ocean using ship motion data (2021). Proceedings of the International Conference on Offshore Mechanics and Arctic Engineering - OMAE, 6, art. no. V006t06a027. https://doi.org/10.1115/OMAE2021-62757

Nielsen UD (2006) Estimations of on-site directional wave spectra from measured ship responses. Mar Struct 19:33–69

Poggi, L., Gaggero, T., Gaiotti, M., Ravina, E., Rizzo, C.M.: Robotic inspection of ship structures: how to fill the gap between available technologies and current survey practices? 2019 IMEKO TC-19 International Workshop on Metrology for the Sea; October 2019 (2019)

Poggi L, Gaggero T, Gaiotti M, Ravina E, Rizzo CM (2020) Recent developments in remote inspections of ship structures. International Journal of Naval Architecture and Ocean Engineering 12:881–891

Poggi L, Gaggero T, Gaiotti M, Ravina E, Rizzo CM (2022) Robotic inspection of ships: inherent challenges and assessment of their effectiveness. Ships and Offshore Structures 17(4):742–756

Shah MS, Gaggero T, Gaiotti M, Rizzo CM (2021) Condition assessment of ship structure using robot assisted 3D reconstruction. Ship Technology Research 68(3):129–146

Shamsuddoha M, Prusty GB, Maung PT, Phillips AW, St John NA (2022) Smart monitoring of a full-scale composite hydrofoil manufactured using automated fibre placement under high cycle fatigue. Smart Mater Struct 2022:31

Shen W, Pang Q, Fan L, Li P, Zhao X (2023) Monitoring and quantification of non- uniform corrosion induced mass loss of steel piles with distributed optical fiber sensors. Autom Constr 148:104769

Silionis, N.E., Anyfantis, K.: On the Detection of Thickness Loss in Ship Hull Structures Through Strain Sensing. Lecture Notes in Civil Engineering, 254 LNCE, pp. 207–216 (2023)

Thompson, I.: Virtual Hull Monitoring: Continuous fatigue assessment without additional instrumentation. International Journal of Maritime Engineering, **160** (Part A3): A-293-A-297 (2018)

Tonelli D, Cappello C, Zonta D (2021) Performance-based design of structural health monitoring systems. Lecture Notes in Civil Engineering 128:238–247

Warsi, Z.H., Irshad, S.M., Khan, F., Shahbaz, M.A., Junaid, M., Amin, S.U.: Sensors for structural health monitoring: a review. Second International Conference on Latest trends in Electrical Engineering and Computing Technologies (INTELLECT), Karachi, Pakistan, 2019, pp. 1–6 (2019)