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State of the art in structural health monitoring of offshore and marine structures

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This paper deals with state of the art in structural health monitoring (SHM) methods in offshore and marine structures. Most SHM methods have been developed for onshore infrastructures. Few studies are available to implement SHM technologies in offshore and marine structures. This paper aims to fill this gap and highlight the challenges in implementing SHM methods in offshore and marine structures. The present work categorises the available techniques for establishing SHM models in oil rigs, offshore wind turbine structures, subsea systems, vessels, pipelines and so on. Additionally, the capabilities of proposed ideas in recent publications are classified into three main categories: model-based methods, vibration-based methods and digital twin methods. Recently developed novel signal processing and machine learning algorithms are reviewed and their abilities are discussed. Developed methods in vision-based and population-based approaches are also presented and discussed. The aim of this paper is to provide guidelines for selecting and establishing SHM in offshore and marine structures.

Keywords: digital twin/fatigue/fracture & fracture mechanics/machine learning/maintenance & inspection/marine structures/maritime engineering/offshore engineering/offshore renewable energy/piles & piling/pipes & pipelines/renewable energy/steel structures/structural analysis/structural design/structural health monitoring

1. Introduction

Existing offshore and marine structures have been designed for a limited lifetime. Failures during their service life may have catastrophic environmental and economic consequences and may cause fatal accidents. More than 50% of the installed offshore and marine structures in the Norwegian continental shelf, the United Kingdom continental shelf and the Gulf of Mexico shelf exceed their design life (Aeran *et al*., 2017a, 2017b). In the past two decades, structural health monitoring (SHM) has become an important research topic in civil engineering (Adeli and Jiang, 2008; Jang *et al*., 2021; Soleimani-Babakamali *et al*., 2022; Zhang and Zhang, 2021). This technology integrates several engineering fields such as sensor technology (Alonso *et al*., 2021; Kalenjuk *et al*., 2021), materials science, artificial intelligence and machine learning (ML) (Gao *et al*., 2021; Maeda *et al*., 2021; Sarmadi and Yuen, 2021), data science and structural engineering. A key goal of SHM is to prevent premature failure and ensure satisfactory performance of the structure (Chandrasekaran, 2019; Ren *et al*., 2021; Xu *et al*., 2021).

The establishment of an SHM system requires three main components: (*a*) planning the system's overall approach, the data acquisition and management method and workflow configuration; (*b*) execution of the plan, instrument configuration and model establishment; (*c*) data processing, feature extraction, interpretation and presentation. Depending on the structural complexities, costs and the importance of the structure or structural components, an SHM system may be created to fulfil one of four different levels: (*a*) damage existence evaluations, (*b*) damage location identification, (*c*) damage severity evaluation and (*d*) remaining life estimation (Jiang *et al*., 2022; Sajedi and Liang, 2022). The demand for SHM tools is also necessary for quality control of high-profile mechanical components in order that safe service performance is achieved (Qarib and Adeli, 2014).

Figure 1 shows an overview of the SHM steps of offshore and marine structures. These structures are typically loaded by waves and wind, which inherently are stochastic in nature causing uncertainty in loading (Hirdaris *et al*., 2014; Yang and Lei, 2022). Especially, large uncertainties in extreme wave predictions have been reported (Vanem *et al*., 2019). Moreover, wave–structure and soil–structure interactions are important issues in the structural dynamic evaluation of marine structures. Therefore, these uncertainties affect the hydrodynamic modelling of marine systems, leading to the consideration of large safety factors in calculating fatigue accumulation. Moreover, marine structures are at risk of accidental actions, such as ship collisions or dropped objects, structural degradation due to corrosive environments (Mansor *et al*., 2014), scouring due to underwater currents (Fazeres-Ferradosa *et al*.,

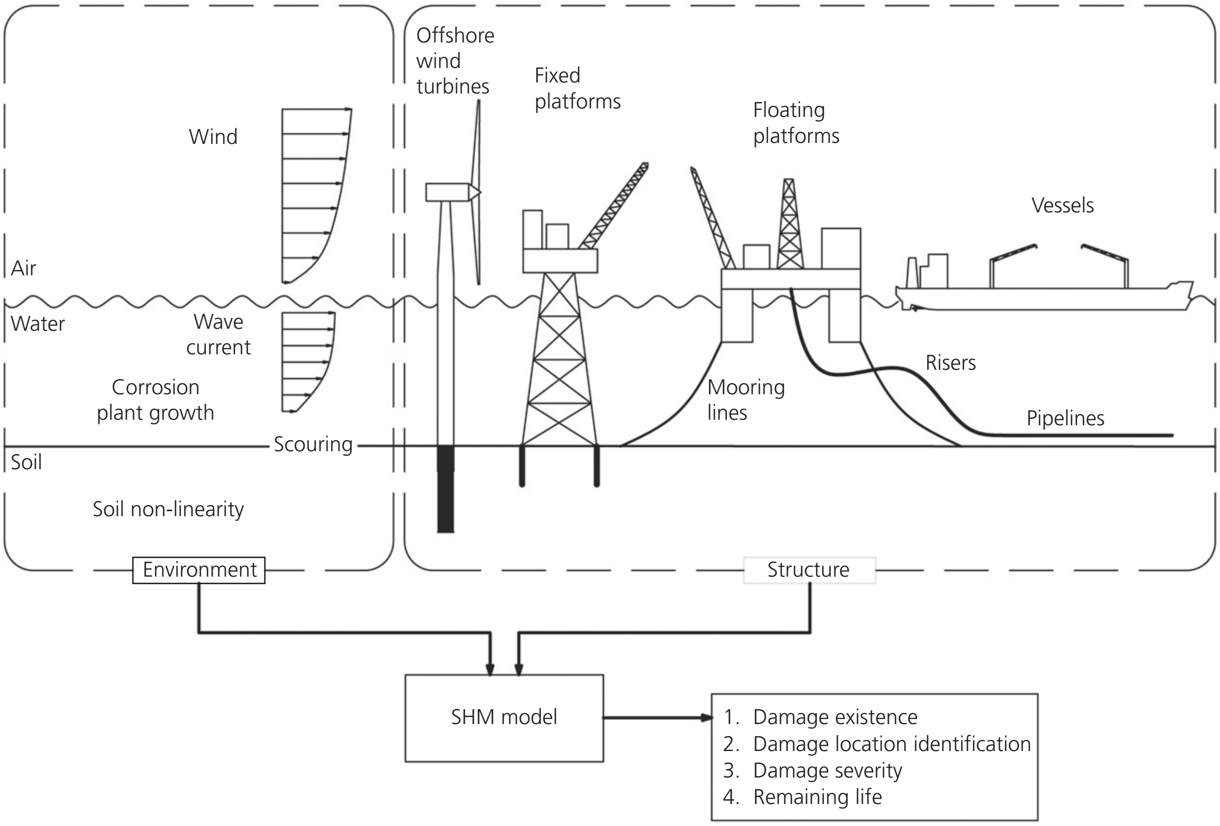

Figure 1. Overview of SHM steps in offshore and marine structures

2018, 2019) and thermal stress (Adedipe *et al.*, 2016). Evaluation of marine structures under these harsh environments requires long-term monitoring to ensure structural integrity and to estimate the remaining life of structural components accurately. With this perspective, the offshore environment must be an integral part of any SHM system for marine structures operating in it.

The main goal of SHM applications for offshore and marine structures is to identify and quantify their damage level. Almost 25% of the reported damage to marine structures is due to fatigue accumulation (Aeran *et al.*, 2019). Fatigue damage is mainly accumulated due to stochastic offshore environmental loadings such as waves and wind. Additionally, structures operating in offshore environments may experience operational changes, such as equipment rearrangements and upgrades and the installation of new equipment during their lifetime, resulting in a variation in their remaining life. Conservative design procedures to cover all the uncertainties in a real operating structure cause life-ended structures to remain operable. Therefore, these structures can be utilised or reused for additional years, providing economic and environmental benefits. For instance, techniques for crack growth retardation (Pavlou, 2018b; Rege *et al.*, 2019) or arrest (Rege and Pavlou, 2019) have been proposed. The important research questions to be answered are how much is the remaining life or how it can be extended. Answering them requires a real-time monitoring system to predict the real behaviour of the structure and identify the current conditions and damage.

Accumulated fatigue damage can be calculated using fatigue accumulation theories (Bjørheim *et al.*, 2022a, 2022b; Mourão *et al.*, 2020; Pavlou, 2018a, 2021, 2022). In real-time fatigue damage assessment (Gulgec *et al.*, 2020), it is crucial to collect global motion data from accelerometers and local strain measurements. In addition, environmental measurements such as wind direction and speed, water surface profile and temperature are as important as structural measurements. Over the years, new sensor technologies and novel data collection tools have been developed (Amezquita-Sanchez *et al.*, 2018). For instance, optical fibres (Hampshire and Adeli, 2000) for local measurement and their application in marine composite joints (Li *et al.*, 2006), terrestrial laser scanning (Nasimi and Moreu, 2021; Park *et al.*, 2007) and motion capture systems (Park *et al.*, 2015) for global motion monitoring have been introduced in the past two decades. In recent years, embedded fibre Bragg gratings

(Mieloszyk *et al.*, 2021) for marine composite materials or wireless sensor networking (Chandrasekaran *et al.*, 2016; Chandrasekaran and Chithambaram, 2019) are some of the advances in structural sensor technology with applications in offshore structures. Furthermore a novel magnetic-based sensor has been introduced in which the variation of the magnetic flux density of a ferromagnetic material is identified as the mechanical stress of any other defect (Angelopoulos *et al.*, 2020). Data collected by sensors contain valuable information about the status of the structure. Extracting them requires the use of statistical methods in addition to structural engineering.

SHM research has been reviewed from several points of view. Sirca and Adeli (2012) reviewed journal articles on system identification of structures, including model-based, biologically inspired, signal-processing-based, chaos theory and multi-paradigm approaches. Qarib and Adeli (2014) reviewed vibrational-based SHM, categorising the proposed methods into parameter and feature estimation based on linear structural behaviour, non-linear structural behaviour, sensor layout and data collection strategies, integration of SHM with vibration control of structures (Fantuzzi *et al.*, 2022), wireless monitoring and application of light detection and ranging. They divided system identification in the vibration-based approach into two main categories: parametric and non-parametric methods. The parametric approach consists of monitoring any variation in modal parameters, such as natural frequencies and damping ratios, while the non-parametric approach deals with time series data collected directly from sensors. Amezquita-Sanchez and Adeli (2015a) reviewed feature extraction and classification techniques in civil structures such as buildings and bridges. Recently, Amezquita-Sanchez *et al.* (2020) presented a survey of structural engineering applications of ML in the past few years. Other reviews on SHM have also been published. For instance, Tibaduiza Burgos *et al.* (2020) categorised the published papers into two approaches – model-driven and data-driven. They briefly reviewed data-driven approaches for damage identification in SHM. In terms of offshore and marine structures, published review papers cover only a few topics in this field, such as wind turbines (Ciang *et al.*, 2008), offshore wind turbines (OWTs) (Martinez-Luengo *et al.*, 2016) and platforms (Zhu, 2021). In addition, fatigue in offshore structures was reviewed by Cheliotis *et al.* (2022) and Jimenez-Martinez (2020), including the application of artificial neural networks (ANNs) in fatigue damage evaluation. Aeran *et al.* (2017a, 2017b) also proposed frameworks for ageing and remaining life estimation of offshore jacket structures.

This paper presents a detailed review of methodologies developed for the health monitoring of offshore and marine structures and smart structure technologies, including those with potential applications for offshore structures. Due to the challenges faced, mainly by the hostile offshore environment on the one hand and the size and complexity of the structures operating in this environment on the other, several methods have been proposed and developed. These methods are categorised into model-based, vibration-based, digital twin and vision-based approaches. The recently developed population-based approaches are also briefly reviewed. Furthermore, this review seeks to find a link between ML methods used in smart structures and SHM of offshore and marine structures and to identify the challenges in this field. The paper could be a guideline for selecting the proper SHM approach for a particular case in this field.

2. Signal processing and ML algorithms for SHM in civil and structural engineering

2.1 Recent methods of signal processing

Amezquita-Sanchez and Adeli (2016) reviewed state-of-the-art signal processing techniques for SHM in civil engineering. A number of signal processing methods and feature extraction techniques were reviewed. They are statistical time series, fast Fourier transform (FFT), short time Fourier transform, Cohsen's class, Kalman filter, wavelet transform (WT) (Karami *et al.*, 2020), S-transform, multiple signal classification (Music), Hilbert–Huang transform (HHT), ensemble empirical mode decomposition (EMD) and blind source separation. Moreover, the following four new signal processing techniques and algorithms were highlighted.

- Fast S-transform is a modified version of the S-transform algorithm that requires fewer data and a narrower window for evaluation.
- Complete ensemble EMD is an improved version of EMD providing better mode spectral separation.
- Synchrosqueezed wavelet transform (SWT) provides a more accurate time–frequency representation for highly noisy signals.
- Empirical wavelet transform (EWT) is an adaptive WT that decomposes signal based on its contained information.

Amezquita-Sanchez and Adeli (2016) suggested that these methods can be applied to SHM of civil structures due to their modifications and improvements compared over traditional techniques.

Amezquita-Sanchez and Adeli (2015a, 2015b, 2015c) integrated Music and EWT methodologies for the time–frequency representation of noisy non-linear and non-stationary signals. The performance of the method was verified by two simulated signals and an experimental signal by demonstrating immunity to noise, isolating frequencies from noise and accurate estimation of the main frequencies. Dealing with non-stationary noisy signals attracted the attention of Perez-Ramirez *et al.* (2016), who proposed a method to extract natural frequencies and damping ratios using the ambient vibration of the structure. The method is based on

SWT and consists of three steps: the random decrement technique to evaluate the free vibration from raw data, SWT to decompose the obtained free vibration into individual mode components, and Hilbert transform and Kalman filter for final estimation of natural frequencies and damping ratios. The authors verified their method by application to several buildings and a bridge. The success of working with ambient vibrations motivated Amezquita-Sanchez *et al.* (2017) to propose a method of extracting the natural frequencies and damping ratios of large civil infrastructures by using low-amplitude, highly noisy ambient vibration data. Their method successfully extracted modal parameters through the low-amplitude ambient vibration in three super high-rise building structures.

Qarib and Adeli (2015) proposed a new adaptive method for feature extraction that is particularly useful for noisy exponentially damped signals through adroit integration of Music, matrix pencil and EMD methods. They verified their proposed model experimentally by transverse vibration of a cantilever beam and evaluated the frequencies accurately. In another study, Qarib and Adeli (2016) compared the performance of four non-parametric and five parametric signal-processing techniques (listed in Table 1) in exponentially damped signals with closely spaced frequencies. They concluded that the non-parametric and parametric methods chosen for their study were highly influenced by the length of the sample the signal and the signal-to-noise ratio. This research led to the development of new and more powerful methods for processing non-stationary noisy signals with closely spaced frequencies.

Table 1. List of signal processing methods compared in the study by Qarib and Adeli (2016)

Non-parametric	Parametric
Fourier transform	Music
Periodogram estimate of power spectral density	EWT
WT	Pony method
EMD with HHT	Matrix pencil method
	Estimation of signal parameters by rotational invariance technique

2.2 Recent methods for feature extraction and classification

The final step in SHM is the interpretation of the processed signals. Amezquita-Sanchez and Adeli (2015a, 2015b, 2015c) categorised feature extraction methods used in SHM as

- artificial neural networks (ANNs)
- wavelet transformation (WT)
- fuzzy logic
- support vector machines (SVM)
- linear discriminant analysis (LDA)
- clustering algorithms
- Bayesian classifiers
- hybrid approaches

The ANN method has proved its capabilities in handling highly non-linear data. In the last decade, researchers have developed new methods capable of handling time-variant problems. A few of these are now briefly described.

- Spiking neural networks (SNN): as opposed to a traditional ANN, the internal state of SNN changes with time, providing a more realistic representation of the problem (Ghosh-Dastidar and Adeli, 2009). This dynamic nature of SNNs offers the ability to recognise the pattern of time-dependent problems. This method is called the third generation of ANNs.
- Enhanced probabilistic neural network (EPNN): the EPNN was developed by Ahmadlou and Adeli (2010) to improve the shortcomings of PNN using local decision circles.
- Neural dynamic classification (NDC): Rafiei and Adeli (2017) proposed a new NDC algorithm. It employs a new feature space with large margins between clusters and proximity within clusters to recognise minor features to reach an accurate classification. The robustness of this new method is indicated by the smoothness of convergence curves.
- Dynamic ensemble learning (DEL): Alam *et al.* (2020) developed the dynamic ensemble ML method. The significant advantages of DEL are designing the ensemble automatically, maintaining accuracy by not scarifying the diversity of neural networks (NNs), and minimising user-defined parameters. Introducing the negative correlation learning for diversity is one of the new features of this method. It has been applied successfully in medical and non-medical applications.
- Finite-element (FE) machine for fast learning: inspired by the FE methodology, Pereira *et al.* (2020: p. 6393) introduced an algorithm for supervised learning problems where ‘each training sample is the center of a basis function, and the whole training set is modeled as a probabilistic manifold for classification purposes’. This method’s major contribution is its ability to deal with large data sets so-called ‘big data’, by taking advantage of the parameterless nature of this algorithm.

3. SHM approaches for offshore and marine structure application

3.1 Model-based approach

The model-based approach for evaluating existing structures is a basic method that collects data from a healthy structure using computer modelling. In this method, mathematical/numerical models of the real structure operating in the offshore environment are developed to represent the response of the structure under arbitrary loading (Ceravolo *et al.*, 2020). The damage status can then be evaluated by comparing the results of the model with standard requirements or scaled experimental tests. In fact, the model-based approach provides an expectation of future damage by way of comparing the behaviour of the structure and its components' damage tolerance. In other words, having the structural behaviour for every possible environmental condition and the components' properties (such as material strength, toughness, *S–N* curves, corrosion rate), the damage status can be evaluated for an incident environmental condition. For instance, in the case of ship collision with a jacket-supported offshore platform, the damage status can be evaluated by applying the corresponding environmental conditions (ship impact loading in this case). Thus, the damage existence, location, severity and the remaining lifetime can be determined, and immediate actions can be taken in the case of severe damage to avoid life-threatening situations.

In addition, the model-based approach can be used in the design phase when the real structure has not yet been constructed. It can provide information about the possible damage status, including damage existence, location, severity and the overall lifetime. Therefore, the damage status can be regulated to minimise the cost of construction and future maintenance and repair. For instance, a component of the structure can be intentionally weakened to localise possible damage. Therefore, the SHM model can be focused on the possible damage areas. Moreover, the model-based approach can be useful in feature selection by identifying their ability to capture possible damage. Some damage can be developed without being detected by selected features. For instance, fatigue damage in the early stages of nucleation is almost impossible to detect. Fatigue cracks cannot be traced in the global response of the structure until it reaches the no-return situation. Therefore, identifying possible hazardous points, known as 'hot spots', is crucial in fatigue damage monitoring. Therefore, a model-based approach of SHM can be established with a focus on these hot spots to evaluate the damage status according to the real environmental condition.

The model-based approach is established by finding a link between the environmental conditions, such as loadings or material degradation, and the structural behaviour. This link answers the question of how the structure reacts or 'responds' to the different conditions of the environment in which it is operating. To do so, mathematical modelling on the basis of FE modelling or analytical solutions can be used to obtain the response of the structure. However, running a simulation to replicate a physical structure requires the creation of very complicated models, which can be very expensive and time-consuming. To understand the behaviour of the structure, repeated simulations need to be run with varying input parameters, which increases the cost even more. Moreover, running a simulation can take hours (or days in some cases) to obtain the results. Therefore, surrogate models such as ANNs can be substituted to do the same job using training data sets obtained from the mathematical models.

The data sets required for training a surrogate model consist of inputs and outputs. Inputs are selected features from the environmental conditions, which could be wave and wind properties as well as the geometrical variation and/or material degradation rate. Outputs can be the structural response, either displacements or stresses, or the damage level depending on the SHM application being established. The process of establishing a surrogate model is depicted in Figure 2. The input values (environmental conditions) can be determined from either recorded measured data or using the proposed spectra. After the training process is complete, the surrogate model can predict the output by only applying the measured environmental condition. Having inputs and outputs as the training data set leads to the supervised learning process.

From the output, the damage evaluation process can be initiated. Depending on the purpose of establishment of SHM, this can be done by estimating the variation of structural parameters such as stiffness or natural frequencies, structural overall stability, fatigue accumulation damage, material degradation or other structural evaluation methods. For the case of fatigue accumulation damage, the existence and severity of damage and the remaining lifetime are evaluated for some specified locations. Therefore, the location of the damage in this case is predefined. Fatigue accumulation damage in the model-based approach can be evaluated by two approaches, directly and indirectly (see Figure 3). The output of the direct method is fatigue accumulation damage while the output of

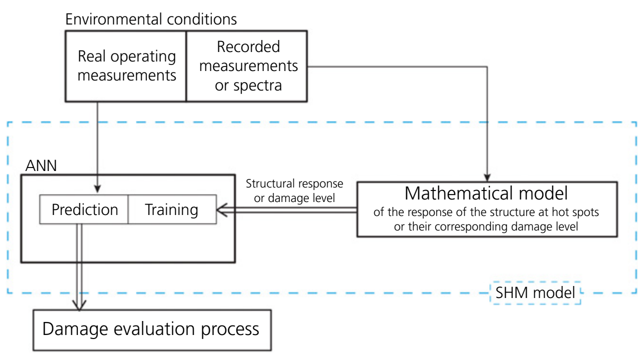

Figure 2. Model-based approach of SHM architecture

the indirect method is the stress history or stress range distribution of some hot spots required for fatigue accumulation damage evaluation.

In the direct method of fatigue accumulation damage evaluation, a data set consisting of some parameters, including stress history or stress range distribution and its associated fatigue accumulated life, is used to train the ANN algorithm (Figure 3(a)). This usage of ANN is helpful for cases where long-term simulated data are available or short-term evaluation is of interest. For instance, using an ANN, Wong and Kim (2018) proposed a framework to predict the fatigue life of a top tensioned riser subjected to a short-term vortex-induced vibration. A data set of fatigue damage accumulation was created by running a total of 21 523 riser models. They chose six input variables as the environmental conditions: the riser outer diameter, riser thickness, water depth, riser top tension and current velocity at the sea surface and the sea bottom. The direct output of the model was fatigue accumulation damage. Therefore, they established their model in the category of a direct method for fatigue accumulation damage evaluation. They trained a feed-forward neural network (FFNN) with a back-propagation (BP) training algorithm in two layers by testing different numbers of neurons in the hidden layer and different activation functions to reach the optimum training accuracy. Data acquisition for the training data set was obtained by modelling the riser using the commercial software OrcaFlex for dynamic simulation and Shear7 for fatigue accumulation damage.

In the indirect framework, the stress history or stress range distribution is the output of the model-based approach (Figure 3(b)). For the case of long-term fatigue damage evaluation, the long-term stress history is required. Obtaining the long-term stress history using mathematical models is very time-consuming. Therefore, an ANN algorithm can be utilised to recognise the short-term stress response pattern and generate the long-term stress history required for fatigue damage evaluation. Chaves *et al.* (2015) used this method to obtain the long-term stress history of flexible pipes used to transport hydrocarbons from a floating offshore oil exploitation to shore. They considered time series of six degrees of freedom of the floater (surge, sway, heave, roll, pitch and yaw) as the input variables and three outputs (axial tension and two curvatures as a function of time at the most critical point). The ANN architecture used in this study was the non-linear auto-regressive network with exogenous input (NARX), which is categorised as a recurrent neural network in two layers. They established three independent ANNs for each output. The training data set was generated by way of a commercial software program (DeepLine) to obtain short-term time series of the tension and two curvatures for the motions of the floater in 88 sea states obtained from the Janswap spectrum. After training the ANNs, the long-term response was obtained for long-term floater motions. Finally, they used these responses to evaluate long-term fatigue damage evaluation using the RainFlow method and the Palmgrem–Miner rule. A similar study was conducted by Cortina *et al.* (2018) in wave-induced fatigue assessment of steel catenary risers. Dynamic FE modelling was utilised to generate a short-term response to provide a data set to train the ANN. The long-term response was predicted by the ANN established by the NARX architecture and the fatigue life was evaluated.

In addition to the stress history, trained ANN algorithms are able to rapidly predict the stress range distribution in real-time environmental conditions. The stress range distribution, as opposed to the time series, is actually generated from the time

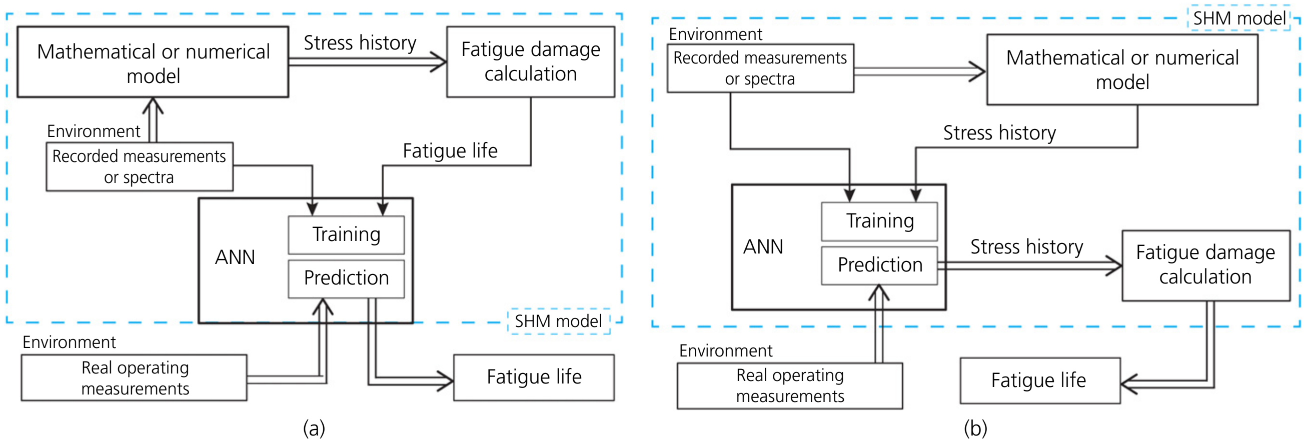

Figure 3. Model-based approach architecture for fatigue accumulation damage evaluation: (a) direct method; (b) indirect method

series response by way of counting methods (Pavlou, 2022). The stress range distribution is then fed to the fatigue accumulation damage model to calculate the fatigue damage. ANNs are useful tools to predict the long-term stress range distribution from the short-term one obtained from mathematical model. Christiansen *et al.* (2013) established a framework to predict the long-term stress range distribution for the fatigue damage evaluation of the mooring lines of a floating platform. The time series of the motion of the floater in six degrees of freedom and the top tension of the mooring line were selected as the input and output parameters, respectively. They attempted to simulate the NARX by introducing the top tension at the end of the last step as input to the next time frame. A two-layer FFNN with a BP training algorithm was established and trained. Simo and Riflex were used to analyse the dynamic response of the floater and the RainFlow counting method was used to generate the corresponding short-term stress range distribution. Fatigue damage was calculated by the Palmgren–Miner rule. Li and Choung (2017) also used the same technique to predict the fatigue damage of the mooring lines of a floating offshore wind turbine (FOWT). However, their input parameters were wind velocity, significant wave height and period, and current velocity. Li *et al.* (2018) continued the same study by introducing the stress range distribution in three different ways, attempting to reduce the total number of output neurons.

Li and Zhang (2020) proposed a probabilistic model for long-term fatigue damage assessment of platform of an FOWT under realistic environmental conditions. Their focus was on fatigue life calculation at three different locations (mooring lines, tower top and bottom sections). Six environmental conditions (wind direction, mean wind speed, significant wave height, peak spectral wave period, mean wave direction and directional spread at the mean wave direction) were selected as input variables. For the output variables, the long-term stress range distribution at every selected point was chosen. They used two surrogate models, Kriging and ANN (FFNN with a BP training algorithm). The training data set was generated from modelling the FOWT using the Fast program for dynamic response analysis and the RainFlow counting method with Goodman correction for generating the stress range history. After the algorithms were trained, the long-term stress range distribution was calculated by the long-term environmental loading obtained by the C-vine copula model. Finally, the accumulated fatigue damage was evaluated by the probabilistic method.

In addition to fatigue damage evaluation, other damage scenarios have been investigated. For instance, stiffness reduction in the tendons used in a FOWT was studied by Sakaris *et al.* (2021). They proposed a new geometry for the support structure of a FOWT consisting of two floating tanks connected by 12 tendons to provide more stability to the floating platform. They modelled different damage scenarios as a stiffness reduction in the connection using commercial software programs (Ansys-AQWA and Fast) to determine the effect of the damage scenarios on the response. They proposed stochastic functional models to represent the damage status as a function of structural response under different environmental loadings and damage magnitudes. They found that the trace of reduced stiffness under 20% was fully masked in the dynamic response of the structure. However, reduction of the stiffness between 20% and 80% showed small effects on the response.

The main reason for establishing model-based SHM using ANNs may be because environmental loads are unpredictable. Running a mathematical simulation to calculate the online response of a structure under live environmental conditions requires expensive software programs and is very time-consuming. ANN algorithms can be substituted for such mathematical simulations due to their ability to recognise complicated patterns and their rapid response evaluation. However, the main problem is the availability and/or generation of training data sets. As mentioned earlier in this section, mathematical simulations have been performed for the sake of data generation. Moreover, scaled experimental tests (de Lautour and Omenzetter, 2010) and analytical solutions can be the source of data set generation in the model-based approach. In recent years, researchers have been working on proposing analytical solutions in the field of offshore and marine structures. For instance, Pavlou and Correia (2019) proposed a solution to obtain the dynamic response of pipelines under flexural loads – that is harmonic loads (transmitted by pumps, compressors, etc.) or transient loads (seismic loads, foundation movement and impact for pipeline inspection). Pavlou (2021) solved the equation of motion of OWTs under wave loading. Pezeshki *et al.* (2022) continued this work to obtain the response as a function useful for generating response data. Novel models for several applications have also been developed. For instance, Shao *et al.* (2022) presented a second-order hydrodynamic model in the time domain for floating structures with large horizontal motions. Huang and Li (2022) reported on the design of a submerged horizontal plate breakwater based on a fully coupled hydroelastic approach. Gortsas *et al.* (2022) described an accelerated boundary element method for large-scale cathodic protection problems in marine environments.

The particular issue in marine structures is the fact that the structural properties are time-dependent due to fluid–structure and/or soil–structure interactions. For instance, the time variation of natural frequencies of OWTs is reported in the literature (Damgaard *et al.*, 2013; Norén-Cosgriff and Kaynia, 2021; Prendergast *et al.*, 2015, 2018). Therefore, establishing SHM systems for complicated structures using only the model-based approach requires a deep understanding of the behaviour of the structure in the offshore environment.

3.2 Vibration-based approach

Unlike the model-based approach, vibration-based SHM deals with real recorded data from sensors installed on the structure (Mariniello *et al.*, 2021; Sajedi and Liang, 2021a). For large and complicated structures, where a model-based approach is unable to evaluate the current operational conditions effectively, analysing measured data will provide vital information of the status of the structure. Vibration-based models rely entirely on the data measured from the sensors. The positioning and types of sensors are essential issues in data acquisition for SHM (Civera *et al.*, 2021). The number of sensors installed on the structure and the recording duration directly affect the amount of data recorded and stored. As illustrated in Figure 1, showing the two main components of offshore and marine structures (i.e. the structure and the environment), real recorded data can be recorded from both components. Therefore, vibration-based SHM can be established in two schemes: using only real structural measurements (Figure 4) and using measurements from both the structure and the environment (Figure 5).

Both schemes have advantages and disadvantages. Establishing vibration-based SHM entirely on structural measurements can be beneficial for applications where long-term evaluation is of interest. Some damage develops very slowly during the lifetime of the structure. Thus, dealing with environmental measurements would be unnecessary and cost inefficient. For instance, material degradation is a time-consuming process and environmental conditions may have negligible effect on the long-term development. Moreover, in some cases, measuring the environmental conditions can be difficult. On the other hand, evaluating recorded data from both the environment and the structure can provide the opportunity of predicting the future damage status or operational performance by the current environmental situation. Due to the fact that environmental conditions are unpredictable and random in nature, online evaluation of the structure relying entirely on structural measurements would be unimaginable. For instance, evaluation of the response of a floater for the current environmental situation based on its response histories is nearly impossible. Therefore, estimating its remaining fatigue life without knowing the current operational situation is unachievable. Moreover, severe operational situations can be avoided by knowing the current damage status for a hazardous damage situation, thus improving operational safety.

In addition, global or local monitoring can be performed in both schemes, as shown in Figures 4 and 5, for general damage assessment and fatigue damage evaluation, respectively. Measured data from strain gauges can be directly fed to fatigue accumulation damage algorithms after data cleansing, as shown in Figure 4, while global measurements such as displacements and/or accelerations that need to be noise-removed through signal processing methods can be examined by recognising any deviation from previous patterns. This can be performed directly on processed signals, known as non-parametric assessment, or

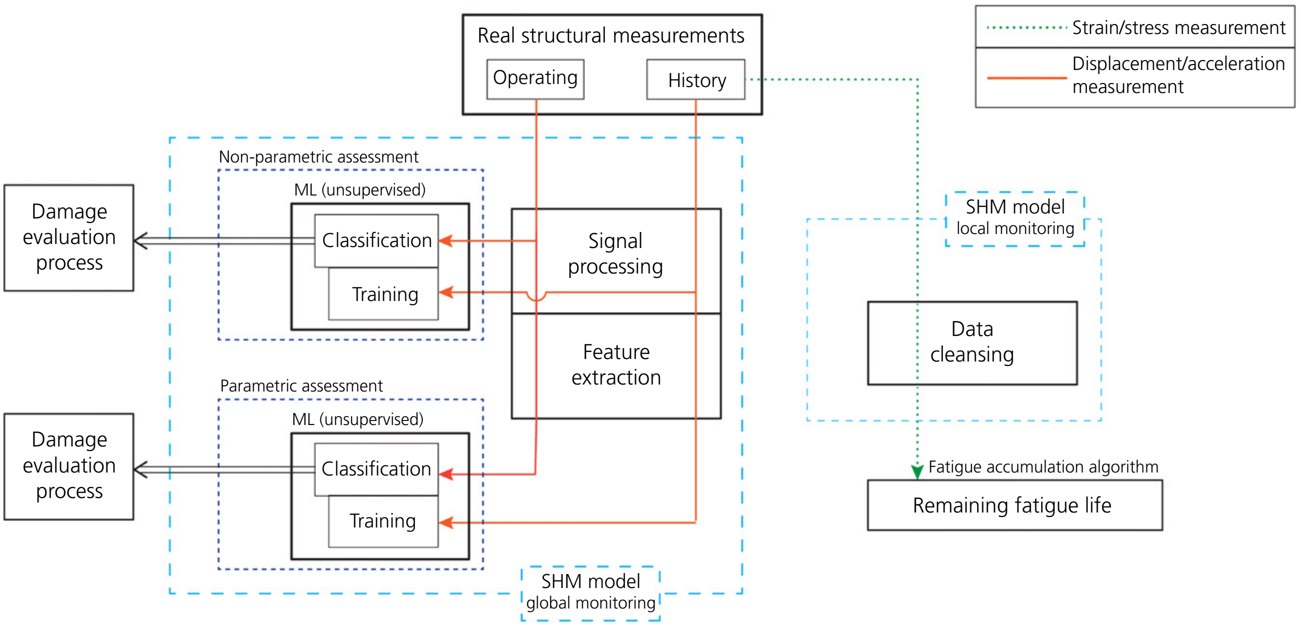

Figure 4. Vibration-based SHM based on structural measurements only

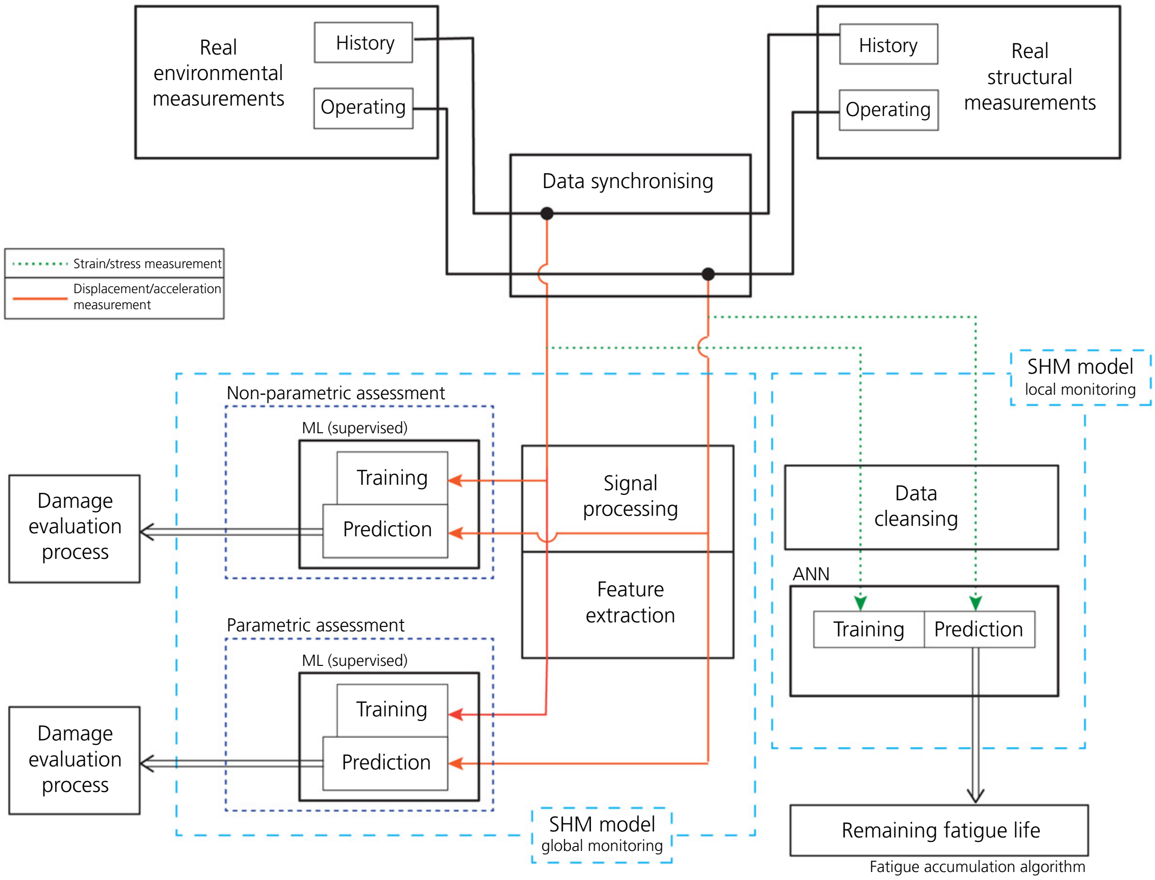

Figure 5. Vibration-based SHM based on both structural and environmental measurements

indirectly by examining the structural properties after implementing feature extraction algorithms through the parametric assessment. For pattern recognition, ML algorithms from unsupervised categories can be selected. Similar procedures can be implemented for cases involving environmental measurements. The main differences are using supervised ML algorithms and data synchronising.

3.2.1 Application of the vibration-based approach

Jiang and Adeli (2008) presented a non-parametric SHM approach for building structures. They introduced a so-called 'pseudospectrum' quantity and a dynamic fuzzy wavelet neural network (WNN) model for damage monitoring. In the first step, the data acquired from sensors are processed using the Music method to obtain the pseudospectrum. Then, the dynamic fuzzy WNN is trained to obtain a damage detection algorithm. Any unusual changes in the pseudospectrum calculated from the sensors of an operating structure can be detected by the trained algorithm and alerted as damage in the structure. This method was verified on a scaled 38-storey concrete building.

Detecting, locating and quantifying damage in high-rise building structures was the subject of another non-parametric study conducted by Amezquita-Sanchez and Adeli (2015a, 2015b, 2015c). After acquiring data from sensors, signal processing was performed by the SWT. As the step of signal interpretation, a quantity called the fractality dimension (FD) was used and calculated. The FD means how many times a pattern in the time series signal is repeated. Any change in the FD can be interpreted as damage to the structure. Damage location can also be found based on abrupt changes in the FD value calculated for every recorded signal. The severity of damage was expressed by introducing a structural damage index (SDI), varying between zero and one. A higher SDI represents more damage. These two non-parametric methodologies have potential to be adopted for offshore and marine SHM. Hillis and Courtney (2011) proposed a non-parametric early damage detection method for offshore jackets by using the bicoherence function of measured structural acceleration. Bicoherence is a squared normalised form bispectrum, the third-order spectrum, used to quantify phase coupling in a signal. They showed that their method is sensitive to fatigue damage while it is insensitive to non-linearity due to the drag term of wave load. Zhang *et al.* (2022) discussed damage detection in non-linear structures using estimations of the probability density ratio.

In a local fatigue assessments the stress history measured from local strain gauges can be directly used for fatigue accumulation calculations. The recorded data in this scheme is long-term measurements, which requires a large memory capacity to store. Due to the limited local storage capacity, data is recorded in time intervals. Therefore, the data essentially do not contain high-frequency noise and the only noise source can be expected from sensor malfunction. Noise removal can be performed by comparing the responses of the sensor to a similar environmental load. Martinez-Luengo *et al.* (2019) proposed this methodology for data management acquired from an operating OWT to assess the remaining life of the support structure (Figure 6). In their framework, data collected from environmental sensors and strain gauges are synchronised to have a data set with 10 min intervals due to the local memory capacity limitation. In the next step, data de-noising is performed by method based on analysing the sensor measurements. According to their method, correlations between sensors that followed the same behaviour or trends in measurements for defined intervals were found. Interval recordings that did not follow the overall trend were diagnosed as noisy data and removed. Then, missing data are added using the ANN (a two-layer FFNN) method with Levenberg–Marquardt training algorithms and finally the remaining fatigue life of the structure can be estimated. Martinez-Luengo *et al.* (2019) compared the fatigue life obtained from noisy and de-noised data and concluded that noisy data underestimated the fatigue life.

In terms of system identification in recent years, Norén-Cosgriff and Kaynia (2021) used three system identification methods (FFT, multichannel autoregressive moving average (Marma) modelling and Music) to estimate the first natural frequency and its associated damping ratio of an OWT from field data. They found a clear correlation between load level and the first natural frequency. They reported that Marma and Music provided better frequency estimation than the FFT. Some studies have also been performed using fuzzy logic (Mojtahedi *et al.*, 2011) and wavelet packet transform (Asgarian *et al.*, 2016) on scaled experimental test data.

3.2.2 Response prediction and missing data interpretation

For long-term evaluation of structures particularly susceptible to fatigue damage in the vibration-based approach, the availability of reliable and durable structural measurements is crucial. However, long-term measured data can be unavailable because of unforeseen problems such as disruption in sensor communications or data loss or a lack of availability of data

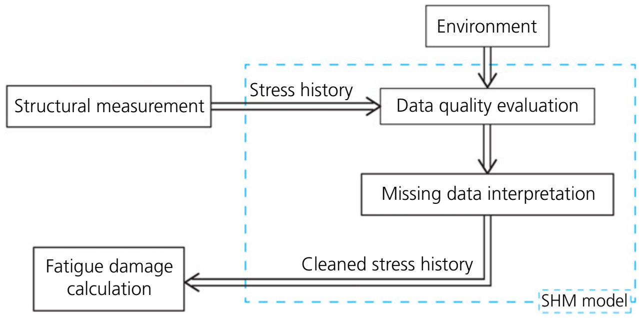

Figure 6. Framework for fatigue assessment and data management of OWTs (adapted from Martinez-Luengo *et al.* (2019))

becasue the structure is in the design phase or is a recently erected structure. Therefore, response prediction methods have been proposed by utilising short-term or defective measurements to construct a long-term response history.

Mondoro *et al.* (2016) studied the response prediction of naval vessels based on the limited available data recorded for some cells. They utilised the linear response surface to extrapolate data for unobserved cells to predict the fatigue life of the vessel. Intending to create complete and accurate data sets for fatigue life assessment of OWT support structures, Martinez-Luengo *et al.* (2019) established a framework for missing data interpretation. A two-layer FFNN was chosen as the ANN with a sigmoid and a linear transfer function in the hidden and output layer, respectively. A BP learning procedure with the Levenberg–Marquardt algorithm was used as the ANN training procedure. The relevant input variables were the environmental conditions, including wind speed, wind direction, active generator power, significant wave height and wave direction; the output was the missing data from the turbine sensors.

Puruncajas *et al.* (2020) conducted a study to convert the signals of accelerometers into a grey-scale multichannel image. Then, a deep convolutional NN (Feng *et al.*, 2021; Peng *et al.*, 2021; Xue *et al.*, 2021) was used to classify the images. They implemented their proposed method in the measurements of a laboratory-scale steel jacket-type OWT.

ANNs have also been used to predict the global response of ships under environmental conditions. Wang *et al.* (2021) proposed a method based on deep learning (Fernandez-Jover and Stambouli, 2021; Lara-Benitez *et al.*, 2021; Ozdemir *et al.*, 2021) to predict ship roll motion in different environmental conditions. They developed two versions, single input–single output and multiple input–single output based on the long short-term memory (LSTM) method (Wang and

Yan, 2020; Xu *et al*., 2021). They introduced bidirectional LSTM convolution and implemented it to predict the roll motion of ships.

The application of ANNs in predicting wave conditions has also been the subject of some studies. Vieira *et al*. (2020) used an ANN (a two-layer FFNN with BP learning procedure with Levenberg–Marquardt algorithm) to fill data gaps in wave records. Deka and Prahlada (2012) hybridised the WT with an ANN (a two-layer FFNN with BP learning procedure with Levenberg–Marquardt algorithm) to introduce a WNN to predict significant wave height up to 48 h lead time.

3.3 Digital twin approach and the concept of model updating

The digital twin (Zotov *et al*., 2021) is a relatively new topic in SHM. A digital twin is the virtual duplication of a physical object (the real structure under operation), including its physical details and associated uncertainties. Its capabilities in dealing with complicated time-dependent engineering problems have motivated researchers to develop this method for SHM of offshore and marine structures.

The development of a high-fidelity model including all structural details and inherent uncertainties such as environmental loading, especially in the case of offshore and marine environments, is very demanding and, in some cases, impossible. Therefore, establishing SHM entirely on the model-based approach does not replicate a structure's physical status, particularly those loaded under the random wave and wind loading in offshore and marine fields. Of course, it can be a platform for building an accurate model of an operating system.

The concept of the digital twin can be explained by the 'white, grey and black box' model (Wagg *et al*., 2020; Worden *et al*., 2007). Considering the model-based approach as a 'white-box model' and the vibration-based model as a 'black-box model', the digital twin approach stands in between these two techniques as a 'grey-box model' by taking the advantages of both model-based and vibration-based approaches. Therefore, the accuracy issues of model-based and the blindness of vibration-based approaches can be covered by combining them in the digital twin approach. In technical terms 'the main idea would be to reduce the epistemic uncertainties from the limitations of the physics-based modeling, using data' (Wagg *et al*., 2020).

A general framework of the digital twin concept in the application of the SHM is illustrated in Figure 7. Matching the performances of a digital twin and its physical twin requires updating the structural model with the measured data recorded from the real structure (Zhu *et al*., 2020). This provides a digital twin to replicate the real-time status of the physical counterpart. Model updating is more critical in offshore and marine applications since wave and wind loads cannot directly be anticipated. Cross-model cross-mode (Mojtahedi *et al*., 2020; Wang *et al*., 2015), the inverse FE method (Kefal, 2019; Li *et al*., 2020), Kriging (Yin *et al*., 2019) and Bayesian NN models (Yin and Zhu, 2020) are some of the model updating methods developed in the last decade.

In an engineering application, the digital twin approach can be used for fatigue life prediction of a structure. Tuegel *et al*. (2011) studied aircraft structural life prediction using the digital twin approach. They integrated multiphysics modelling, including a computational fluid dynamics model, a structural dynamics model, a thermodynamic model, a stress analysis model and a fatigue cracking model (FCM), with environmental and operational conditions such as air temperature. Their model was updated with measured information recorded by several sensors installed in the aircraft. They concluded that the digital twin approach could offer a better understanding of the life prediction of a system under unpredictable operational conditions.

Tygesen *et al*. (2018) used the digital twin approach in fatigue monitoring of offshore platforms in the North Sea on industrial bases. The development of their digital twin model for the case of fatigue accumulation was presented in five levels.

- Level 1: screening and diagnostics.
- Level 2: FE model updating.
- Level 3: wave load calibration.
- Level 4: quantification of uncertainties.
- Level 5: accumulated fatigue monitoring.

In level 1, the existing platform model (the 'original digital twin' in their study) is evaluated by comparing the modal parameters obtained from measurements and the existing model. The mass and stiffness of the actual system are updated in the FE model in level 2 to match the modal parameters with the measured ones. In level 3, the wave load, consisting of the sea surface evaluation and its associated measured wave directions,

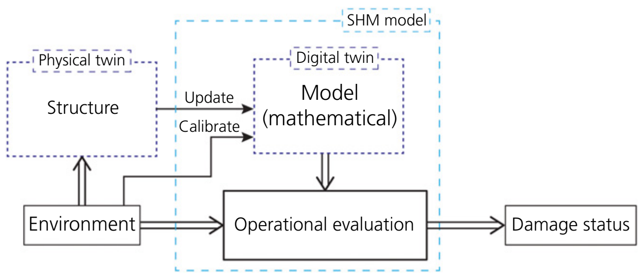

Figure 7. Digital twin approach of SHM

is calibrated in the model to represent the actual condition of the operating platform. The updated model's accuracy and continuous fatigue life monitoring are performed in levels 4 and 5, respectively. The general overview of their proposed framework is illustrated in Figure 8. Tygesen *et al.* (2018) also reported that the continuous measurements from accelerograms installed at several points on the platform are enough for the fatigue life prediction of all the structural elements as measurements from strain gauges can be used for model updating and accuracy control. They claimed that this framework could update fatigue damage bi-yearly. It should be noted that they used the term 'true' for the digital twin because they considered the platform's original model as a digital twin.

Thompson (2019) investigated application of the digital twin approach in ship hull fatigue assessment. The relevant fatigue assessments in this field were reviewed and it was concluded that a digital twin could compensate for the uncertainties related to the operational conditions and the complexities of ship structures.

Wagg *et al.* (2020) reviewed applications of the digital twin approach in structural dynamics. They also proposed a digital twin framework for wind turbine asset management, shown in Figure 9. In their framework, numerical model(s) provide the first-principles information for the wind turbine, updated by recorded data from its physical twin and physical testbed(s). A workflow coordinates their interactions and represents feedback to users by way of visualisation and quantitative data. Additionally, evaluations in the workflow can also control and schedule the physical twin.

Yeratapally *et al.* (2020) and Leser *et al.* (2020) studied the feasibility of the digital twin approach in non-deterministic fatigue life prediction of an aluminium alloy. They concluded that the digital twin framework can predict fatigue damage, ranging from initiation to failure, microstructure to macrostructure. The model updating process based on in situ

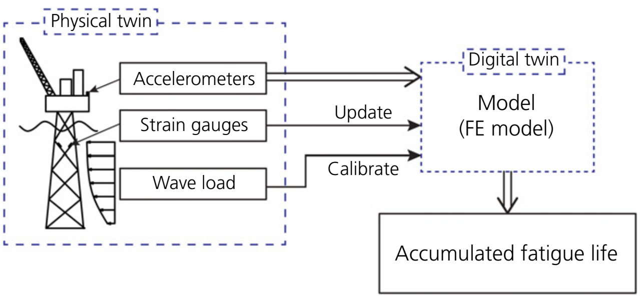

Figure 8. Digital twin framework in SHM of an offshore platform (adapted from Tygesen *et al.* (2018))

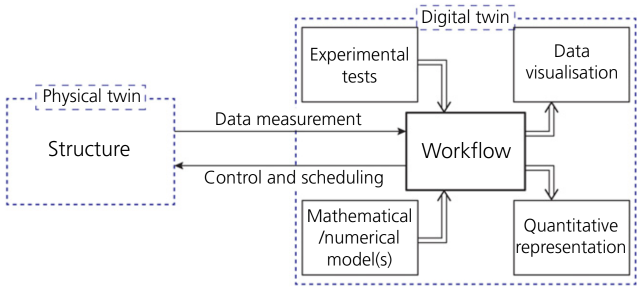

Figure 9. Digital twin approach for asset management of a wind turbine (adapted from Wagg *et al.* (2020))

information enables this framework to predict fatigue life in uniaxial loadings.

Nabuco *et al.* (2020) used the FE updating technique to predict the fatigue stress estimation of an offshore jacket structure. They used operational modal analysis to extract the modal parameters of the structure from ambient operational measurements. These modal parameters were then updated in the FE model using the expansion technique. To predict the stress history in the entire structure, they used modal expansion in a virtual sensing technique by assuming that the operational loads were random vibrations. They verified their approach on a real offshore platform.

Wu and Li (2021) proposed a framework for using the digital twin approach for the life prediction of a jet engine. In their framework recorded data from an operating edging is fed to the digital twin model using an LSTM NN to dynamically update the model. Therefore, the up-to-date remaining useful life of the operational engine could be evaluated. Additionally, by comparing LSTM with the other ML algorithms such as linear regression and FFNNs, they concluded that their model could provide more accurate life estimation for aircraft engines.

3.4 Vision-based SHM

Monitoring structures using a vision-based approach is a growing field in the SHM community (Chun *et al.*, 2021; Miao *et al.*, 2021; Tian *et al.*, 2021). Due to its advantages (non-contact, long-distance, rapid etc.) it has high potential for development in the SHM field. Dong and Catbas (2021) reviewed this approach at local levels (such as crack, spalling, delamination, rust and loose bolt detection) and global levels (such as displacement measurement, structural behaviour analysis, vibration serviceability, modal identification, model updating, damage detection, cable force monitoring, load factor estimation and structural identification using input–output information) for application to civil structures and infrastructures. Sajedi and Liang (2021b) conducted a study to quantify the uncertainty of deep vision SHM using Monte

Carlo dropout sampling. They developed deep Bayesian NNs for vision-based structural inspection. They suggested that this framework could be applied in quantifying the confidence of the predictive model. Ngeljaratan *et al.* (2021) proposed compressive sensing for vision-based target-tracking time signal processing. They claimed that their proposed method is capable of signal compression, recovery and upsampling when malfunction of data collection occurs.

In the case of offshore and marine structures, Liu *et al.* (2022) reviewed robot-based damage assessment in OWTs. They reviewed robotic platforms such as unmanned aerial, underwater and climbing vehicles carrying optical and infrared cameras and X-ray equipment. Image analysis and damage assessment algorithms were also categorised and their applications summarised. Finally, they discussed the technical challenges and opportunities in robotic platforms, inspection devices and data analysis. The application of vision-based measurement in the structural response of offshore structures has also been investigated. Tödter *et al.* (2021) used three-dimensional digital image correlation (DIC) processing to measure the structural response of offshore monopiles to vortex-induced vibration in a scaled experimental study.

Vision-based assessment on the local scale has also been the subject of researchers' studies in offshore and marine structures. For instance, Khodabux and Brennan (2021) used image processing techniques to detect and evaluate pitting corrosion in OWT structures installed in the North Sea. Qvale *et al.* (2021) utilised the DIC technique for fatigue damage assessment of the corroded surface of an offshore mooring chain. They paired DIC measurements with FE analysis to correlate fatigue damage at the initiation phase due to the stress concentration that occurred by pitting corrosion.

3.5 Population-based SHM

The idea of population-based SHM is to transfer and use existing information in a similar system based on graph theory (Hu *et al.*, 2021; Zhao *et al.*, 2021). A team of researchers has recently developed this technique and reported it in three parts: part 1: (Bull *et al.*, 2021), part 2 (Gosliga *et al.*, 2021) and part 3 (Gardner *et al.*, 2021). They stated that lacking or missing data could be filled by similar systems – (i.e. populations) and developed the method based on the type of population. In part 1, they presented homogeneous populations. These homogeneous populations, which are buildings or structures, are constructed based on the same design and details so they can be referred to as nominally identified. An example of this population is wind turbines on a wind farm. In parts 2 and 3 (Gardner *et al.*, 2021; Gosliga *et al.*, 2021) they introduced the methodology and formulation for heterogeneous populations, respectively. They defined this category as non-identical but containing common substructures. For instance, Gosliga *et al.* (2021) state that 'a bridge and an aeroplane do not share any common features; however, the propellor of an aeroplane and the blades of a wind turbine may share similar behaviour, which allows transfer of damage detection and location capability'.

4. Fatigue damage evaluation process

According to (Boyer, 1986), metal fatigue is defined as the progressive, localised, permanent structural change that occurs in materials subjected to fluctuating stresses and strains that may result in cracks or fracture after a sufficient number of fluctuations. In terms of offshore structure worthiness, the severity of their impact may be assessed by estimating the accumulated fatigue damage, which in turn requires the recurrent collection, analysis and interpretation of actual usage data. Therefore, estimation of the fatigue life of a structure depends on the accuracies of the stress history monitoring and the fatigue damage accumulation calculation.

Two phases of fatigue damage accumulation occur: the crack initiation phase and the crack propagation phase. Estimation of the crack propagation phase is usually more accurate and has fewer uncertainties than the crack initiation phase. Some researchers, including Pavlou (2002a, 2002b), Mavrothanasis and Pavlou (2007, 2008) and Rege *et al.* (2019), have worked on developing accurate tools for stress intensity factors. Furthermore, techniques for crack growth retardation or arrest have been proposed by Pavlou (2018b) and Rege *et al.* (2019), and reliable models for fatigue crack growth estimation under service loading have been developed (Pavlou, 2000).

The estimation of fatigue crack initiation is more challenging. Recent concepts of fatigue crack initiation modelling are based on the *S*–*N* curve and the concept of iso-damage lines. These models assume non-linear damage functions against fatigue life. Depending on their assumptions, non-linear models based on the *S*–*N* curve are classified into four groups: (*a*) models assuming iso-damage straight lines converging at the 'knee point', (*b*) models assuming iso-damage lines converging at the point where the *S*–*N* curve intersects the *S*-axis, (*c*) models based on the Manson–Halford concept and (*d*) models based on the continuum damage theory. Apart from the above groups, more complicated models based on the dissipated energy during fatigue have also been proposed.

A promising new non-linear macroscopic model for fatigue crack initiation prediction has been recently proposed by Bjørheim *et al.* (2022a) and Pavlou (2021). The idea of this model, which is based on the theory of the *S*–*N* fatigue damage envelope (Pavlou, 2018a), is that the area bounded by the *S* and *N* axes and the *S*–*N* curve reflects the macroscopic consequences of the damage mechanisms for any *S*–*N* pair. Therefore, it can demonstrate a characteristic damage map for each material. With the aid of FEs, damage maps are derived. The iso-damage path on these maps is non-linear and converges both at the knee point and at the point where the *S*–*N* curve intersects the *S*-axis. The new concept is a generalisation of most fatigue models based on the *S*–*N* curve. Using the proposed concept of the curved iso-damage lines, the prediction of the remaining life under stepwise variable loading histories was verified successfully in specimens subjected to two-stage loading.

Accurate fatigue damage estimation and life prediction are challenging because of the following reasons.

- The exact material properties depend on the manufacturing process.
- The microstructure of structural steels is not uniform.
- The quality of welded joints depends on the welding technology, the welder and so on, and welding always contains flaws.
- Welding leads to residual stresses that are difficult to quantify.
- The stress distribution is not always uniaxial. Very often, the stress state is multiaxial.
- Stress concentrators like notches or other surface discontinuities usually exist in structures.
- The loading history during service is not deterministic – that is, the wave loads are irregular.

Existing research works in fatigue have been mainly carried out at laboratory scale and usually ignore the above seven factors. All these uncertainties influence the fatigue life of a real structure, making the prediction of a precise fatigue life very challenging.

5. Technical challenges and opportunities

Looking through the literature related to the subject of SHM of offshore and marine structures, researchers have proposed numerous approaches, as summarised in Table 2. Techniques to monitor structures' safety range from conventional to novel approaches. However, there are still challenges in the SHM of offshore and marine structures.

5.1 Challenges

The complexities involved in designing and maintaining offshore and marine structures are not the structure itself, but the environment in which these structures operate. Environmental loads such as wind and waves are highly non-linear, stochastic and unpredictable, imposing challenges in evaluating fatigue life. Besides, floating objects experience buoyancy loads, increasing difficulties in response prediction and safety assessment of their structures. Interactions between seawater and moving objects, corrosive environments, plant growth and so on are challenging load and response prediction issues. Therefore, SHM in offshore and marine fields faces uncertainties arising from their operating environments.

5.2 Research gaps

The model-based approach to establish SHM still has potential for growth and development. In most recent publications on conventional model-based SHM, researchers have used

Table 2. Summary of advantages and disadvantages of SHM approaches

Advantages	Disadvantages
Model-based approach	
• Can provide a general overview of the behaviour of the structure • In the case of lacking data, can generate data to establish SHM • Can verify in situ data in terms of sensor performance and so on	• Creating a mathematical model describing detailed behaviour is very difficult • Verification and validation of mathematical models are always questionable
Vibration-based approach	
• Represents the actual behaviour of the operating structure	• Presents the local situation of the structure • Provides the current behaviour of the structure • Requires reliable historical recording to provide an estimation of long-term behaviour • In some cases, it is not feasible to measure data from some points of the structure
Digital twin approach	
• Benefits from the advantages of both model-based and vibration-based approaches	• Can be costly to establish • Requires an understanding of model updating techniques
Vision-based approach	
• Provides a rapid estimation of the current situation, especially in the case of accidents	• Primarily assesses the surface of the structure • The surface of the structure should be accessible
Population-based approach	
• In the case of lacking data, can generate data to establish SHM	• Still under development

numerical models in commercial software programs, which are significantly time-consuming and costly. However, developing analytical solutions instead of numerical models can rapidly estimate a system's response thanks to the developments in programs handling heavy mathematical calculations. Analytical solutions can also provide massive data sets for the training of pattern recognition algorithms.

Recorded data from sensors installed on structures operating in offshore environments, considering the above-mentioned uncertainties and complexities, can be expected to contain complex valuable information. Processing and interpreting them requires the development of novel algorithms capable of handling the data. The developments of novel algorithms in signal processing and ML could be utilised and extended to apply vibration-based SHM to marine and offshore structures. For instance, methods proposed for the application of ambient vibration (low-amplitude) by Perez-Ramirez *et al*. (2016) can also be used in offshore and marine structures due to their low-amplitude, high-cycle vibration. Additionally, non-parametric damage recognition can be developed by defining (fatigue) damage indexes for this application.

6. Conclusions

Methods proposed for SHM of offshore and marine structures have been reviewed. Two conventional methods, the model-based approach and the vibration-based approach, were assessed. The section on vibration-based approaches summarised recent advancements in developing novel signal-processing and ML algorithms. The digital twin concept and its application in SHM of offshore and marine structures have been reviewed. Finally, developments in vision-based methods were introduced and a new method, the so-called population-based SHM, was briefly discussed. The advantages and disadvantages of the reviewed SHM methods were presented. The challenges of offshore environments were presented and the research gaps in the development of SHM for these structures were identified.

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