Journal of Marine Science and Application (2022) 21: 26-54
https://doi.org/10.1007/s11804-022-00298-3

Review

Review on Artificial Intelligence-aided Life Extension Assessment of Offshore Wind Support Structures

B. Yeter[1], Y. Garbatov[1] and C. Guedes Soares[1]

Received: 18 May 2022 / Accepted: 18 July 2022

Abstract

The primary objective of the present literature review is to provide a constructive and systematical discussion based on the relevant development, unsolved issues, gaps, and misconceptions in the literature regarding the fields of study that are building blocks of artificial intelligence-aided life extension assessment for offshore wind turbine support structures. The present review aims to set up the needed guidelines to develop a multi-disciplinary framework for life extension management and certification of the support structures for offshore wind turbines using artificial intelligence. The main focus of the literature review centres around the intelligent risk-based life extension management of offshore wind turbine support structures. In this regard, big data analytics, advanced signal processing techniques, supervised and unsupervised machine learning methods are discussed within the structural health monitoring and condition-based maintenance planning, the development of digital twins. Furthermore, the present review discusses the critical failure mechanisms affecting the structural condition, such as high-cycle fatigue, low-cycle fatigue, fracture, ultimate strength, and corrosion, considering deterministic and probabilistic approaches.

Keywords Offshore wind; Life extension; Artificial intelligence; Fatigue; Structural integrity; Corrosion-related cracking; Risk-based maintenance

1 Introduction

Europe has achieved its goal for 2020 regarding fighting climate change and enabling sustainable energy production. This success could not be possible without the aid of offshore wind farms. Moreover, offshore wind farms have continuously expanded with larger and more powerful offshore wind turbines (Díaz and Guedes Soares, 2020a). The SET-Plan objectives published by the European Commission for the medium term (2020-2030) urge continuous growth in both onshore and offshore wind farms, the expansion of deep offshore technology on an industrial scale, and further cost reductions. Moreover, the installed capacity reaches 400 GW, annual installations reach 20 GW, half offshore in 2030, and wind energy is expected to account for 33% of EU electricity consumption. For the long-term (2030-2050), the primary energy market will be offshore wind and is expected to provide 50% of the EU's electricity needs (Amanatidis, 2019).

Despite a promising future for offshore wind, the expected levelised cost of energy (LCOE) for offshore wind turbines (OWT) is still higher than onshore (Castro-Santos et al., 2016). Moreover, unforeseen operational cost related to corrosion and corrosion-induced cracking has caused LCOE to be much higher than the targeted values (Hilbert

Article Highlights

- The historical background and new developments in intelligent structural integrity management are discussed within the scope of the life extension of offshore wind turbine support structures;
- Big data analytics, advanced signal processing techniques, supervised and unsupervised machine learning methods are discussed within the scope of structural health monitoring and condition-based maintenance planning;
- Relevant literature on high-cycle fatigue, low-cycle fatigue, fracture, ultimate strength, and corrosion are critically reviewed within the context of the structural integrity of offshore wind structures;
- The risk-based structural assessment is highlighted for an early warning and optimal remedial action for ageing support structures.

✉ Y. Garbatov
yordan.garbatov@tecnico.ulisboa.pt

[1] Centre for Marine Technology and Ocean Engineering (CENTEC), Instituto Superior Técnico, Universidade de Lisboa, Lisbon, Portugal

et al., 2011). The unprecedented corrosion issues in monopile foundations in the European offshore zone, particularly in the North Sea (Momber, 2011), were one of the first warnings that indicated a paradigm shift in the life-cycle design of OWTs. Hence, the greatest challenge for offshore wind is to reduce costs significantly to achieve the EU's long-term targets.

From the structural assessment standpoint, OWT structures have been treated as though they are very much similar to conventional offshore Oil & Gas platforms, which can be valid to some extent. However, offshore wind turbine structures differ considerably from the traditional offshore platform, both fixed and floating, from the loading, operation, consequence, risk-involved and risk management.

For instance, offshore wind farms have been capital-intensive engineering projects as the capital cost may go up to 80 per cent (Aswathanarayana and Divi, 2009). Consequently, the design philosophy has been towards the "safe life" philosophy. However, as the number of OWTs in a wind farm and useful service life increases, the operational costs increase; consequently, the importance of finding optimal inspection and maintenance strategies is expected to be more important than ever.

All the life-cycle phases, design, construction and operation are intertwined and must be dealt with in a holistic approach that incorporates all life-cycle phases and interactions between them. Substantial progress in reducing LCOE can be achieved by holding a holistic view, covering construction, inspection and maintenance of the OWTs, which may mean not only maintenance planning would undergo some update but also the design (Yeter et al., 2019a). In this sense, the design philosophy is called "design for maintainability", in which the importance of operation and maintenance is paramount during the project development and design phases.

Decommissioning has been seen as the last phase of a life cycle of an offshore wind farm by default. Apart from decommissioning, the project owners can also decide to extend the service life of the assets, and this decision can be put into practice in various forms, such as retrofitting and operational intensity reduction, so long as the appropriate certification is provided for the continuation of the service life.

The life extension can be seen as a viable option for the ageing offshore wind turbines as long as the profit (benefit) obtained from the operation overcomes the economic consequence of structural failure (cost). Nevertheless, before going with the life extension decision, the life extension projects need to be certified by classification societies. In this regard, DNV (2016a) and DNV (2016b) reported principles, technical requirements and guidance for the lifetime extension of offshore wind turbines, which finds both practical and analytical assessments to ensure the intended life extension without compromising the operational safety and serviceability of offshore wind turbines.

From the practical assessment standpoint, structural components of the offshore wind turbine should go through inspections of the wind turbine, taking into account the maintenance/ operational history. The practical part can be enhanced by continuous structural health monitoring and sensors. Furthermore, DNV (2016a) and DNV (2016b) also suggest three analytical assessment approaches that can accompany the practical assessment part: simplified approach, detailed approach and probabilistic approach.

The simplified approach focuses on the fatigue limit state, ensuring the structural integrity of all components based on a comparison of the fatigue loads. The detailed approach also focuses on the fatigue limit state and structural integrity; however, it requires the wind turbine design documentation and site-specific environmental conditions (wind, wave, temperature, humidity, ice aggregation, salt content of the air etc.), soil conditions, and the influence of wind farm configuration. A detailed approach is a deterministic approach, neglecting the uncertainty associated with the wind load calculation, the fatigue failure mechanism and the numerical and analytical assessment methods. To solve this issue, the probabilistic approach involving structural reliability analysis is suggested.

There are many challenges identified with the life-cycle extension certification and decisions, although the guideline provided by classification societies give some insight regarding the life extension certification. As of now, there is no up-to-date guideline that is comprehensive enough for the life extension assessment incorporating emerging technological development and economic conjuncture.

For optimised life extension performance, the introduction of intelligent monitoring and maintenance systems using artificial intelligence is inevitable. Appropriate input can be supplied for the supervised machine learning algorithms to create predictive models, whereas unsupervised machine learning techniques can provide information regarding unprecedented damage. Furthermore, the intervention schemes gain higher effectiveness once the risk-based assessment is incorporated into the intelligent life extension management systems.

The present work aims to contribute to the literature by reviewing the most relevant and recent publication with respect to the life extension assessment of offshore wind support structures aided by artificial intelligence (advanced statistical analysis, signal processing techniques, machine learning and deep learning algorithms). The present work presents the literature review under four sections that are deemed to be the main building block of AI-aided life extension assessment for offshore wind turbine support structures.

The first section focuses on the acquisition, pre-processing and analysis of the big data gathered from the condition monitoring system and non-destructive inspections. The second section discusses the structural integrity assessment for life extension within the context of high- and low-cycle fatigue, crack growth subjected to underload/overload, corrosion-induced cracking, and the ultimate strength. The following section reviews a selection of studies that discuss the development of data-driven intelligent maintenance management systems. Particular attention is given to early warning systems for potential failures and minimal human involvement in inspection and maintenance. The final section is dedicated to the multi-dimensional risk-based framework for life extension assessment of offshore wind turbine support structures, covering the structural reliability of correlated failure-prone components, the target reliability for life extension, and the probabilistic evaluation of life extension performance accounting for both technical and economic criteria.

2 Big data collection, preprocessing and analysis using artificial intelligence

In a careful attempt to push the limits of the possible design space without taking drastic measures in terms of safety margins, structural health monitoring (SHM) systems have risen as an appropriate answer to meet the growing demand for inexpensive offshore wind energy. The responsibility of the SHM system is to detect and identify damages so that necessary measures can be taken promptly to secure structural integrity and serviceability.

In this regard, the concept of an AI-aided maintenance system integrated into life-cycle management has a vast potential; yet, there is much to explore and investigate as the use of such complex systems is in its infancy. Further, introducing an integrated intelligent maintenance system within the scope of life extension and certification poses an interesting multi-disciplinary optimisation problem. This optimisation problem covers all the costs associated with developing such complex systems, implementation to the offshore wind farm, substantial storage and processing capacities, and the monetary consequence of not implementing such systems.

Lian et al. (2019) emphasised the importance of data-driven structural integrity management by stating that several failure cases where the failures from different parts of the OWTs could have been avoided if the decision-makers had provided more information or data and the proper methods to analyse the given big data. They also considered insufficient supervision together with insufficient structural strength, fracture, resonance and human faults as the primary cause of failures. An overview of failure data of wind turbines can be found in Santos et al. (2015a).

The current economic losses caused by unprecedented maintenance actions due to the lack of information on the structural condition indicated the significance of the structural health monitoring systems combined with the safety evaluation techniques for offshore wind turbine components. Some applications of condition-based maintenance and SHM for wind turbine components were reviewed by Martinez-Luengo et al. (2016) and Lian et al. (2019) with a thorough presentation of monitoring system techniques, data acquisition, feature extraction and safety evaluation. However, the development of a framework for intelligent maintenance management fed with the structural condition data from the SHM systems lacks the support structure subjected to environment-assisted degradation mechanisms such as corrosion and fatigue.

Martinez-Luengo et al. (2016) suggested employing supervised and unsupervised machine learning techniques. It was recommended that after proper treatment of noisy data using sophisticated signal processing approaches such as wavelet time-frequency analysis (Antoniadou et al., 2015), the multilayer ANN for the pattern recognition and prediction model can be employed for the SHM procedure incorporated into the intelligent maintenance system.

Antoniadou et al. (2015) discussed the latest advances in structural health monitoring (SHM) and condition-based maintenance systems for wind turbine components. The study indicated that data-driven vibration-based analysis methods appear to be very promising, although difficulties exist related to the operational conditions of wind turbine systems. In this case, the resulting non-stationarity should be considered. Advanced signal processing methods such as time-frequency analysis or co-integration could successfully perform the feature extraction part of a complete SHM system integrated into intelligent maintenance systems. Antoniadou et al. (2015) also highlighted the importance of pattern recognition and machine learning approaches for the SHM procedure, as it was stated.

Ziegler et al. (2018) argued that the life extension assessment of OWTs could benefit from training the big data provided by SCADA and sensors fatigue life of critical hotspots. The discussion highlighted the fact that condition monitoring does not involve model uncertainty, whereas it is subjected to measurement uncertainty. It was also stated that the trained model could be used for other OWTs; however, the study did not mention how the correlation between the OWTs could be included in the trained artificial intelligence models. To deal with the whole offshore wind farm, Weijtens et al. (2016) proposed the fleet leader concept, in which a limited number of representative turbines are instrumented with accelerometers and strain gauges. The fatigue damage assessment is based on the damage equivalent loads for different turbulence and site conditions. The results from these turbines are extrapolated to the entire farm using an empirical formula.

The offshore wind industry has widely employed supervisory control and data acquisition (SCADA) systems and condition monitoring systems to be able to monitor structural health. The wireless networks of sensors can measure and transmit big operational data such as vibrational acceleration, displacement, strain, temperature and wind speed and direction, rotor speed, output active and reactive power at the different sampling rates to detect possible damages and inform their criticality through structural integrity assessment.

However, the development of such complex systems is a challenging task. The big data collected through structural health monitoring systems, embedded sensors and acoustic emission require to be cleaned from artefacts using the denoising and nonlinear detrending methods. Due to the number of channels and variables, dimensionality reduction techniques need to extract the most significant features that explain the damage output.

In this regard, Yeter et al. (2021) performed a systematical data analysis of structural health monitoring data for ageing fixed offshore wind turbine support structures following the methodology presented in Figure 1.

The methodology presented involved several steps, starting from the time-domain wind load simulation combined with the noise originating from different resources. The resulting noisy time signal goes through a data pre-processing procedure involving mean-centring, detrending and high and low-pass filtering. Subsequently, the methodology checks whether the original signal and the reprocessed signal come from the same population via parametric and non-parametric statistical tests to confirm the success of the data pre-processing procedure.

The methodology illustrated below was developed to be applied to the time-domain structural assessment of a 5 MW NREL wind turbine supported by a monopile structure, where the mean wind speed (U) is 11.8 m/s, the turbulence intensity (I) is 0.12, and the natural frequency is 0.218 Hz, which is needed for the dynamic amplification factor (DAF).

In terms of high pass filters to smoothen the noisy signal, the Gaussian filter, running mean, and running median can be applied, as illustrated in Figure 2. Figure 2 (a) illustrates the mudline bending moment time signal filtered by the Gaussian filter, and Figure 2 (b) shows the running median using a kernel size (window width) of 40 ms.

Both the running mean and the Gaussian filter can smoothen the noisy data provided that the kernel size is chosen carefully. Nevertheless, both filters can yield erroneous results when the measurement is subject to sharp and sudden irregularities. To address this issue, Yeter et al. (2021) suggested using the Teager-Kaiser energy operator (TKEO) (see Figure 3 (a)) in combination with the running median. Figure 3 (b) demonstrates the success of the running-median filter when it comes to denoising the faulty measurement merged with noisy data.

As TKEO calculates the instantaneous energy of a signal at varying frequency bands, revealing the sudden change in instantaneous energy level, the running median smoothens the signal because it is insensitive to outliers.

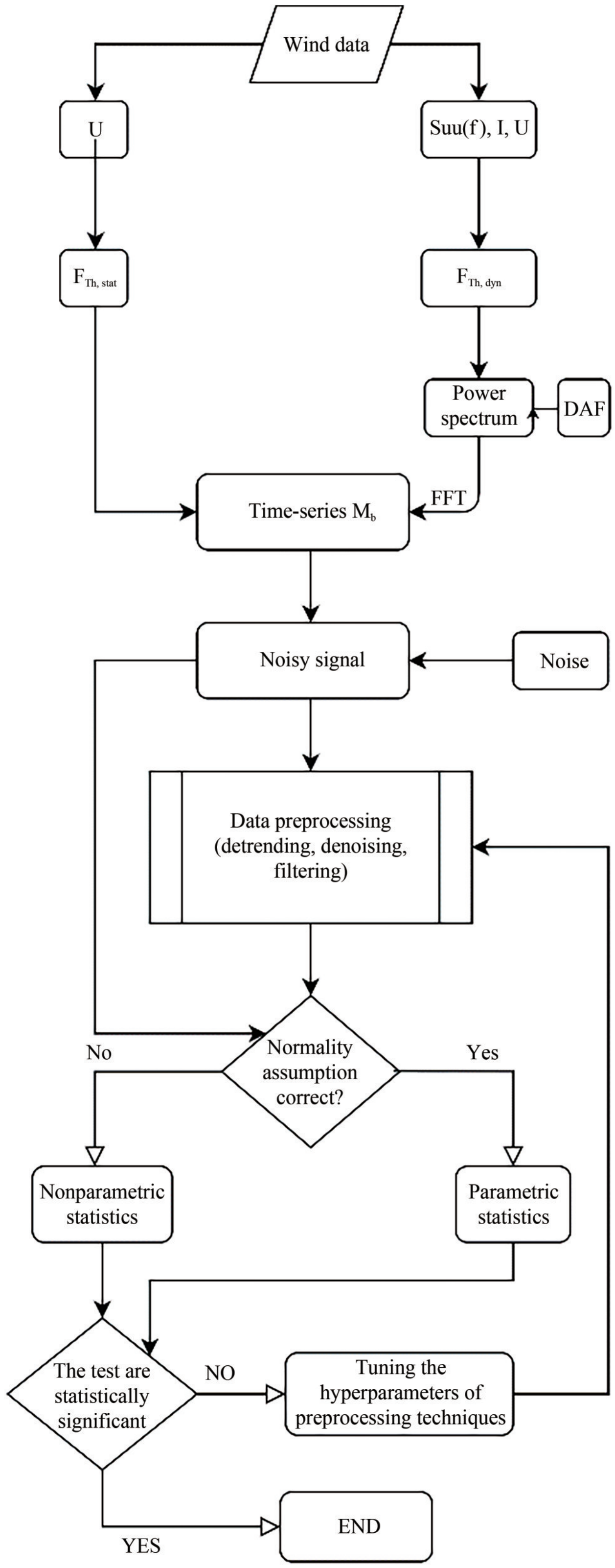
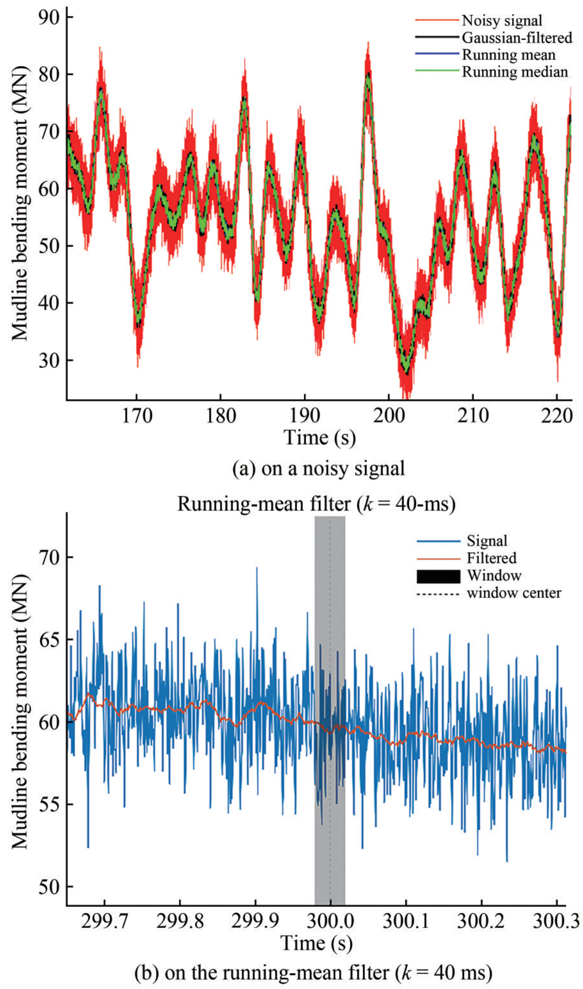


Figure 1 Methodology for the SHM data preprocessing (Yeter et al., 2021)

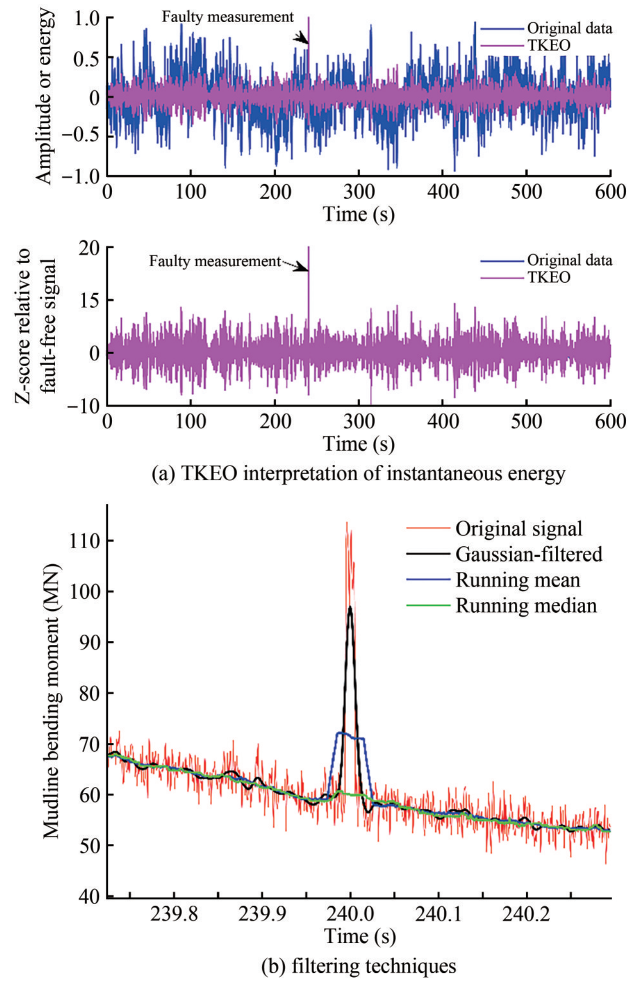
Within the scope of the AI-based structural health monitoring data preprocessing, the Principal Component Analysis (PCA) and the Welch method can also be discussed. PCA



(a) on a noisy signal

(b) on the running-mean filter (k = 40 ms)

Figure 2 Different denoising techniques (Yeter et al., 2021)



(a) TKEO interpretation of instantaneous energy

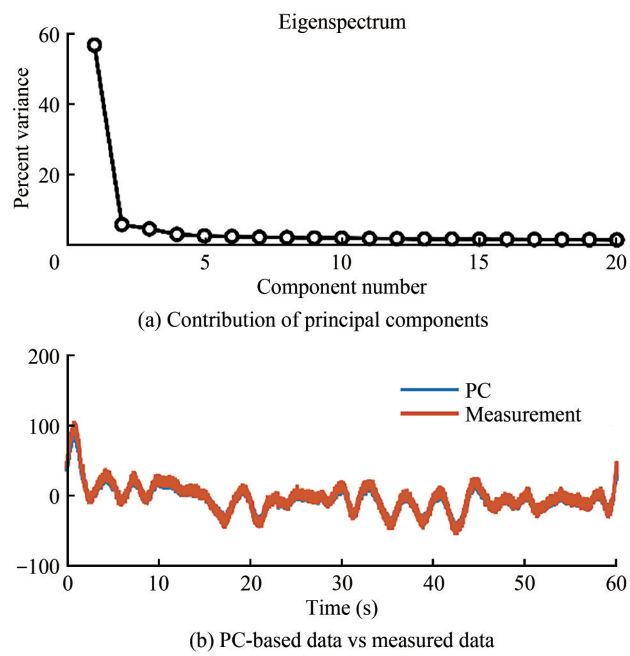
(b) filtering techniques

Figure 3 interpretation of noisy and faulty signals and application of filtering techniques (Yeter et al., 2021)

can deal with feature extraction, separating the artefact data from the measurements, yielding the SHM data with fewer dimensions that account for most of the spread in the original data. Whereas the Welch method provides a frequency domain solution to deal with a noisy time signal, especially when the SHM data shows a nonstationary behaviour or has a low signal-to-noise ratio.

In the example presented in Figure 4, a comparison between a noisy time signal collected from a sensor on a monopile support structure and the data generated using the obtained principal components. The data generated based on the first two principal components seem to be very much coherent with the measured data, which allows for the extracted core features, in turn, the principal component (PC), to simulate new data for further analysis. Also, PCA can be considered a very useful tool to deal with the multivariate time series that are emerged from the same origin and are subjected to different intermediary processes or noise caused by environment or machine operation.

In Figure 5, the difference between the power spectra obtained through the static FFT and short-time Fourier



(a) Contribution of principal components

(b) PC-based data vs measured data

Figure 4 Application of PCA (Yeter et al., 2021)

Transform is shown. It is evident that the Welch method smoothens the power spectrum of a cleaner signal, which allows for a much more accurate replication of the time signal to be used for further analysis related to structural integrity.

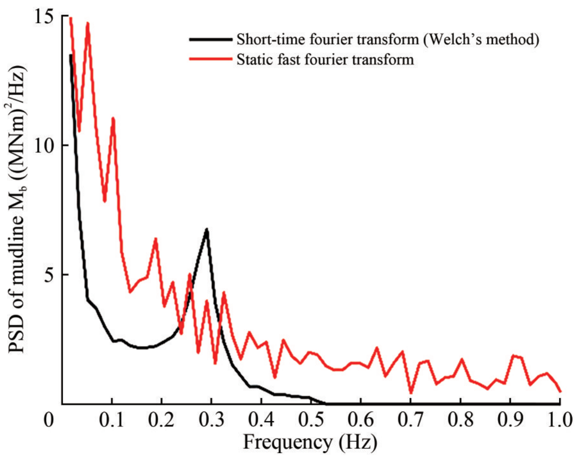


Figure 5 Comparison of between static FFT and the Welch Method (Yeter et al., 2021)

In addition to the above, Martinez-Luengo et al. (2016) gave a detailed review regarding other advanced monitoring technologies employed at offshore wind farms, such as laser interferometry, photogrammetry, X-ray imaging and laser Doppler vibrometry. In addition to the condition monitoring technologies, thermography technologies can detect abnormalities in the material based on the subsurface temperature gradients by using infrared cameras. The damage in the material can be seen by observing the change in thermal diffusivity. Also, combined technologies such as vibro-thermographic and acoustic emission ultrasonic wave-based monitoring can locate cracks and measure their dimensions.

Although these advanced methods have been promising for support structure implementation, the cost-benefit analysis of the implementation has yet to be demonstrated. In this regard, (Carden and Fanning, 2004) suggested several issues resulting from the noise in the measures, which makes the measurements, in turn, analysis, less reliable. The noise is usually caused by instrumentation, hostile environments, marine growth, corrosion and temporal changes in the condition of the support structure.

Acoustic sensors (AE) have also been an efficient way to detect corrosion of different types, such as uniform corrosion, corrosion pitting, stress corrosion cracking, and erosion-corrosion. The advantages of using AE to investigate stress-corrosion cracking and corrosion pitting have been shown in numerous studies. Calabrese et al. (2016) stated that different damage mechanisms could be identified with the help of AE, such as hit duration and rise time, burst average frequency, crack index, and hit energy. Low energy hits, low rise-time and low duration, are associated with the pit initiation and growth, while high energy hits, high rise-time and high duration are associated with the crack opening mechanisms.

Another study by Delaunois et al. (2016) regarding chloride-induced stress corrosion cracking on stainless steel AISI 304L found that the rise-time and amplitude were the most significant AE parameters. Alvarez et al. (2012) observed similarities between the acoustic emission signals originating from both transgranular and intergranular SCC under the same experimental conditions and concluded that similar AE parameters could be valuable for monitoring SCC via AE. Kovač et al. (2015) have also proposed employing AE parameters such as burst time and power spectra features to monitor and detect stress corrosion cracking stainless steel material. Jomdecha et al. (2007) used the AE technique to identify short- and long-range crack propagations as a result of high stress intensity at the nucleated SCC crack tip and anodic dissolution at the crack tip, respectively. Wu et al. (2016) stated that the low-energy signals originated from the hydrogen-bubble evolution inside the pits, while the high-energy signals were attributed to the pit rupturing during pit growth.

Despite the successful application of the AE technique for monitoring overall corrosion and the extent of the damage caused by corrosion, there are still challenges in finding the local corrosion pits and pit dimensions. For this sake, the scope of the data acquisition needs to be extended. In this regard, Price and Figueira (2017) highlighted the importance of monitoring to increase the level of understanding of conditions inside the foundations. Manual or online data acquisition regarding corrosion parameters can include dissolved oxygen, temperature, salinity, pH values, and potentials. From the condition-based maintenance and health monitoring point of view, it is essential to use the field data like strain sensors in the remaining fatigue life of offshore wind turbine structures.

Prior to developing and training the prediction models with machine learning techniques, the collected big data needs to go through data pre-processing. The data pre-processing involves removing missing data, filtering or denoising noisy measurements, completing the missing data with statistically appropriate values, outlier identification and treatment. Yeter et al. (2021) suggested using nonparametric statistical tests to confirm the SHM data pre-processing appropriateness. Figure 6 (a) shows the processed SHM data tested and failed to comply with the normality assumption; thus, a nonparametric statistical test was found appropriate to confirm the success of the SHM data pre-processing, as seen in Figure 6 (b).

Depending on the nature of the data, the techniques used for pre-processing can vary. Moreover, these techniques should be applied carefully because the algorithm used for filtering or outlier detection can easily corrupt actual meaningful data even though the aim is to decrease the

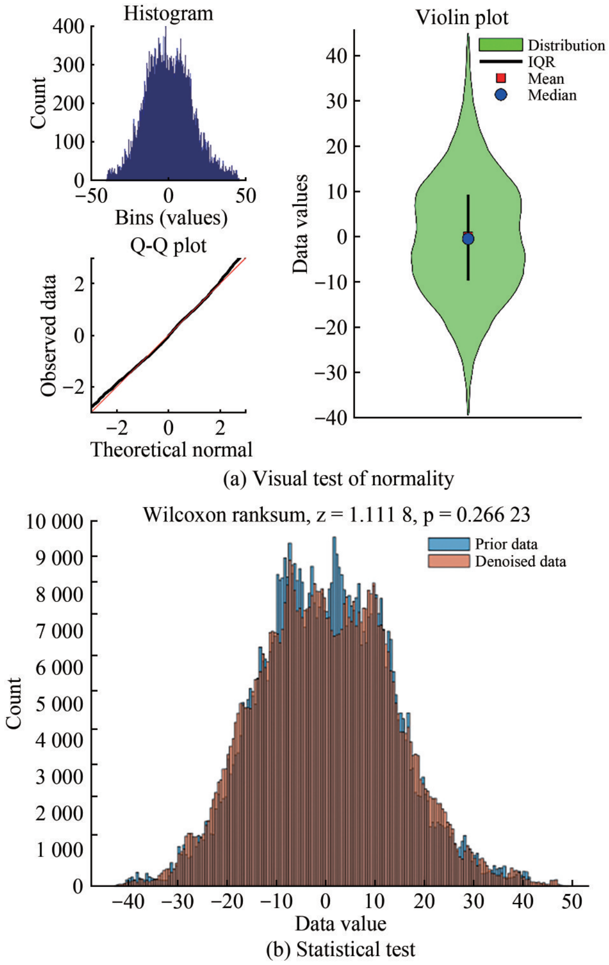


Figure 6 Application of nonparametric statistics on processed structural health monitoring data (Yeter et al., 2021)

error level. Thus, expertise in data analysis and the phenomenon on which the data analyst works is essential. A careless application or overdoing can jeopardise the success of both data AI-based prediction models.

As far as damage extraction is concerned, machine learning algorithms combined with signal processing techniques can provide reliable mathematical relationships that explain the damage status based on the structural natural frequency. Marti-Puig et al. (2018) suggested predefining the absolute and relative ranges of variables based on the expertise to not miss out on any failure state of the wind turbine due to outlier filtering methods such as quantile filter, extreme studentised deviate test and the Hampel identifier. Stetco et al. (2019) gave an extensive review of the machine learning methods for wind turbine condition monitoring. The review covered several filtering and feature selection methods that can be used for more efficient machine learning modelling. Some of these methods such as wrapper methods for which a forward or backward selection can be adopted. The forward selection starts with a small number of features, and more features are added to the system to improve the prediction performance, whereas backward selection starts with all features and based on the performance, the features are filtered (Kohavi and John, 1997). In addition to the wrapper methods, there are embedded methods that take the feature selection as part of the model's training and filter methods that rank and filter the features based on the significance test between feature and outcome (Langley, 1994).

The Fourier transform and the wavelet transform can be employed to translate a time-domain signal into its constituent frequency components. The wavelet transform provides information on both the time and frequency domains. Both the Fourier transform and the wavelet transforms lose their suitability when the signal is trended or non-stationary (Riera-Guasp et al., 2014).

The expert opinion becomes useful not only in filtering but also in selecting variables to process as well. This phase is named feature selection. In the feature selection phase, the most relevant variables that would be used to predict the desired outcome are identified. While the methods mentioned above are for feature selection, feature projection transforms the multi-dimensional collected data into space with fewer dimensions, such as the principal component analysis. In this regard, linear and nonlinear principal component analysis can yield the desired solution; however, Postma et al. (2009) stated that linear techniques are often more successful than non-linear dimensionality techniques. Jiménez et al. (2018) and Jiménez et al. (2019) presented an approach based on signal processing and machine learning techniques for detecting and diagnosing the delamination of wind turbine blades. The effects of environmental and operational variation were dealt with through a normalisation of the signal and the signal denoised by wavelet transform.

There is a vast literature on big data collection and analysis for SHM systems, damage identification, signal processing and machine learning. However, the literature becomes very limited in terms of interdisciplinary research covering the mentioned fields of study within the scope of life-cycle assessment and life extension certification. Furthermore, the long-term economic implications of using AI-aided structural health monitoring systems have yet to be studied thoroughly. The majority of the studies regarding OWTs focused on the blades, gearbox, and tower are performed under laboratory conditions for a single structure, which means there are still many unresolved issues for the ageing offshore wind farm with multiple OWTs approaching the end of their service life.

3 Structural integrity assessment of ageing offshore wind support structures

The structural condition is a key parameter for the life extension decisions, which directly affects the inspection and maintenance cost, in turn, offshore wind projects' profitability. A structural capacity above the permissible limit within the desired service life is a prerequisite for offshore wind turbine structures to be certified to extend their useful service life.

The allowable limit must cover all possible failure mechanisms that affect the serviceability of an offshore wind turbine (OWT) support structure. Therefore, it is imperative to reassess the structural capacity with respect to different failure mechanisms so that the structural condition is verified for the continuation of the service life. Structural reassessment not only provides the means to verify the structural design but also gives a chance to validate or update the assumptions on the design basis, such as offshore site conditions and structural condition.

The extended lifetime estimation would undoubtedly benefit from the updated knowledge as the results of a structural reassessment would be more precise due to the need for fewer assumptions. Thus, optimal life extension management can be planned, aiming to keep the OWTs operating as much as possible with minimal operational cost. Furthermore, decision-makers need to consider repowering or reducing the power capacity of the wind turbine depending on the reassessment of the structural condition. The number of years for life extension, maintenance policies, and power output are many parameters that form a complex multi-dimensional optimisation problem.

The remaining life of marine structures can be estimated based on the S-N approach and fracture mechanics, where the S-N approach is oriented towards the fatigue design life, and the fracture mechanics approach (Paris and Erdogan, 1963) is oriented towards the remaining life of structural details with an initial crack (Shittu et al., 2021). The S-N approach is considered to be a more reliable design approach than fracture mechanics as fracture mechanics require more additional input variables to be considered (e.g. crack growth rate, toughness, and residual stress distributions) (Anderson, 2017). Nevertheless, several limitations exist with the S–N data approach concerning offshore wind turbine structures, such as design for inspection, the effect of larger defect size, new welding processes, new materials, and the shakedown effect (Amirafshari et al., 2021). In the S-N approach, three stress approaches can be employed: nominal stress, hot spot stress and effective notch stress (Niemi et al., 2004). Moreover, the hot spot stress approach is one of the most practical methods for fatigue damage assessment (Niemi et al., 2004; Niemi et al., 2018a; Niemi et al., 2018b; Hobbacher, 2009).

The fatigue design methodologies used for OWT support structures have benefited immensely from the experiences gained from the wind turbine industry and offshore oil & gas industry (Barltrop et al., 1991). With the introduction of powerful numerical tools and the studies carried out to verify the existing codes (IEC 61400-3, 2009), the approaches used for the dynamic analysis of OWT support structures have aimed to integrate load and strength analyses in the time domain (Brennan et al., 2012). The rain flow cycle (RFC) counting method (Rychlik, 1987) is the most commonly used technique to address the fatigue damage of structures using the time history of either stress or strain (Singha and Ranganatha, 2007). Yeter et al. (2015a) adopted the three-point cycle counting technique in the time-domain fatigue damage assessment of a fixed OWT support structure. The study compared the time-domain solution with the spectral approach (Yeter et al., 2014a) (frequency-domain solution) and closed-form approach (Yeter et al., 2014b) (analytical solution) for the fatigue damage assessment.

van der Tempel and de Vries (2005) stated that the fully coupled time domain simulations captured the non-linearity of the wind turbine operation accounting for the entire structural assembly and dynamic control system. Nevertheless, it was also stated that the spectral approach as an alternative, especially in the absence of a complete model of offshore wind turbine characteristics. Yeter et al. (2015a) showed that the success of the time-domain and spectral approach in predicting fatigue damage depends very much on the bandwidth of the loading spectrum acting on a structural detail. Several different methods have been presented for that purpose in terms of using a correction factor (Wirsching, 1980; Benasciutti and Tovo, 2004; Oritz and Chen, 1987; Kim et al., 2007; Benasciutti, 2004), deriving equivalent stress in a closed-form (Chaudhury and Dover, 1985) and proposing more complicated statistical models to predict the long-term stress distribution based on the statistical moments of the stress spectrum (Tunna, 1986; Zhao and Baker, 1992; Dirlik, 1985). Benasciutti and Tovo (2006) reviewed the fatigue analysis on the wideband Gaussian stochastic process, and a comparison of these methods has been reported in (Halfpenny, 1999; Mrsnik et al., 2013). Yeter et al. (2016a) reviewed the methods developed based on both narrow and wide-band load assumptions and evaluated the predictive success of these methods based on the Akaike (1973) information criterion (AIC) (see Figure 7).

Furthermore, Gentils et al. (2017), Alati et al. (2013), Yeter et al. (2017a) and Dong et al. (2011) also conducted fatigue damage assessment based on the S-N approach so as to verify the structural design of fixed offshore wind turbine support structures.

The high-cycle fatigue (HCF) prediction can be a statistical estimate with a large scatter allocation to establish an allowable stress range within the material's elastic limit for intact structures. However, the low-cycle fatigue (LCF) prediction method is a deterministic measure aiming to find the actual number of cycles to failure Ramberg and Osgood (1943) at the local level covering both elastic and

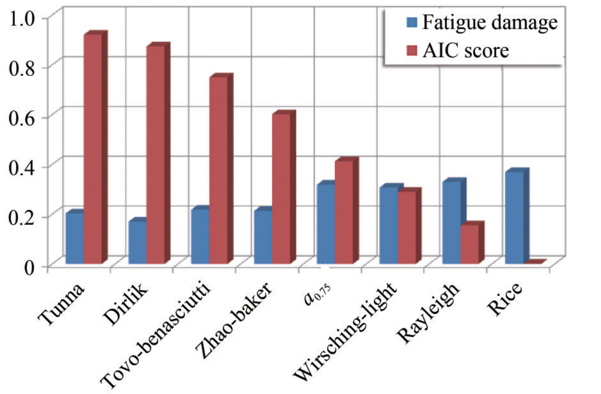


Figure 7 Spectral fatigue damage model evaluation (Yeter et al., 2016a)

plastic strain ranges. Low-cycle fatigue (LCF) is also deemed the leading cause of the rapid crack formation after several large-scale plastic strains (Kim et al., 2005), which may happen under high-stress concentration due to deterioration mechanisms such as corrosion, fatigue and plastic deformations. Yeter et al. (2015b), Yeter et al. (2016b), and Yeter et al. (2018) conducted some of the few existing studies addressing the rapid crack initiation using the local strain-based approach for OWT support structures. Figure 8 demonstrates the stress ranges normalised by the material's yield stress as a function of the number of cycles to initiate a crack size of 0.1 mm.

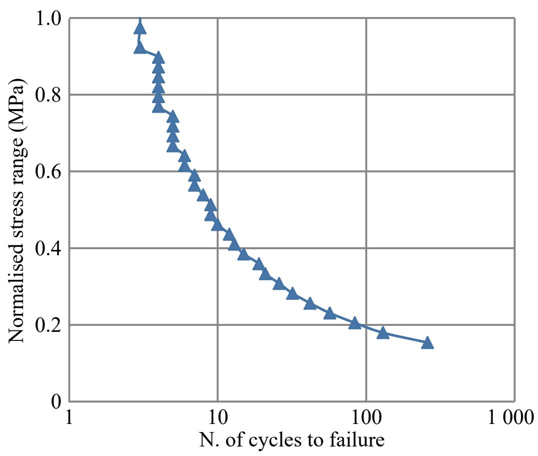


Figure 8 Relationship between stress ranges and the number of cycles under LFC loading regime (Yeter et al., 2015b)

When the crack size exceeds the threshold presumed for a physical crack size, the failure mechanism is best explained by fracture mechanics. Fracture mechanics provide the techniques to assess crack growth and monitor its criticality. Through experiments, it is well-known that fatigue crack growth follows a particular curve (Suresh, 1998), which can be divided into three regions based on two characteristic stress intensity factor ranges threshold stress intensity factor (Ibrahim, 1989) and the critical stress intensity factor (Irwin, 1957).

Stable crack growth is observed over the central region between the threshold stress intensity and the critical stress intensity factors (Anderson, 2017). Paris et al. (1961) suggested using the Irwin stress intensity factor range (Irwin, 1957) to describe the crack growth rate per cycle, presuming that the central region includes the dominating part of the fatigue life.

The Paris crack growth law is widely used to calculate the crack life in offshore and ship structures since the remaining crack life can be directly estimated by integrating the Paris law. Further, the cycle-by-cycle approach accounts for the load interaction (retardation) and sequence effect of random variable amplitude loading, which are neglected by the characteristic approach employing the statistically equivalent constant amplitude loading (Barsom, 1976). More details on this type of analysis are given in (Skinn et al., 1994; ASM, 1996). The mechanism underpinning the retardation phenomenon is similar to the plasticity-induced crack closure, which provides the basis of other retardation models called the yield-zone retardation model, mostly known as the Wheeler model (Wheeler, 1972) and the Willenborg model (Willenborg et al., 1971). A more exhaustive review on the yield-zone retardation phenomenon is given in (Anderson, 2017; Suresh, 1998; Schijve, 2001).

In terms of the application of fracture mechanics in the remaining life estimation of offshore wind structures, there is rather a limited number compared to other marine structures such as ship and offshore oil & gas platforms. Furthermore, the crack growth assessments have been mostly conducted to aid the decision-making process regarding the inspection and maintenance actions.

Ziegler et al. (2016) investigated the impact of weather seasonality on the structural integrity of monopile OWT support structure and concluded that the effect of loading sequence on the crack propagation was negligible; however, it becomes considerably relevant in case of a detected crack under overloads. Moghaddam et al. (2020) carried out a parametric study of plate thickness, and load ratio for both singular and multiple cracks on a spar-type floating offshore wind turbine, which concluded that the cracks under severe corrosion might lead to failure within 20 years of service life. Long et al. (2020) calibrated the fracture mechanics model with the S-N curve to quantify in-service deterioration for the structural integrity management of welded-tubular joints of OWT structures. Amirafshari et al. (2021) presented a fracture mechanics framework for optimising the design and inspection of offshore wind turbine support structures. Jacob and Mehmanparast (2021) stated that a corrosive environment has a more pronounced effect on the fatigue crack growth rate at the beginning of the propagation than in the later stages of propagation of a long crack.

Fajuyigbe and Brennan (2021) presented a fitness-for-purpose assessment of a cracked offshore wind turbine monopile based on the failure assessment diagram, which involves linear elastic, elastic-plastic and plastic failure mechanisms. A cycle-by-cycle approach that sums up the incremental crack growth related to each load cycle is proposed and applied to estimate the overall crack life (Yeter et al., 2015c; Yeter et al., 2015d).

In this regard, Yeter et al. (2022a) explained the cycle-by-cycle approach for the crack growth assessment within a structural integrity assessment framework, which consists of three main parts (see Figure 9).

As seen in Figure 9, the first part is related to the structural health monitoring data analysis, which is followed by a crack growth assessment accounting for the load interaction effect (both acceleration and retardation). The final part involves the remaining crack life estimation through the failure assessment diagram and the O&M cost analysis.

Yeter et al. (2022a) pointed out that the overloads and underloads can significantly alter the crack growth projection; therefore, a structural integrity assessment accounting for load interaction effects is essential to achieve a more reliable crack life prediction, which is translated into a more reliable availability and annual energy production estimate.

A detailed look into the crack growth simulation outcome for retardation over a short period of ongoing retardation is shown in Figure 10 (b). This implies that by considering the load interaction effects, the study was able to achieve a less conservative crack monitoring capability, resulting in optimal maintenance and life extension decisions.

Past experiences regarding corrosion on monopile OWT enforce current management strategies to prevent costly mistakes from repeating for life extension decisions. In this sense, it is imperative to study corrosion and corrosion-related failure mechanisms more in-depth, considering the cost associated with the actions, such as galvanic cathodic protection or epoxy coating, without neglecting the environmental consequence of the remedial actions.

Corrosion-related failure mechanisms can be investigated under two categories. The first one is the structural integrity assessment, and the latter one is the ultimate strength assessment.

In the presence of a tensile stress perpendicular to an existing crack, the crack opens, letting more electrolytes in and causing further crack propagation. This electromechanical process causes substantial structural integrity problems reducing the remaining life of structures. In this context, there are two prominent failure types: corrosion fatigue (CF) under cyclic load and stress-corrosion cracking (SSC) under sustained load (Bayoumi, 1996).

The susceptibility of a metal that suffers from SCC tends to increase with the materials' yield strength. Furthermore, it is suggested that there is a threshold related to the yield strength for SCC to occur. In this regard, Crooker

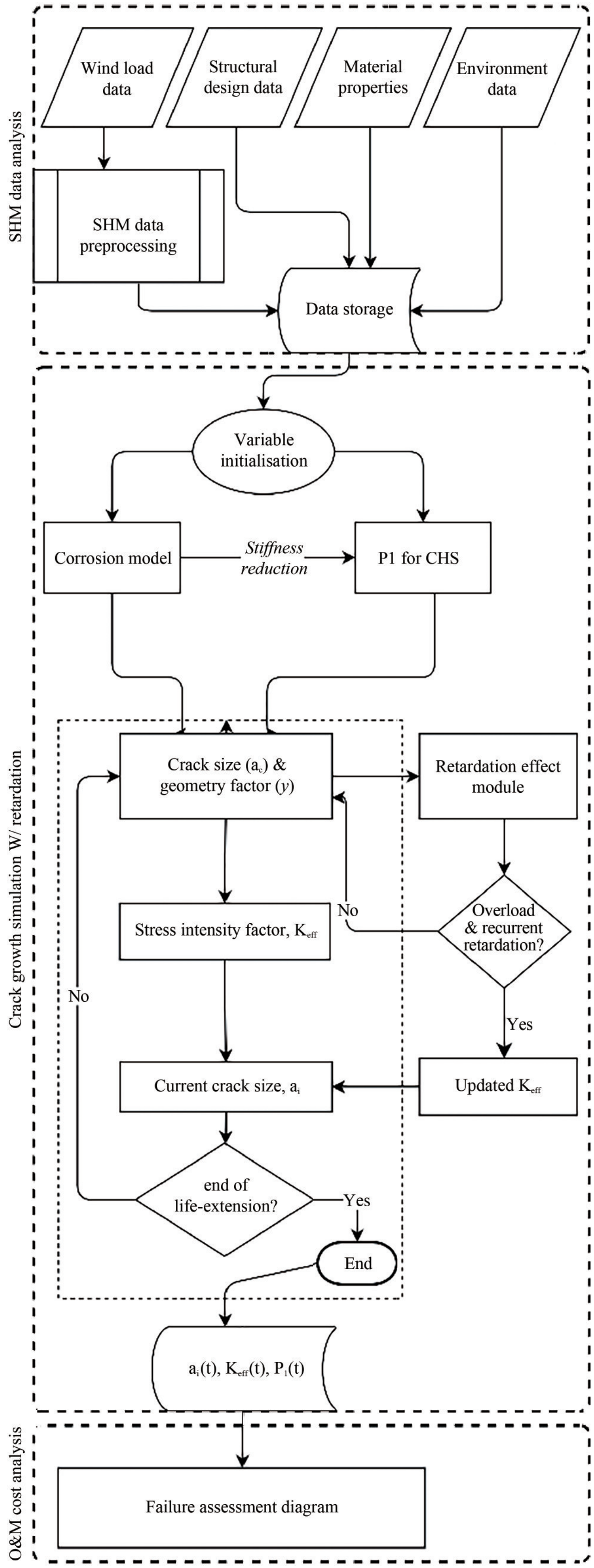


Figure 9 Methodology for structural integrity analysis (Yeter et al., 2022a)

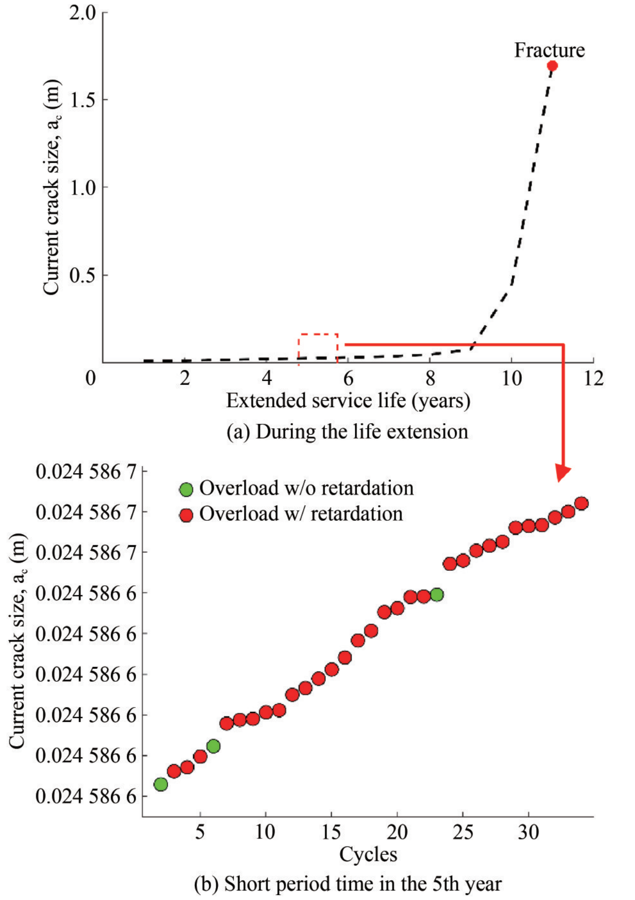


Figure 10 Crack growth analysis accounting for retardation (Yeter et al., 2022a)

(1983) stated that if coupled with SCC, corrosion-induced fatigue posed long-term threats to advanced high-strength ship structures' reliability and life-cycle costs. The given statement is also valid for offshore structures such as offshore wind turbines, as they are made of high-strength steel.

The present work aims to tackle emergent corrosion problems on monopile OWTs by investigating to what extent corrosion may affect the structural capacity and serviceability of ageing OWTs. Within the scope of this section, the corrosion and the effect on the load carrying capacity and structural integrity are reviewed thoroughly.

The corrosion degradation coupled with a cyclic or constant mechanical load is identified as the most significant danger to the structural integrity of the OWTs structures by Momber (2011), as repeatedly reported for the internal part of monopiles that are designed not to have coating protection (Hilbert et al., 2011).

The hydrogen in the seawater caused may give rise to hydrogen penetration into the material. Consequently, the resulting hydrogen embrittlement may cause a significant reduction of bulk elastic modulus following the deformation of larger grains, cracks, and blisters(Wasim and Djukic, 2020, Djukic et al., 2014). Further, the resulting hydrogen embrittlement of the material may accelerate the initiation of surface flaws under cyclic loading (Suresh, 1998). The microstructure, fabrication method, welding procedure, residual stresses, mean stresses, material, environment, load conditions, frequency and stress ratio are among many factors influencing the corrosion-assisted fatigue crack growth (FCG) (Adedipe et al., 2016). All the effects mentioned above may generate a degraded structural state, which jeopardises structural safety, and they are to be included in damage-tolerant assessments for life extension decisions.

Concerning the corrosion and corrosion protection of OWTs, Momber (2011) has given a matrix that links corrosion types to major structural parts of OWTs. The matrix associated the foundation, like the flange and tower surface, with several types of corrosion, such as uniform corrosion, pitting corrosion, aeration cells, galvanic corrosion, and stress corrosion cracking. Masi et al. (2018) also reviewed materials and solutions against corrosion in OWT structures, mainly focusing on the coating system selection. It was stated that the coating cost is not fully correlated with the coating thickness since the labour cost of applying the coating is much higher than the applied paint. For this reason, only by reducing the number of layers in coating a reduction in coating cost can be achieved, which also brings reliability and durability issues since less redundant coating application would mean higher chances of having a through coating defect.

Nøhr-Nielsen (2018) identified areas of concern for both the internal and external sides of the monopiles. For the external side, distance to the anodes and high current demand, durability of the coating and clashing with support vessels are the main concerns in terms of corrosion protection. The internal side, whose corrosion protection was somehow neglected, may suffer from stress corrosion cracking, hydrogen-induced stress cracking, and microbiologically influenced corrosion around the mud zone.

Duguid (2017) claimed that there was a perceived lack of guidance from industry standards based on interviews with experts from the offshore wind industry. It was stated that the current standards were often considered inappropriate because the standards have not been developed for OWT per se; rather, they were derived from the outdated standards of other industries. Moreover, Black et al. (2015) highlighted the need for an update for further documentation and guidelines on corrosion protection of OWT support structures based on the experiences reported within the industry over the last decade.

Corrosion degradation is generally assumed as uniformly distributed, approximated as 0.1 mm/year steel in seawater is approximately 0.1 mm/year, which has been supported by multiple studies (Garbatov et al., 2007). However, it may also exhibit a very large scatter depending upon the location in the structure. In this sense, corrosion can be modelled as a random time-variant surface (Silva et al., 2013) accompanied by changing material properties (Garbatov et al., 2014a; Garbatov et al., 2014b) during the service so that the corrosion effect is explicitly accounted for in the structural integrity assessment.

Although corrosion cannot be singled out as a prevailing failure mechanism, its effect on the ultimate strength and fatigue cracking cannot be overlooked. The initial studies on fatigue in corrosive environments date back to 1930 (Gilbert, 1956). These studies were oriented to study the fatigue behaviour of both intact structures and structures with a fracture initiated by pitting or slip bands under cyclic loading. Most of the fatigue life is spent in crack nucleation; however, under a corrosive environment, the crack propagation phase dominates fatigue life by large.

The degradation affects the performance of the material by increasing the crack growth rate. In this regard, even pits of the order of a grain size may considerably degrade a material. Wallace et al. (1985) named the cause of corrosion pits as localised chemical or mechanical damage to the protective oxide film due to acidity, low dissolved oxygen concentrations, and high chloride concentrations (as in seawater). Besides, Grolvlen et al. (1989) investigated the effect of corrosion pits on the fatigue strength of welded-tubular and multi-planar joints of offshore platforms to give an insight into the inspection and repair measures. Similarly, Ricles et al. (1995) assessed the residual strength of offshore platforms' dented and corrosion-damaged tubular brace members.

Hoeppner (1979) introduced a conceptual model by combining the pit growth rate theory with the Linear Elastic Fracture Mechanics (LEFM), aiming to estimate the time to crack initiation for a Mode I crack from a pit under cyclic loading. The presented conceptual model was formulated using an empirical pitting rate curve and a Weibull fit of the appropriate crack growth data. Jakubowski (2015) studied the influence of stresses on the general corrosion rate and corrosion pit nucleation and growth rate using two distinct approaches: either a pit as a stress riser or an equivalent crack. It was also discussed in detail the relation between the statistical distribution of pit depth and corrosion fatigue.

Kawai and Kasai (1985) showed that a corrosion pit could be treated as an elliptical crack with a similar depth and surface length, which allows developing a method to determine a reasonable, allowable stress level in corrosion fatigue. Smith et al. (2003) conducted an experimental test on the fatigue life of laboratory-produced corrosion pits to an electro-discharged machined (EDM) semi-circular disc-shaped flaw, and the test revealed that the EDM notch and corrosion pits of similar size had similar fatigue lives under high local stress.

Kondo (1989) showed that the corrosion-fatigue life of material could be determined by estimating the critical pit level using the SIF relation and the pit growth rate relation. Lindley et al. (1982), too, adopted the concepts of LEFM in an attempt to describe the development and growth of cracks originating from shallow corrosion pits. Rokhlin et al. (1999) analysed the crack initiation and growth from artificial pits with different depths using a 3-D fracture mechanical model to derive a relation between the pit depth and the crack life. Mao et al. (2014) assumed semi-ellipsoids for the morphology of the corrosion pit, which was characterised by the aspect ratio. In terms of the time to initiate a crack, the proposed model and experimental data available in the literature showed a good agreement.

The studies mentioned above indicated that the total corrosion fatigue life could be reasonably estimated based on the assumptions such as modelling corrosion pits in a hemispherical geometry and defining critical pit depth employing the stress intensity relation. Simplifying these assumptions is also possible by assuming the volumetric pit as a sharp crack and isolating the mechanical and environmental contributions separately. However, the simplified models have shown low generality and high dependence on the varying system conditions. This assertion was confirmed by Larrosa et al. (2018) in a review article. The efforts made to address corrosion-fatigue life for various materials by both academia and different industries.

In the numerical studies on the modelling and analysis of stress-corrosion cracking, Moghaddam et al. (2019) assessed the crack growth originating from corrosion pits using the XFEM technique. Non-uniform random distribution is used for pit dimensions in 3D, and elliptical cracks are embedded at critical points of weldment for a spar-type floating OWT. Shi et al. (2019) conducted a numerical study of SCC in corrosion pits based on the recently developed peridynamic method to simulate cracks in pitted pipes. The study aimed to find critical loads to initiate a macroscopic crack. In addition, Shittu et al. (2020) carried out a corrosion-induced crack growth analysis using the finite element method accounting for the stochastic nature of the critical pit depth, applied stress range, material's fatigue properties, the shape of the corrosion pit, thrust force and final crack depth.

A comprehensive analysis recommended that the preventive measures are of utmost importance for safety and economic reasons. Wu et al. (2019) suggested that in-situ acoustic emission (AE) monitoring could detect localised corrosion and corrosion-related cracking; thus, AE can be used to monitor against SSC-related failures. For the corrosion case, a low-frequency cluster was related to corrosion-induced cracking, whereas a high-frequency cluster was related to hydrogen-bubble evolution. Kirchgeorg et al. (2018) investigated the long-term environmental effects of OWTs and found no clear evidence of a negative impact of corrosion protection systems on the marine environment due to the chemical emissions; however, they also pointed out that it may become more relevant for the marine environment with increasing numbers of OWTs.

The ultimate strength is affected by corrosion because the degradation in the material leads to the loss of structural load-carrying capacity. Further, localised damage, such as pitting, can also cause the structure to reach the buckling phase earlier than the intact condition.

From the ultimate strength standpoint, Feng et al. (2020) conducted an experimental and numerical analysis to study the effect of pitting corrosion on the strength of steel plates. A positive linear relationship was observed between the degree of pitting and ultimate strength reduction. The study also suggested that the degree of pitting above one-fourth of the thickness of the intact plate could be deemed as a threshold for the considerable ultimate strength reduction.

Yeter et al. (2020a) conducted a multi-dimensional failure assessment for three jackets offshore wind turbine structures (see Figure 11), which coupled the loss of gradual structural integrity and the ultima load-carrying capacity within a single numerical FEA.

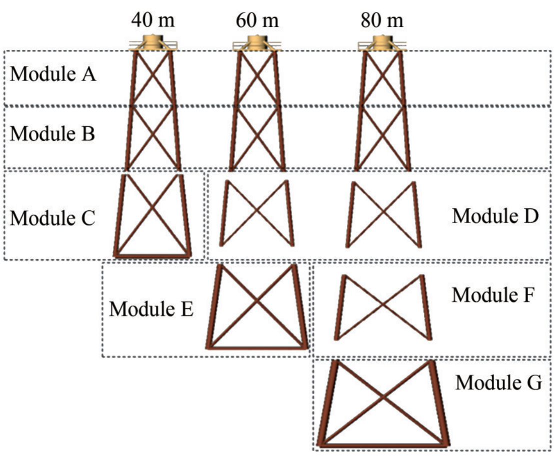


Figure 11 Modular design concept for the jacket support structure (Yeter et al., 2020a; Yeter et al., 2019b)

The results in Figure 12 ruled out some possible assumptions such as: the longer the leg length is, the lower the ultimate strength becomes because of the additional redundancy and stiffness; also, the deeper are the waters the jacket OWT structure is designed for, the higher its ultimate strength and stiffness become. Furthermore, the loss of structural integrity due to the low-cycle fatigue load was simulated in 10 steps, and a significant decrease (min 60%) was determined in the global ultimate strength of "redundant" jacket OWT structures.

Yeter et al. (2020a) extended the scope of the previous analysis to study the effect of the loss of the leg components on the ultimate strength. When the structure lost all the leg components up to Module F, the calculated ultimate strength is almost six times lower than an intact jacket support structure (see Figure 13).

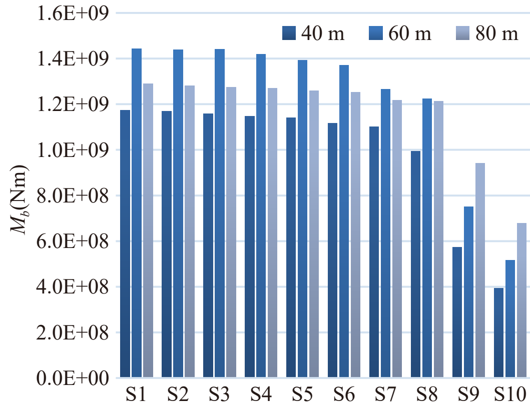


Figure 12 Ultimate strength of Jacket OWTs subjected to a progressive rupture (Yeter et al., 2020a)

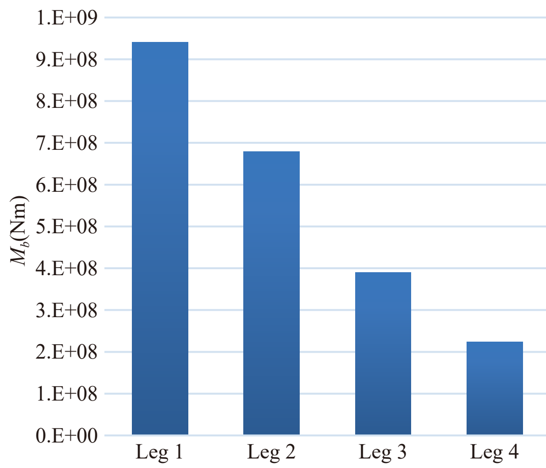


Figure 13 Ultimate strength of a jacket OWT after the leg components are fully ruptured (Yeter et al., 2020a)

In light of the mentioned studies, it can be claimed that there are three requisites for stress corrosion cracking to occur: a susceptible material, a corrosive environment, and a (high) stress or stress intensity factor. Depending on the combinations of these requisites, other corrosion-related mechanisms also occur, such as material degradation under only corrosion under no stress-strain or the corrosion-fatigue mechanism. The corrosion-related cracking mechanisms can lead to catastrophic failures if the life-cycle management of offshore wind turbine structures does not involve both prevention and control to be able to deliver an acceptable useful lifetime. The decision-makers, such as designers, operators, project owners, and project surveyors, need to acknowledge these failure mechanisms and then need to have the expertise to deal with them if or when they happen. Hence, the life extension assessment must involve prediction models for the significant failure mechanisms given the resources to design the most effective strategy that maximises the performance with minimum cost.

In essence, the approach to stress corrosion cracking would cover crack nucleation in a probabilistic manner, followed by fracture mechanics formulations with adequate adjustments, including threshold stress intensity factor. The approach would yield an estimated cracking life and structural safety measure such as a reliability index. The risk-based inspection and maintenance present the most advanced way to manage the life-cycle of the OWT structures subjected to corrosion, fatigue and corrosion-related damage mechanisms.

4 Condition-based maintenance planning for support structures

Given that the unattended degradation on a structure can cause loss of structural integrity or ultimate load-carrying capacity over time, leading to costly catastrophic failure, the risk associated with the structural degradation needs to be managed through remedial actions such as maintenance or repair. Thereby, a maintenance system that manages the risks by means of preventive actions at minimal cost is essential for already operative OWTs, the life extension of these OWTs, and also the future wind farms.

The monitoring systems such as SCADA, condition monitoring (CM), and structural health monitoring (SHM) systems provide important information for the structural health system on the history of the structural condition and the operational condition. The acquired information can be used to identify damages and extract significant damage features. Moreover, mathematical relationships can be established between the operating conditions such as wind speed, wave height, temperature, salinity, and the prediction models to be used in the maintenance planning can be created provided that these relationships are given as a function of time. For instance, a comprehensive monitoring system can correlate the frequency of measurements with the overall structural performance of the monopile foundations by strategically located bidirectional accelerometers, as reported in (Yang and Jiang, 2011). Liu et al. (2018a) also dealt with the optimal location of sensors for the damage identification model developed for a more complex structure like jacket structures(Liu et al., 2018b, Liu et al., 2018c).

The operational modal analysis and system identification techniques can also identify the events affecting the structural performance, such as resonance, foundation instability, and yielding of the structural material, based on the acceleration responses (Gomez et al., 2013).

The introduction of artificial intelligence (AI) in the shipbuilding and offshore industry has opened many opportunities to improve the efficiency of engineering projects at every phase. From design to manufacturing, from operation to life extension, artificial intelligence-based models can deliver a tremendous amount of tasks that humans cannot perform. The success of AI in engineering projects goes along with the ever-increasing computational power, which allows benefiting from the use of big data. All aforementioned statements are also valid for the offshore wind industry as well.

With state of the art machine learning techniques, historical and new data can be used to learn existing patterns and trends without human interaction. These machine learning models can be trained to make accurate predictions that result in higher success in the decision-making process related to maintenance planning and life extension.

The structural integrity assessment is one of the critical elements of an intelligent maintenance system. A system that defines the action to be taken to prevent structural failure requires profound and interdisciplinary modelling. The multilayer artificial neural network (ANN) can read the big data coming from multiple monitoring systems to learn the complex degradation mechanisms affecting structural safety and can provide prediction and classification models. This helps decision-making related to maintenance planning and life extension. In the case of not having any specific outcome as a failure, the associated data can be used to classify abnormalities to be able to make an educated guess on the subject by unsupervised learning.

In this regard, Nasiri et al. (2017) gave an extensive review of the application of artificial intelligence methods on mechanical fault detection. The studies existing in the literature were discussed under four topics: (a) failure mode and failure mechanism identification, (b) damage and failure detection and diagnosis, (c) fault and error detection, diagnosis and (d) mechanical fracture and fracture parameters. Also, recently, Stetco et al. (2019) reviewed the machine learning methods used for the condition monitoring of OWTs. The study stated that AI-aided condition monitoring mostly utilises SCADA and simulated data, and there were few cases where the experimental data or image and audio data were used. The classification approach for learning from categorical data has been used more than the regression condition monitoring of wind turbine components.

Stetco et al. (2019) also highlighted the fact that the deep ANN has recently gained overall recognition for being capable of learning complex non-linear functions, achieving superior performance compared to the other models, especially when dealing with big data.

The use of machine learning methods is not limited to condition monitoring. Hameed and Wang (2012) addressed the maintenance of offshore wind turbines using ANN, aiming with a special focus on access, weather, and logistic issues. The study followed an approach that consisted of cluster analysis and the categorisation of similar wind turbines using Self Organizing Map ANN. The prediction of the expected power output of OWTs within the same cluster was strongly correlated with the failure rate.

Lu et al. (2018) adopted ANN to be able to predict failure-time distribution using the condition monitoring data, which was later used for an optimisation problem aiming to achieve the lowest expected maintenance cost. The opportunistic maintenance strategy was explored with the use of a threshold associated with two-level failure probability, aiming to minimise the maintenance expenditure.

Jiménez et al. (2018) addressed the delamination problem in blades and their maintenance. Prior to developing the prediction models using different classifiers, the time-signals were pre-processed by filtering using Wavelet (Daubechies) Transform and denoising by normalisation. The study also ranked the used classifiers, such as quadratic discriminant analysis, k-nearest neighbours, decision trees, and multilayer perceptron ANN in the recall, specificity, precision, and F-score.

Fu et al. (2019) showed that the deep neural network method is a promising solution regarding the big data problems emerging with the increase in the number of wind farms. The time signal data provided by the SCADA are used to build convolutional neural networks with multiple filters that can extract data features and the hidden topological feature.

Yeh et al. (2019) predicted the long-cycle maintenance time of OWT using the real-time data obtained from the sensor placed in two different wind farms. A hybrid neural network was built based on the deep neural networks and support vector machine (SVM) method to deal with this task. Santos et al. (2015b) reported a comparison between deep neural networks and the SVM technique. The results indicated that the SVM method needed much less training and tuning time, whereas the prediction accuracy of the two methods was similar. Kang et al. (2020) also used SVM in condition-based maintenance of offshore wind turbines, which expanded the scope of their earlier studies on opportunistic maintenance policies (Kang and Guedes Soares, 2020; Kang et al., 2019).

Bach-Andersen et al. (2018) stated that the performance of the deep learning techniques was superior to more shallow architectures for automated drive train fault detection. The developed prediction models could detect a fault signal even months before the human non-causal expert. The study mentioned that the probabilistic output provided by the model could be of great use for decision support systems. Ray et al. (1996) attributed the increasing number of applications of ANN techniques to several problems in naval architecture and marine engineering to the fact that ANN techniques can handle problems with highly nonlinear and complex data, even if the data is imprecise and noisy.

Ok et al. (2007) applied ANN to derive empirical formulae to study the effects of localised pitting corrosion on the ultimate strength of unstiffened plates using the data obtained from nonlinear FE analyses. It was reported that the prediction model related to the single-edge pitting corrosion was slightly more accurate than the one related to double-edge pitting corrosion.

Nasiri et al. (2017) claimed that the success of AI applications in solving problems related to fracture failure mechanisms could only increase when a hybrid intelligent system is provided. Also, Cheng (2002) processed the data related to the corrosion fatigue crack growth monitoring using the ANN method and concluded that the corrosion-fatigue life prediction model provides a practical solution that only requires the relation between the length of the crack and the number of cycles of the given load and the data on the material and environment parameters were not needed.

Gope et al. (2015) successfully predicted crack growth direction after training ANN using experimental test results. The experiment was performed for less than 100 samples considering different crack sizes and configurations. The ANN model consisted of nonlinear logistic (sigmoid and tangent hyperbolic) activation functions and two hidden layers. The prediction capability of ANN has encouraged many other studies that deal with complex problems in the research fields of fatigue and fracture, such as fracture mechanics and crack growth (Dinda and Kujawski, 2004; Pidaparti and Palakal, 1995; Sadananda et al., 1999; Zhang et al., 2016), S-N curve development (Artymiak et al., 1999; Bučar et al., 2006) and strain-life fatigue properties (Genel, 2004).

A decision support tool such as an intelligent maintenance system must cover all aspects influencing structural safety and provide an optimal manner to maintain the structure above the required safety levels with minimum cost. Many studies attempted to incorporate maintenance with monitoring systems in various industries and achieved considerable improvement in maintenance efficiency (Hameed et al., 2010; Márquez et al., 2012; Tian et al., 2011; Ossai et al., 2016; Bangalore and Patriksson, 2018). A rare study focusing on the economic side of implementing the monitoring systems was reported by Martinez-Luengo et al. (2016). The study showed that an increase in the percentage of instrumented assets would reduce operational expenditure, and this reduction was considerably higher than the cost of SHM implementation.

Although these studies are promising within the scope of their research, these studies were limited to improving modelling and optimisation techniques for certain components. As Lian et al. (2019) suggested, there are serious doubts about the application in practice for large-scale offshore wind farms, including other components beyond the wind turbine as such (Liu et al., 2010; Kusiak et al., 2013).

Moreover, the size of the OWT farm and its distance to the shore are other factors that most probably change the way the industry approaches operation and maintenance (Yeter et al., 2018). Extending the service life and retrofitting are the topics that need to be incorporated into the research to provide more insightful decision-makers. However, as new issues are emerging, the difficulties concerning big data acquisition, transmission, and analysis have yet to be fully resolved. The comprehensive condition frameworks that involve the integration of online health monitoring and reliability evaluation are far from being devised. Nevertheless, establishing a maintenance framework based on big data analysis is of great significance for innovating the techniques used for monitoring, inspection and maintenance methods.

5 Risk-based life-cycle assessment of offshore wind assets

In the previous sections, a detailed review of the AI-aided structural assessment of offshore wind turbine support structures for life extension. Firstly, a discussion is given on how to process and analyse the structural health monitoring data through advanced statistical, signal processing and machine learning techniques. Later on, the structural integrity assessment for ageing offshore wind turbine support structures is discussed from the standpoint of prevailing failure mechanisms such as high- and low-cycle fatigue, corrosion-induced cracking, crack growth and ultimate strength. Subsequently, considering the failure mechanism mentioned above, the development of condition-based maintenance planning using artificial intelligence and machine learning techniques is discussed.

The discussions regarding how to assess the structural condition of offshore wind turbine support structures and maintain it above an acceptable level through remedial actions were made using deterministic approaches. However, following a probabilistic approach would be more appropriate for accurate and precise estimates of structural safety.

An advanced life extension analysis requires a probabilistic approach where the uncertainties involved in modelling, loads, structural response and material properties are taken into account in structural reassessment. The structural reliability analysis is a fundamental element of the intelligent maintenance system. It is, in this way, possible to create an early warning system accounting for both physical and modelling uncertainties associated with the multiple failure mechanisms.

Both fatigue damage assessment and ultimate strength assessment involve several steps consisting of several parameters with uncertainty. These parameters need to be modelled as stochastic variables. The uncertainties can be characterised as the physical uncertainty donating the natural variability, the statistical uncertainty due to the limited sample sizes of observed quantities, the measurement uncertainty related to imperfect measurements, and the model uncertainties regarding imperfect knowledge (Sørensen and Toft, 2010).

To deal with the uncertainties associated with the structural failure mechanism and structural assessment, the structural reliability method has been proven to be useful. The structural reliability is often analysed based on the assumption that the probability of failure during a period is equal to the probability of occurrence of any crossing of the processes out of the safe domain during that period. This approach can be further elaborated to find a system structural reliability estimate considering the failure mechanisms have a certain correlation, and the probabilistic nature of these failure mechanisms is time-variant.

The structural system reliability can be done by using the Monte Carlo simulations, first-order reliability method (FORM) and second-order reliability method (SORM), these methods have a long history to assess marine structures probabilistically (Yeter and Garbatov, 2022).

The first-order second-moment method, too, has an extensive application in structural reliability. It is considered suitable to use in cases that far more sophisticated models cannot be solved with the given stochastic models (Guedes Soares and Garbatov, 1996).

In terms of the structural integrity of the ship and offshore structures, the studies regarding the fatigue reliability based on the S-N approach mainly focus on the design optimisation, and the studies regarding the structural reliability based on the fracture mechanics focus on the inspection and maintenance planning. In this regard, Moan (2008) stated that reliability methods could be used at the design stage to assess the optimal choice of scantlings and materials as well as the inspection plan. Besides, these methods can continuously be employed to evaluate safety during the operation to provide information in updating the inspection plan and other safety measures to maintain the safety level.

A maintenance strategy that allows the use of information continuously acquired from the SCADA, condition monitoring and inspections can evaluate the confidence in the OWT asset to perform its intended service by means of a reliability index. This approach can be elaborated even further by considering that failure mechanisms have a certain correlation, and the probabilistic nature of these failure mechanisms is not time-invariant. Yeter et al. (2020b) suggested a risk-based approach where the reliability index estimation can be extended to multiple dimensions considering possible measures for a given reliability index. Consequently, risk-based life-cycle management is achieved via intelligent maintenance strategies that use their capacities to keep the OWT asset functional so long as it is profitable. This implies that the global and local economic conditions under offshore wind projects must also be considered.

Duguid (2017) listed these challenges: lack of a standardised approach and requirement for scheduled inspection; reactive inspection and maintenance approach rather than proactive; lack of a risk-based approach that supports proactive and flexible measures and learns from the experience. Life extension management can also be optimised by correcting some of the practices and misconceptions inherited from the traditions of other industries. In this context, the consequences of structural failure for OWT structures is lower than the consequences of failure for oil & gas platforms; therefore, the safety constraints defined of OWT structures, such as reliability target for unmanned platforms, need to be revisited. The revaluation of the target reliabilities presents more opportunities for further cost reductions (Yeter et al., 2019a).

There is a vast literature on the application of structural reliability methods for marine structures, especially in ship structures. Only very recently, there have been a few publications on the fatigue reliability of OWT support structures. They are mostly centred on creating the basis of a framework for optimum inspection planning.

Sørensen and Tarp-Johansen (2004), Sørensen and Tarp-Johansen (2005) studied the reliability of the tower turbine structure accounting for wind and wave loading, economic aspects and optimal inspection intervals. The benefits of reliability and risk-based inspection and maintenance planning were reported by Straub et al. (2006). The reliability-based approach has also been employed to calibrate the fatigue design factor for support structures in (Márquez-Domínguez and Sørensen, 2012; Sørensen, 2012). As far as the support structure is concerned, Dong et al. (2012a) performed the fatigue reliability assessment of a jacket OWT in the time-domain accounting for the effect of corrosion, inspection and repair. Furthermore, fatigue reliability assessments were performed for different support structures such as monopile, jacket and tripod (Sørensen, 2012; Dong et al., 2012a; Karmakar et al., 2016).

Brennan (2013) discussed the methodologies to optimise life-cycle costs by adopting probabilistic approaches for OWT support structures' risk-based design, inspection, and maintenance. Dong and Frangopol (2015) addressed a multi-objective optimisation problem accounting for structural deterioration scenarios and various uncertainties. The objective function was formulated to find the optimum inspection and repair planning of ship structures through a genetic algorithm by considering the flexural failure and the expected total inspection and maintenance cost as independent objectives.

Sørensen (2006) formulated a reliability-based design optimisation of wind turbine parks where the design parameter is the distance between wind turbines. Sørensen and Toft (2010) presented an integrated reliability-based design method for wind turbine blades within a numerical example that considers both ultimate and fatigue limit states. Partial safety factors for use in the traditional deterministic design are estimated using stochastic models. Moreover, Thoft-Christensen and Murotsu (1986) and Madsen and Sørensen (1990) integrated an inspection and repair strategy for the reliability-based optimal design problem.

Song et al. (2018) presented an integrated optimisation of offshore wind farm layout design and turbine opportunistic condition-based maintenance. In the first stage, GA optimisation is used to search candidate locations for the optimal number of turbines and their corresponding placement. Then, a pattern search algorithm is applied to further improve turbine placement by searching continuous location variables to maximise profit. Nguyen and Chou (2018) also proposed an optimal maintenance schedule for both one turbine and multiple turbines with the objective of minimising the maintenance cost. The proposed approach took into account the parameters that are usually overlooked, such as system reliability, weather condition, maintenance duration, power generation loss during maintenance, and offshore wind system location.

Within the scope of the life-cycle assessment, Madsen and Sørensen (1990) and Madsen et al. (1991) formulated the mathematical modelling of design, inspection and maintenance optimisation. The total expected cost for the life-cycle of the marine structure was aimed to be minimised. Event trees involving the possible events from design until the end of the service life were modelled concerning different repair strategies. Sørensen et al. (1991) and Faber et al. (1992) presented a framework for optimal inspection and repair planning. They addressed the optimisation problem to minimise the total expected cost in the structure's life-cycle. The number of inspections, inspection times and efforts, repair, and crack size limit were described as optimisation variables.

Moan (1998) addressed the target levels for structural reliability and the risk analysis of offshore structures. Moan (2005) also studied the reliability-based management of inspection, maintenance and repair of offshore structures. Shafiee et al. (2015) presented the optimisation model for a condition-based maintenance policy for a wind turbine subjected to stress corrosion cracking. The maintenance policy involved both opportunist and preventive maintenance in such a way that the condition-based assessment alerts the system for opportunist maintenance for a blade; meanwhile, preventive maintenance was to be performed for the other blades, aiming to minimise the average long-run maintenance cost per blade.

Onoufriou (1999) emphasised the importance of using a more refined system reliability approach, which can be implemented to study and compare various inspection planning strategies, including a range of inspection methods and acceptance criteria. Shabakhty et al. (2003) estimated the system reliability of the jack-up structure by considering the sequence of fatigue failures. The results pointed out the significant effect of systems, which the probability of structural failure is larger than the probability of failure for an individual section.

Moan and Song (2000) analysed the influence of the inspection of certain joints on the reliability of a series system. They found that the system reliability is significantly affected by the implemented inspection policies. Ayala-Uraga and Moan (2002) formulated the occurrence of two fatigue failures in sequence for highly correlated components in a simple parallel system to visualise the potential implementation of system reliability and updating procedures in offshore structures subjected to fatigue and overload. While Madsen et al. (1987) also discussed that updating after inspection and repair could be carried out simply by using the FORM applied to parallel systems.

The system reliability of offshore wind turbines has not been addressed broadly. However, some works have been published on the fatigue reliability of offshore wind turbine support structures, such as (Márquez-Domínguez and Sørensen, 2012; Dong et al., 2012b; Yeter et al., 2015e; Yeter et al., 2015f).

Besides, machine learning methods, especially supervised learning using ANN, have been employed to build predictive models for other research fields. One prominent example of it is structural reliability analysis. Deng (2006) and Deng et al. (2005) trained the multilayer and radial basis function ANN by using a small batch of data obtained by FEA to approximate the implicit limit state function values for the Monte-Carlo Simulation and the first and second-order derivatives of limit state function. The proposed approach achieved a very similar reliability index with less computational effort. Gomes and Awruch (2004) also claimed that multilayer ANN and response surface method with quadratic polynomials were alternatives to the Monte Carlo simulation and first-order structural reliability method. The study also suggested using multilayer neural networks for the nonlinear large structural system. Papadrakakis et al. (1996) applied a backpropagation neural network algorithm to deal with the structural reliability of a system subjected to plastic collapse. The approach successfully produced approximate estimates of the critical load factors and, thus the very close prediction of the probability of failure independent of the complexity of the problem. Papadrakakis and Lagaros (2002) implemented an ANN algorithm into an evolutionary optimisation algorithm to reduce the computational cost in reliability-based optimisation problems of structures with elastoplastic behaviour. The computational cost was reduced by one order of magnitude in sequential and by two orders of magnitude in parallel mode with the neural network technique. Additional references can be found in Chojaczyk et al. (2015), who presented a review of the applications of ANN models in reliability analysis of steel structures.

Yeter and Garbatov (2021) developed a risk-based approach to find optimal solutions for life extension management for OWTs based on Markowitz's modern portfolio theory, adapted from finance. The study utilised the *k*-means unsupervised machine learning algorithm to classify offshore wind assets with different expected returns and risks.

The *k*-means unsupervised machine learning algorithm aims to reduce the variance within a cluster and maximise the distance cluster through an iterative process. Since the *k*-means algorithm cannot determine the number of clusters by default, qualitative and quantitative tests can be employed to measure the performance of the *k*-means algorithm in terms of the number of clusters. Figures 14 and 15 show qualitative (visual) and quantitative (metric-based) tests for the *k*-means clustering algorithm.

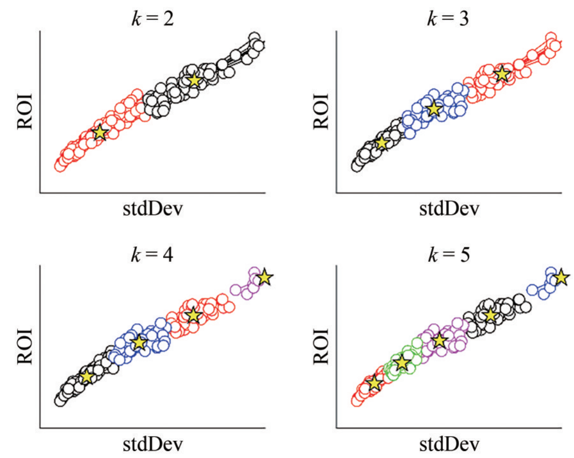


Figure 14 Qualitative test for *k*-means clustering (Yeter and Garbatov, 2021)

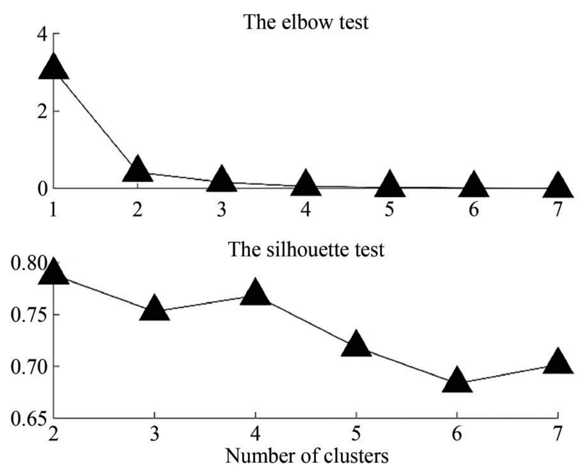


Figure 15 Quantitative test for k-means clustering (Yeter and Garbatov, 2021)

As far as the quantitative test is concerned, the silhouette test measures how similar a data point is, and higher values indicate the appropriateness of the clustering. The other way of assessing the success of clustering is the elbow test which measures the intra-cluster Euclidian distance relative to the inner-cluster Euclidian distance. Unlike the silhouette test, the elbow test seeks the minimum test score; hence, it can be argued that k = 2 or k = 3 is a reasonable choice for the number of clusters.

From a life extension assessment point of view, the probabilistic techno-economic assessment can provide such risk-return diagrams that allow for the classification of offshore wind turbine life extension decisions.

The finding of the studies reported by Yeter and Garbatov (2021) and Yeter et al. (2022b) suggested that it was possible to develop a dynamic life extension management strategy.

A reasonable scenario would be starting in the region with high-risk and high-return. The offshore wind assets can move into low-risk and low-return regions by manipulating the operational intensity and hedging options at the later stages of the life extension (see Figure 16).

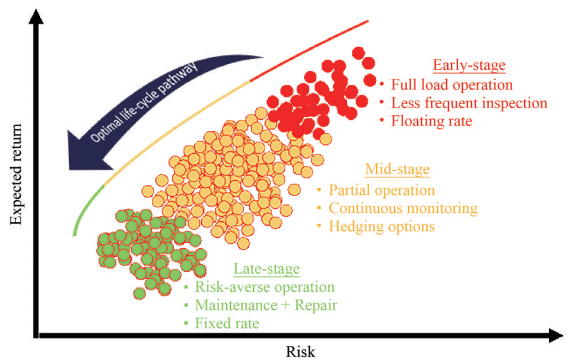


Figure 16 Framework for a dynamic life extension management

Yeter and Garbatov (2021) also stated that the size of the OWT farm and its distance to the shore are other factors that most probably change the way the industry approach operation and maintenance. The extension of the service life and retrofitting are the topics needing more attention in future works to provide more insightful tools for decision-makers.

The overall life-cycle cost per unit of energy production is influenced strongly by the risk associated with the OWT support structure since any permanent damage occurring in the support structure may cause the serviceability of the OWT. Nonetheless, only a few studies include the risk in life-cycle cost modelling (Koukal and Breitner, 2013). In contrast, some studies can be found in literature focusing on the life-cycle-oriented optimisation of design, inspection, and maintenance of marine structures, as reported in (Rouhan and Schoefs, 2003; Okasha and Frangopol, 2009; Barone and Frangopol, 2014; Lee et al., 2016; Soliman et al., 2016). Frangopol (2011) highlighted the importance of a risk-based approach for assessing the life-cycle performance of structural systems.

Thöns et al. (2013) also developed a framework for quantifying the expected life-cycle costs for wind turbine structures to facilitate and support optimal decisions. The framework was built upon the approaches of structural reliability theory and Bayesian decision theory. Levitt et al. (2011) performed an analysis of the breakeven price of electricity for offshore projects in various countries with a cash-flow model considering the variances in the investment or operating costs through a sensitivity analysis. Levitt et al. (2011) also argued that the levelised cost of energy could be a useful way to evaluate the support structure and find an optimal structure accounting for all the costs associated with the life-cycle. The past, present and future of the levelised cost of offshore wind were reported in several studies (Kost et al., 2013; Lantz et al., 2012; Greenacre et al., 2010), and the possible cost reduction pathways were discussed by Davey and Nimmo (2012).

Blanco (2009) assessed the roles and tendencies of its cost components in the life-cycle of offshore wind turbines. The study argued the usefulness of learning curves as a tool to predict the long-term cost reduction potential of this industry and the role that public policies can play in the economics of wind energy. The life-cycle assessment for marine structures has been the focus of many studies.

These studies have emphasised the risk management planning that is appropriately integrated into a comprehensive life-cycle framework (Rouhan and Schoefs, 2003; Okasha and Frangopol, 2009; Soliman et al., 2016; Frangopol, 2011; Thöns et al., 2013; Yeter et al., 2017b). Furthermore, a decision support system for assessing offshore wind energy potential in the North Sea was presented by Schillings et al. (2012). The study aimed to aid the conflict between cost assumptions for offshore wind farms and their expected electricity yield, which leads to the identification of desirable areas for offshore wind energy deployment in the North Sea. Studies for the optimal location of wind farms have also been conducted using multi-criteria decision making together with GIS and spatial planning principles by Díaz and Guedes Soares (2020b) and Ramos et al. (2021).

The life extension process involves several steps. The structural reassessment considering the health monitoring system, decides the estimated extended life of each asset in an offshore wind farm. The framework also consists of an adequate inspection and maintenance strategy that will maximise the revenue obtained from the offshore wind farm, provided that the annual probability of failure of structural components is still acceptable.

Votsis et al. (2018) stated that the parties involved in the management of marine structures realise the benefits of monitoring, and there is an ongoing research effort in the academic and industrial community to enhance further the current methods, equipment and monitoring systems to improve the effectiveness of a management system. Also, the review of the pertinent literature on the topic of integrity monitoring of offshore structures showed that it is a fast-growing sector with developments in sensing technologies, data acquisition and processing customised for the harsh marine environment.

Ziegler et al. (2018) provided one of the few studies regarding the life extension for wind energy assets. The study presented a detailed review varying for different countries. It was stated that the countries with favourable legal and economic conditions for repowering and market prices of electricity uneconomic for small wind turbines were likely to experience less interest in life extension in the following years. The uncertainties regarding lifetime extension assessments and market prices were identified as the primary challenges.

Ziegler et al. (2018) extended the scope of the earlier study and developed a framework for the life extension assessment for monopile OWT. The developed framework involved a data acquisition system for fatigue load and the supervised machine learning technique K-nearest neighbour to predict equivalent damage loads. Although the study is far from complete, the AI-aided monitoring and maintenance system showed promising results.

Rubert et al. (2018) presented a methodology to support an economic life extension. The proposed method reduces LCOE considerably by manipulating the life extension parameters such as extension duration, input economic assumptions such as pessimistic, central, optimistic, and investment types such as retrofits.

Yeter et al. (2022b) investigated the appropriate key metrics to be used for measuring the operational performance of offshore wind farms at different life extension stages. The key performance metrics are the gross profit margin (GPM), the return on tangible asset (ROA), the levelised cost of energy (LCOE), and compounded annual growth rate (CAGR). The study involved a probabilistic techno-economic assessment that resulted in statistical descriptors of the studied key performance metrics (see Figure 17).

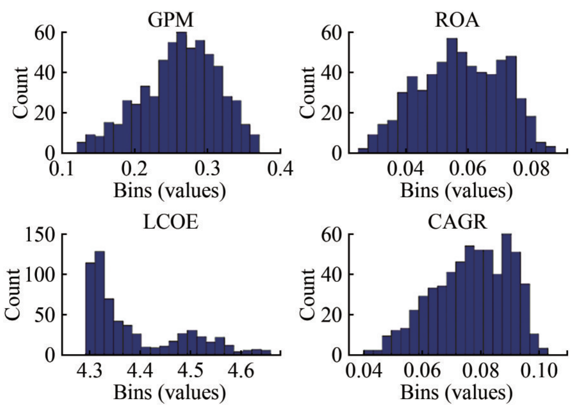


Figure 17 Histograms of performance metrics (Yeter et al., 2022b)

The probabilistic techno-economic assessment accounted for the uncertainty propagation throughout the life extension, divided into five phases. In this regard, the study assumed higher variability and lower correlation among the offshore wind assets towards the later phases of the life extension.

To be able to interpret and compare the metrics, the results are normalized by the maximum value encountered through different phases. How the performance metric change over the life extension is shown in terms of the normalised mean value and the normalised coefficient of variation (COV) in Figure 18.

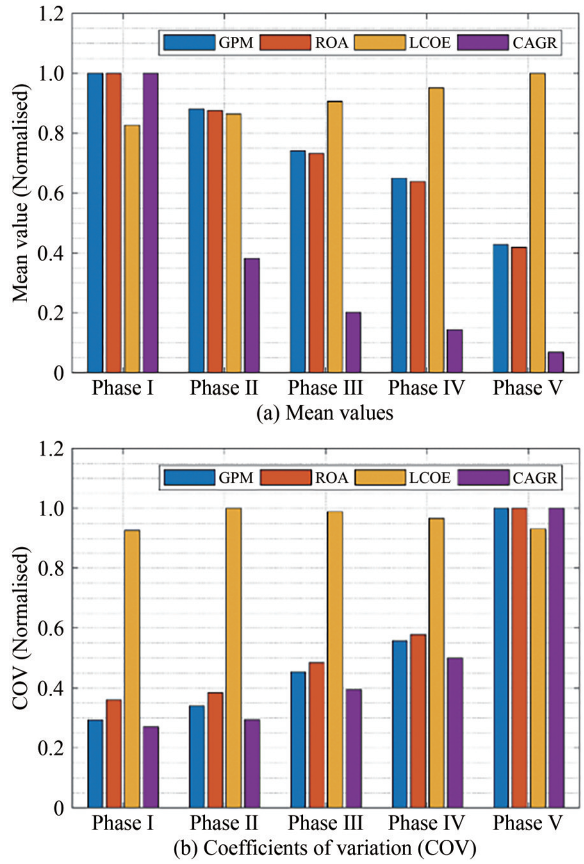
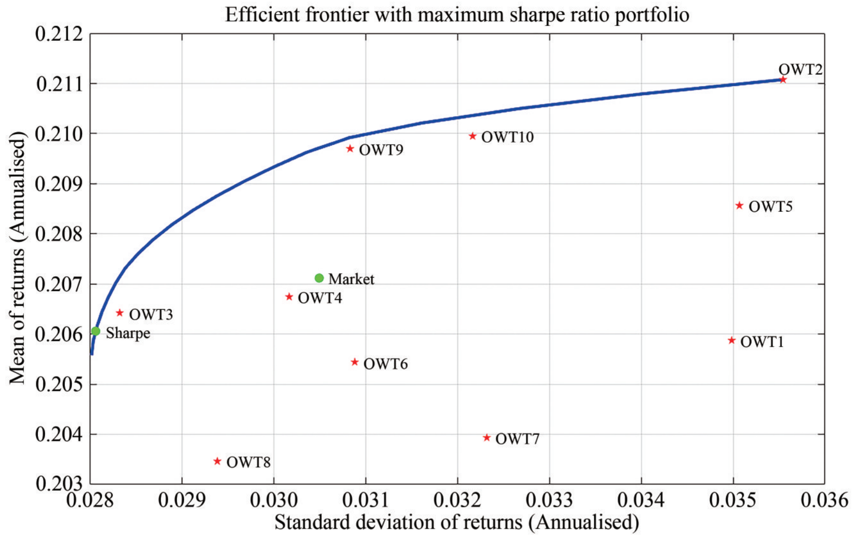


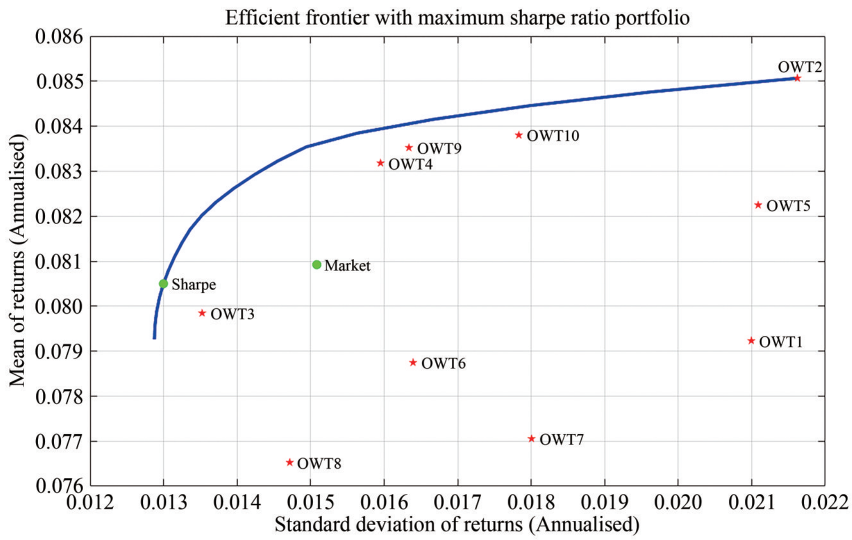
Figure 18 Statistical descriptors of the key performance metrics at different phases of life extension (Yeter et al., 2022b)

The results shown in Figure 18 indicate that the normalised mean value decreases over time for all performance metrics except for the levelised cost of energy. In particular, compounded annual growth rate, which represents compounded return on investment over multiple years, decreases substantial compared to the return on asset and the gross profit margin. This can be explained by the fact that the returns in the future are reduced with a higher discount factor towards the later phases of life extension. Figure 18 also shows that COV increases over the course of the life extension, especially during Phase IV. Like the normalised mean value, LCOE is the exception to the general trends observed in GPM, ROA, and CAGR.

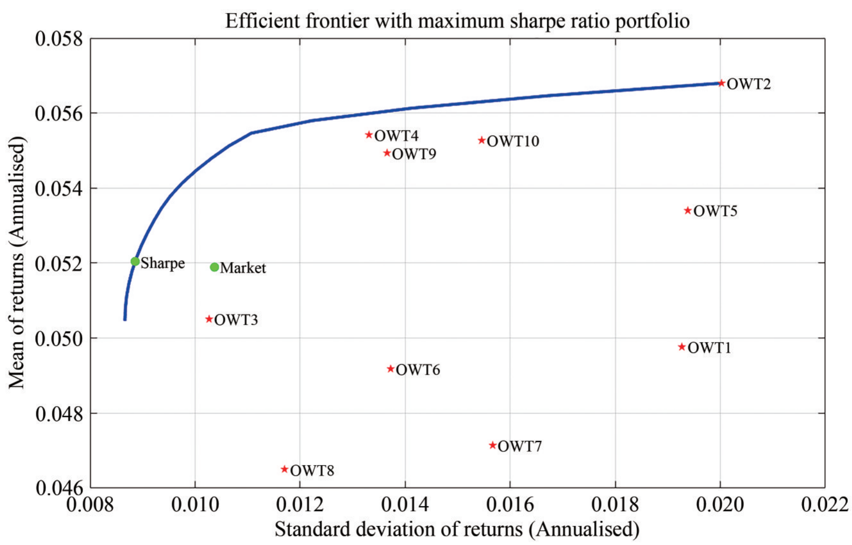
Yeter et al. (2022c) employed the key performance metric CAGR to present the risk-return diagram for a fictitious ageing offshore wind farm with ten offshore wind assets. The modern portfolio optimisation was performed to the maximum risk-adjusted ratio, namely the Sharpe ratio. The findings of this study, shown in Figure 19, indvicated that



(a) Phase I



(b) Phase II



(c) Phase III

Figure 19 Risk-return diagram at different phases for the moderate scenario (Yeter et al., 2022c) a less riskier operational strategy can be achieved by optimising the operational intensity of offshore wind turbines instead of keeping the operational intensity the same for offshore wind turbines.

Nielsen and Sørensen (2021) suggested reconsideration of the target reliability index, stating that the economic consequences in case of failure would not be the same for a new offshore wind asset and one considered for life extension. The study showed that the target reliability β could be below 2.5 when the internal rate of return is much higher than the interest rate the project is subjected to. Nielsen and Sørensen (2021) also compared the probabilistic approach for the life extension decision of wind turbine structural components to the deterministic approach. The study revealed that probabilistic fatigue damage assessment would yield longer fatigue life (beyond 25 years of service life), which potentially lead to higher profitability of offshore wind project. Moreover, if the lower target reliability is to be accepted such as $\beta = 3.1$, an additional 15 years of fatigue life.

Yeter and Garbatov (2022) discussed the future trends in intelligent integrity management systems. It was pointed out that structural integrity management systems should be enhanced by probabilistic approaches to deal with uncertainties propagating over the service life of support structures, with an independent objective of minimising human involvement in both inspection and maintenance actions. Moreover, probabilistic modelling and assessment would be expected to gain more importance, especially for the digital representation of physical assets.

Yeter and Garbatov (2022) also stated that the target reliability index considered for the OWT support structures needed to be revisited. To achieve an optimal target reliability index for life extension, the study recommended conducting a techno-economic life cycle assessment whose main objective is to come up with dynamic maintenance policies reducing the standard deviation of the expected return, in turn, the discount rate used for the levelised cost of energy.

The main conclusion to be deduced from the studies discussed above is that life extension is viable so long as the profitability metrics are strong relative to the overall risk of the offshore wind project, however, in an economic environment where high O&M costs and low power prices can hinder the profitability of offshore wind projects and affect life extension decisions.

6 Conclusions and future work

The present study provided an extensive review of the risk-based life extension assessment for ageing offshore wind structures using supervised and unsupervised machine learning techniques. The review focused on the application of artificial intelligence together with statistics and advanced signal processing on the data acquisition, pre-processing, structural integrity assessment, condition-based maintenance and risk-based life-cycle and life extension assessment. The current corrosion issues on monopile foundations were addressed from the structural integrity standpoint. Even though corrosion is not a direct cause of catastrophic failure, corrosion-induced cracking can lead to failure with high monetary consequences.

Following the review presented in the present paper, it can be argued that continuous structural health monitoring with AI-based predictive models could be of great use for intelligent life extension management systems. The success of AI applications in the offshore wind industry is possible by incorporating data pre-processing techniques, statistics, and signal process methods. Moreover, analysing such big data also gives rise to the possibility of collecting more data, which dramatically changes the way the operation has been managed for many years.

The maintenance systems can benefit from AI in myriad ways, such as online, operational data analysis for fault detection, robotics for remote inspection, image processing for the degree of structural degradation and high-fidelity remaining life prediction models for optimal autonomous and intelligent maintenance decisions in real-time.

The economic aspect of these implementations cannot be overlooked either. In this regard, the test equipment and embedded onboard diagnostics for condition monitoring increase the cost in the short term; however, it is expected to pay itself off due to the saving coming from system logistics, operation and maintenance footprint if it is implemented correctly, which is also another common worry.

Another aspect is that the severity of the failure consequence can justify the increase in the structural cost. The failure consequence, including the opportunity cost due to the interrupted energy production, due to the maintenance and repair actions, may be so severe that a higher level of structural reliability may be required. Therefore, performing a risk-based techno-economic assessment is recommended to measure profitability and target reliability index for life extension projects. Moreover, the difference between the compounded annual rate of return on initial investment and the weighted average cost of capital can be considered an appropriate key metric for life extension performance.

Finally, one cannot think of operation as an isolated lifecycle phase that needs to be optimised. The operation is interconnected with the other phases: design, manufacturing, structural health system, life extension, and life extension certification. Hence, more advancement in AI in the offshore wind industry is expected with wider topics and a greater number of applications.

A paradigm shift in offshore wind asset reliability management has already started to take place with the introduction of high-performance computing, advanced machine learning, efficient meta-heuristic optimisation algorithms, the internet of things, and autonomous ocean vehicles. Consequently, there has been a significant increase in terms of research that focused on the integration of big data-driven models with physics-based analytical and numerical simulations.

Based on the trends seen in the literature and the offshore wind industry, it is reasonable to argue that significantly more research on the development of big data-driven machine learning models with real-time prediction capabilities should be expected. The rise of artificial intelligence-aided offshore wind asset reliability management leaves the door wide open for applying a model-based systems engineering approach.

The model-based systems engineering approach allows for multi-disciplinary and integrated engineering models that could be tailored-made based on the stakeholder's demands. The substantial growth in the development of digital twins for offshore wind asset management is a clear indication to see where the future lies. The digital representation of any infrastructure assets must consist of data acquisition, processing, analysis, probabilistic future prediction, and an intelligent decision-support system, which is essentially what was covered within the scope of the present work.

References

Adedipe O, Brennan F, Kolios A (2016) Review of corrosion fatigue in offshore structures: Present status and challenges in the offshore wind sector. Renewable and Sustainable Energy Reviews 61: 141-154. https://doi.org/10.1016/j.rser.2016.02.017

Akaike H (1973) Information Theory as an Extension of the Maximum Likelihood Principle. Proceedings of the Second International Symposium on Information Theory 267-281

Alati N, Nava V, Failla G, Arena F, Santini A (2013) Fatigue analysis of offshore wind turbines on fixed support structures. Key Engineering Materials, City 539-546.

Alvarez MG, Lapitz P, Ruzzante J (2012) Analysis of acoustic emission signals generated from SCC propagation. Corrosion science 55: 5-9. https://doi.org/10.1016/j.corsci.2011.08.014

Amanatidis G (2019) European Policies on Climate and Energy towards 2020, 2030 and 2050.

Amirafshari P, Brennan F, Kolios A (2021) A fracture mechanics framework for optimising design and inspection of offshore wind turbine support structures against fatigue failure. Wind Energy Science 6(3): 677-699. https://doi.org/10.5194/wes-6-677-2021

Anderson TL (2017) Fracture mechanics: fundamentals and applications. CRS press, Taylor & Francis Group. https://doi.org/10.1201/9781315370293

Antoniadou I, Dervilis N, Papatheou E, Maguire AE, Worden K (2015) Aspects of structural health and condition monitoring of offshore wind turbines. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 373 (2035): 20140075. https://doi.org/10.1098/rsta.2014.0075

Artymiak P, Bukowski L, Feliks J, Narberhaus S, Zenner H (1999). Determination of S–N curves with the application of artificial neural networks. Fatigue & Fracture of Engineering Materials & Structures 22(8): 723-728. https://doi.org/10.1046/j.1460-2695.1999.t01-1-00198.x

ASM MI (1996) ASM Handbook. ASM International

Aswathanarayana U, Divi RS (2009) Energy portfolios. CRC Press. https://doi.org/10.1201/9780203876602

Ayala-Uraga E, Moan T (2002) System reliability issues of offshore structures considering fatigue failure and updating based on inspection. 1st International ASRANet Colloquium, Glasgow

Bach-Andersen M, Rømer-Odgaard B, Winther O (2018). Deep learning for automated drivetrain fault detection. Wind Energy 21(1): 29-41. https://doi.org/10.1002/we.2142

Bangalore P, Patriksson M (2018) Analysis of SCADA data for early fault detection, with application to the maintenance management of wind turbines. Renewable energy 115: 521-532. https://doi.org/10.1016/j.renene.2017.08.073

Barltrop NDP, Adams AJ, Hallam MG (1991). Dynamics of fixed marine structures. Butterworth-Heinemann Oxford.

Barone G, Frangopol DM (2014) Life-cycle maintenance of deteriorating structures by multi-objective optimization involving reliability, risk, availability, hazard and cost. Structural Safety 48: 40-50. https://doi.org/10.1016/j.strusafe.2014.02.002

Barsom JM (1976) Fatigue Crack Growth Under Variable-Amplitude Loading in Various Bridge Steels. Fatigue Crack Growth under Spectrum Loads 595: 217-235

Bayoumi MR (1996) The mechanics and mechanisms of fracture in stress corrosion cracking of aluminium alloys. Engineering Fracture Mechanics 54(6): 879-889. https://doi.org/10.1016/0013-7944(93)E0027-Z

Benasciutti D (2004) Fatigue analysis of random loadings. PhD. Thesis University of Ferrara, Italy

Benasciutti D, Tovo R (2004). Rainflow cycle distribution and fatigue damage in Gaussian random loadings. University of Ferrara, Italy Report No. 129

Benasciutti D, Tovo R (2006) Comparison of spectral methods for fatigue analysis of broad-band Gaussian random processes. Probabilistic Engineering Mechanics, 21(4): 287-299. https://doi. org/10.1016/j.probengmech.2005.10.003

Black AR, Mathiesen T, Hilbert LR (2015) Corrosion protection of offshore wind foundations. NACE International

Blanco MI (2009). The economics of wind energy. Renewable and sustainable energy reviews 13(6-7): 1372-1382. https://doi.org/10.1016/j.rser.2008.09.004

Brennan F (2013) Risk Based Maintenance for Offshore Wind Structures. Procedia CIRP 11: 296-300. https://doi.org/10.1016/j.procir.2013.07.021

Brennan FP, Falzarano J, Gao Z, Landet E, Le Boulluec M, Rim CW, Sirkar J, Sun L, Suzuki H, Thiry A, Trarieux F, Wang CM (2012) Report of Specialist Committee V.4 - Offshore Renewable Energy.

18th International Ship and Offshore Structures Congress (ISSC 2012)
Bučar T, Nagode M, Fajdiga M (2006) A neural network approach to describing the scatter of S−N curves. International journal of fatigue 28(4): 311-323. https://doi.org/10.1016/j.ijfatigue.2005.08.002
Calabrese L, Galeano M, Proverbio E, Di Pietro D, Cappuccini F, Donato A (2016) Monitoring of 13% Cr martensitic stainless steel corrosion in chloride solution in presence of thiosulphate by acoustic emission technique. Corrosion Science 111: 151-161. https://doi.org/10.1016/j.corsci.2016.05.010
Carden EP, Fanning P (2004) Vibration based condition monitoring: a review. Structural health monitoring 3(4): 355-377. https://doi.org/10.1177/1475921704047500
Castro-Santos L, Martins E, Guedes Soares C (2016) Methodology to calculate the costs of a floating offshore renewable energy farm. Energies 9(5): 324. https://doi.org/10.3390/en9050324
Chaudhury GK, Dover WD (1985) Fatigue analysis of offshore platforms subjected to sea wave loadings. International Journal of Fatigue 7(1): 13-19
Cheng P (2002) A Reliability Based Design Methodology for Extreme Responses of Offshore Wind Turbines. PhD. Thesis Delft University of Technology, DUWIND
Chojaczyk AA, Teixeira AP, Neves LC, Cardoso JB, Guedes Soares C (2015) Review and application of artificial neural networks models in reliability analysis of steel structures. Structural Safety 52: 78-89. https://doi.org/10.1016/j.strusafe.2014.09.002
Crooker TW (1983) Corrosion Fatigue: Mechanics, Metallurgy, Electrochemistry, and Engineering: a Symposium. ASTM International
Davey HE, Nimmo A (2012) Offshore Wind Cost Reduction, Pathways Study. Cost Reduction Study. The Crown Estate, London, United Kingdom
Delaunois F, Tshimombo A, Stanciu V, Vitry V (2016) Monitoring of chloride stress corrosion cracking of austenitic stainless steel: identification of the phases of the corrosion process and use of a modified accelerated test. Corrosion Science 110: 273-283. https://doi.org/10.1016/j.corsci.2016.04.038
Deng J (2006) Structural reliability analysis for implicit performance function using radial basis function network. International journal of solids and structures 43(11-12): 3255-3291. https://doi.org/10.1016/j.ijsolstr.2005.05.055
Deng J, Gu D, Li X, Yue ZQ (2005) Structural reliability analysis for implicit performance functions using artificial neural network. Structural safety 27(1): 25-48. https://doi.org/10.1016/j.strusafe.2004.03.004
Díaz H, Guedes Soares C (2020a) Review of the current status, technology and future trends of offshore wind farms. Ocean Engineering 209: 107381. https://doi.org/10.1016/j.oceaneng.2020.107381
Díaz H, Guedes Soares C (2020b) An integrated GIS approach for site selection of floating offshore wind farms in the Atlantic continental European coastline. Renewable and Sustainable Energy Reviews 134: 110328. https://doi.org/10.1016/j.rser.2020.110328
Dinda S, Kujawski D (2004) Correlation and prediction of fatigue crack growth for different R-ratios using Kmax and ΔK+ parameters. Engineering Fracture Mechanics 71(12): 1779-1790. https://doi.org/10.1016/j.engfracmech.2003.06.001
Dirlik T (1985) Application of computers in fatigue analysis. PhD. Thesis Warwich University
Djukic MB, Zeravcic VS, Bakic G, Sedmak A, Rajicic B (2014) Hydrogen embrittlement of low carbon structural steel. Procedia Materials Science 3: 1167-1172. https://doi.org/10.1016/j.mspro.2014.06.190
DNV (2016a) Lifetime extension of wind turbines. DNVGL-ST-0262
DNV (2016b) Certification of lifetime extension of wind turbines. DNVGL-ST-0263
Dong WB, Moan T, Gao Z (2011) Long-term fatigue analysis of multi-planar tubular joints for jacket-type offshore wind turbine in time domain. Engineering Structures 33: 2002-2014. https://doi.org/10.1016/j.engstruct.2011.02.037
Dong WB, Moan T, Gao Z (2012a) Fatigue Reliability Analysis of the Jcket Support Structure for Offshore Wind Turbine Considering the Effect of Corrosion and Inspection. Reliability Engineering & System Safety, 106, 11-27. https://doi.org/10.1016/j.ress.2012.06.011
Dong WB, Moan T, Gao Z (2012b) Fatigue reliability analysis of the jacket support structure for offshore wind turbine considering the effect of corrosion and inspection. Reliability Engineering & System Safety 106: 11-27. https://doi.org/10.1016/j.ress.2012.06.011
Dong Y, Frangopol DM (2015) Risk-informed life-cycle optimum inspection and maintenance of ship structures considering corrosion and fatigue. Ocean Engineering 101: 161-171. https://doi.org/10.1016/j.oceaneng.2015.04.020
Duguid L (2017) Offshore Wind Farm Substructure Monitoring And Inspection, PN000205-LRT-001
Faber MH, Sørensen JD, Kroon IB (1992) Optimal inspection Strategies for Offshore Structural Systems. International Conference on Offshore Mechanics and Arctic Engineering, Aalborg, 145-151
Fajuyigbe A, Brennan F (2021) Fitness-for-purpose assessment of cracked offshore wind turbine monopile. Marine Structures 77: 102965. https://doi.org/10.1016/j.marstruc.2021.102965
Feng L, He J, Hu L, Shi H, Yu C, Wang S, Yang S (2020) A parametric study on effects of pitting corrosion on steel plate's ultimate strength. Applied Ocean Research 95: 102026. https://doi.org/10.1016/j.apor.2019.102026
Frangopol DM (2011) Life-cycle performance, management, and optimisation of structural systems under uncertainty: accomplishments and challenges 1. Structure and Infrastructure Engineering 7(6): 389-413. https://doi.org/10.1080/15732471003594427
Fu J, Chu J, Guo P, Chen Z (2019) Condition monitoring of wind turbine gearbox bearing based on deep learning model. IEEE Access 7: 57078-57087. https://doi.org/10.1109/ACCESS.2019.2912621
Garbatov Y, Guedes Soares C, Parunov J (2014a) Fatigue Strength Experiments of Corroded Small Scale Steel Specimens. International Journal of Fatigue 59: 137-144. http://dx.doi.org/10.1016/j.ijfatigue.2013.09.005
Garbatov Y, Guedes Soares C, Parunov J, Kodvanj J (2014b) Tensile Strength Assessment of Corroded Small Scale Specimens. Corrosion Science 85: 296-303. https://doi.org/10.1016/j.corsci.2014.04.031
Garbatov Y, Guedes Soares C, Wang G (2007) Nonlinear Time Dependent Corrosion Wastage of Deck Plates of Ballast and Cargo Tanks of Tankers. Journal of Offshore Mechanics and Arctic Engineering 129(1): 48-55. https://doi.org/ 10.1115/1.2426987
Genel K (2004) Application of artificial neural network for predicting strain-life fatigue properties of steels on the basis of tensile tests. International Journal of Fatigue 26(10): 1027-1035. https://doi.org/10.1016/j.ijfatigue.2004.03.009
Gentils T, Wang L, Kolios A (2017) Integrated structural optimisation of offshore wind turbine support structures based on finite element analysis and genetic algorithm. Applied energy 199: 187-204. https://doi.org/10.1016/j.apenergy.2017.05.009
Gilbert PT (1956) Corrosion-Fatigue. Metallurgical reviews 1(1): 379-417
Gomez HC, Gur T, Dolan D (2013) Structural condition assessment of offshore wind turbine monopile foundations using vibration monitoring data. Nondestructive Characterization for Composite

Materials, Aerospace Engineering, Civil Infrastructure, and Homeland Security 2013, 86940B
Gomes HM, Awruch AM (2004) Comparison of response surface and neural network with other methods for structural reliability analysis. Structural safety 26(1): 49-67. https://doi.org/10.1016/S0167-4730(03)00022-5
Gope D, Gope PC, Thakur A, Yadav A (2015) Application of artificial neural network for predicting crack growth direction in multiple cracks geometry. Applied Soft Computing 30: 514-528. https://doi.org/10.1016/j.asoc.2015.02.003
Greenacre P, Gross R, Heptonstall P (2010) Great expectations: The cost of offshore wind in UK waters. UK Energy Research
Grolvlen M, Bardal E, Berge S, Eide O, Engesvik K, Haagensen PJ, Orjasaether O (1989) Localized Corrosion on Offshore Tubular· Structures: Inspection and Repair Criteria. Offshore Technology Conference
Guedes Soares C, Garbatov Y (1996) Fatigue reliability of the ship hull girder accounting for inspection and repair. Reliability Engineering & System Safety 51(3): 341-351. https://doi.org/10.1016/0951-8320(95)00123-9
Halfpenny A (1999) A frequency domain approach for fatigue life estimation from finite element analysis. Key Engineering Materials 167: 401-410
Hameed Z, Ahn S-H, Cho YM (2010) Practical aspects of a condition monitoring system for a wind turbine with emphasis on its design, system architecture, testing and installation. Renewable Energy 35(5): 879-894. https://doi.org/10.1016/j.renene.2009.10.031
Hameed Z, Wang K (2012) Development of optimal maintenance strategies for offshore wind turbine by using artificial neural network. Wind Engineering 36(3): 353-364. https://doi.org/10.1260/0309-524X.36.3.35
Hilbert LR, Black AR, Andersen F, Mathiesen T (2011) Inspection and monitoring of corrosion inside monopile foundations for offshore wind turbines, Paper no: 4730. EUROCORR, 1-14
Hobbacher A (2009) Recommendations for Fatigue Design of Welded Joints and Components. IIW doc. 1823-07, Welding Research Council Bulletin 520. International Institute of Welding
Hoeppner DW (1979) Model for prediction of fatigue lives based upon a pitting corrosion fatigue process. Fatigue Mechanisms
Ibrahim FK (1989). Threshold stress intensity behaviour of cracked steel structural components. Fatigue & Fracture of Engineering Materials & Structures 12(6): 543-552. https://doi. org/10.1111/j.1460-2695.1989.tb00562.x
IEC 61400-3 (2009) Wind Turbines. Part 3: Design requirements for offshore wind turbines
Irwin GR (1957) Analysis of Stresses and Strains near the End of a Crack Traversing A Plate. Journal of Applied Mechanics, ASME 24: 361-364. https://doi.org/10.1115/1.4011547
Jacob A, Mehmanparast A (2021) Crack growth direction effects on corrosion-fatigue behaviour of offshore wind turbine steel weldments. Marine Structures 75: 102881. https://doi. org/10.1016/j.marstruc.2020.102881
Jakubowski M (2015) Influence of pitting corrosion on fatigue and corrosion fatigue of ship and offshore structures, part II: load-PIT-crack interaction. Polish Maritime Research 22(3): 57-66
Jiménez AA, Gómez Muñoz CQ, García Márquez FP (2018) Machine learning for wind turbine blades maintenance management. Energies 11(1): 13. https://doi.org/10.3390/en11010013
Jiménez AA, Márquez FPG, Moraleda VB, Muñoz CQG (2019) Linear and nonlinear features and machine learning for wind turbine blade ice detection and diagnosis. Renewable energy 132: 1034-1048. https://doi.org/10.1016/j.renene.2018.08.050
Jomdecha C, Prateepasen A, Kaewtrakulpong P (2007) Study on source location using an acoustic emission system for various corrosion types. NDT & E International 40(8): 584-593. https://doi.org/10.1016/j.ndteint.2007.05.003
Kang J, Wang Z, Guedes Soares C (2020) Condition-based maintenance for offshore wind turbines based on support vector machine. Energies 13(14): 3518. https://doi.org/10.3390/en13143518
Kang J, Guedes Soares C (2020) An opportunistic maintenance policy for offshore wind farms. Ocean Engineering 216: 108075. https://doi.org/10.1016/j.oceaneng.2020.108075
Kang J, Sobral J, Guedes Soares C (2019) Review of condition-based maintenance strategies for offshore wind energy. Journal of Marine Science and Application 18(1): 1-16. https://doi.org/10.3390/en13143518
Karmakar D, Bagbanci H, Guedes Soares C (2016) Long-term extreme load prediction of spar and semisubmersible floating wind turbines using the environmental contour method. Journal of Offshore Mechanics and Arctic Engineering 138(2): 021601-021601-021609. https://doi.org/10.1115/1.4032099
Kawai S, Kasai K (1985) Considerations of allowable stress of corrosion fatigue (focused on the influence of pitting). Fatigue & Fracture of Engineering Materials & Structures 8(2): 115-127. https://doi.org/10.1111/j.1460-2695.1985.tb01198.x
Kim B, Wang XZ, Shin YS (2007) Extreme load and fatigue damage on FPSO in combined waves and swells. 10th International symposium on practical design of ships and other floating structures, 203-210
Kim KS, Kim BO, Kim YK, Lee CH, Lee SW (2005) A study on the low cycle fatigue behavior of the steel for shipbuilding industry. Key Engineering Materials, 10-15. https://doi. org/10.4028/www.scientific.net/KEM.297-300.10
Kirchgeorg T, Weinberg I, Hörnig M, Baier R, Schmid M, Brockmeyer B (2018) Emissions from corrosion protection systems of offshore wind farms: Evaluation of the potential impact on the marine environment. Marine pollution bulletin 136: 257-268. https://doi.org/10.1016/j.marpolbul.2018.08.058
Kohavi R, John GH (1997) Wrappers for feature subset selection. Artificial intelligence 97(1-2): 273-324. Wrappers for feature subset selection
Kondo Y (1989) Prediction of fatigue crack initiation life based on pit growth. Corrosion 45(1): 7-11. https://doi.org/10.5006/1.3577891
Kost C, Mayer JN, Thomsen J, Hartmann N, Senkpiel C, Philipps S, Nold S, Lude S, Saad N, Schlegl T (2013) Levelized cost of electricity renewable energy technologies. Fraunhofer Institute for Solar Energy Systems ISE
Koukal A, Breitner MH (2013) A decision support tool for the risk management of offshore wind energy projects. Proceedings of the 11th International Conference on Wirtschaftsinformatik, Leipzig, 1683-1697
Kovač J, Legat A, Zajec B, Kosec T, Govekar E (2015) Detection and characterization of stainless steel SCC by the analysis of crack related acoustic emission. Ultrasonics 62: 312-322. https://doi.org/10.1016/j.ultras.2015.06.005
Kusiak A, Zhang Z, Verma A (2013) Prediction, operations, and condition monitoring in wind energy. Energy 60: 1-12. https://doi.org/10.1016/j.energy.2013.07.051
Langley P (1994) Selection of relevant features in machine learning. Proceedings of the AAAI Fall symposium on relevance, 245-271
Lantz E, Wiser R, Hand M (2012) The past and future cost of wind energy. National Renewable Energy Laboratory, Golden, CO; Report No. NREL/TP-6A20-53510
Larrosa NO, Akid R, Ainsworth RA (2018) Corrosion-fatigue: a

review of damage tolerance models. International Materials Reviews 63(5): 283-308. https://doi.org/10.1080/09506608.2017.1375644
Lee S-y, Jo C, Bergan P, Pettersen B, Chang D (2016) Life-cycle cost-based design procedure to determine the optimal environmental design load and target reliability in offshore installations. Structural Safety 59: 96-107. https://doi.org/10.1016/j.strusafe.2015.12.002
Levitt AC, Kempton W, Smith AP, Musial W, Firestone J (2011) Pricing offshore wind power. Energy Policy 39(10): 6408-6421. https://doi.org/10.1016/j.enpol.2011.07.044
Lian J, Cai O, Dong X, Jiang Q, Zhao Y (2019) Health monitoring and safety evaluation of the offshore wind turbine structure: a review and discussion of future development. Sustainability 11 (2): 494. https://doi.org/10.3390/su11020494
Lindley TC, McIntyre P, Trant PJ (1982) Fatigue-crack initiation at corrosion pits. Metals technology 9(1): 135-142. https://doi.org/10.1179/030716982803286403
Liu K, Yan R-J, Guedes Soares C (2018a) Optimal sensor placement and assessment for modal identification. Ocean Engineering 165: 209-220. https://doi.org/10.1016/j.oceaneng.2018.07.034
Liu K, Yan R-J, Guedes Soares C (2018b) Damage identification in offshore jacket structures based on modal flexibility. Ocean Engineering 170: 171-185. https://doi.org/10.1016/j.oceaneng.2018.10.014
Liu K, Yan R-J, Guedes Soares C (2018c) An improved model updating technique based on modal data. Ocean Engineering 154: 277-287. https://doi.org/10.1016/j.oceaneng.2018.02.011
Liu W, Tang B, Jiang Y (2010) Status and problems of wind turbine structural health monitoring techniques in China. Renewable Energy 35(7): 1414-1418. https://doi.org/10.1016/j.renene.2010.01.006
Long L, Mai QA, Morato PG, Sørensen JD, Thöns S (2020) Information value-based optimization of structural and environmental monitoring for offshore wind turbines support structures. Renewable Energy 159: 1036-1046. https://doi.org/10.1016/j.renene.2020.06.038
Lu Y, Sun L, Zhang X, Feng F, Kang J, Fu G (2018) Condition based maintenance optimization for offshore wind turbine considering opportunities based on neural network approach. Applied Ocean Research 74: 69-79. https://doi.org/10.1016/j.apor.2018.02.016
Madsen HO, Skjong RK, Tallin AG (1987) Probabilistic fatigue crack growth analysis of offshore structures, with reliability updating through inspection. Proceedings of Marine Structural Reliability Engineering Symposium, Arlington, 45–55
Madsen HO, Sørensen JD (1990) Probability-based optimization of fatigue design, inspection and maintenance. Proceedings of Fourth International Symposium on Integrity of Offshore Structures, 421-432
Madsen HO, Torhaug R, Cramer EH (1991) Probability-based cost benefit analysis of fatigue design, inspection and maintenance. Marine Structural Inspection, Maintenance and Monitoring symposium
Mao M, Zhang X, Tu S, Xuan F (2014) Prediction of crack initiation life due to corrosion pits. Journal of Aircraft 51(3): 805-810. https://doi.org/10.2514/1.C032436
Márquez-Domínguez S, Sørensen JD (2012) Fatigue Reliability and Calibration of Fatigue Design Factors for Offshore Wind Turbines. Energies 5(6): 1816-1834. https://doi.org/10.3390/en5061816
Márquez FPG, Tobias AM, Pérez JMP, Papaelias M (2012) Condition monitoring of wind turbines: Techniques and methods. Renewable Energy 46: 169-178. https://doi.org/10.1016/j.renene.2012.03.003
Marti-Puig P, Blanco-M A, Cárdenas JJ, Cusidó J, Solé -Casals J (2018) Effects of the pre-processing algorithms in fault diagnosis of wind turbines. Environmental modelling & software 110: 119-128. https://doi.org/10.1016/j.envsoft.2018.05.002
Martinez-Luengo M, Kolios A, Wang L (2016) Structural health monitoring of offshore wind turbines: A review through the Statistical Pattern Recognition Paradigm. Renewable and Sustainable Energy Reviews 64: 91-105
Masi G, Matteucci F, Tacq J (2018) State of the Art Study on Materials and Solutions against Corrosion in Offshore Structures
Moan T (1998) Target Levels for Structural Reliability and Risk Analysis of Offshore Structures. Risk and Reliability in Marine Technology, 351-368
Moan T (2005) Reliability-based management of inspection, maintenance and repair of offshore structures. Structure and Infrastructure Engineering 1(1): 33-62. https://doi.org/10.1080/15732470412331289314
Moan T (2008) Reliability of aged offshore structures. Condition assessment of aged structures, 287-352
Moan T, Song R (2000) Implications of inspection updating on system fatigue reliability of offshore structures. Journal of Offshore Mechanics and Arctic Engineering 122(3): 173-180. https://doi.org/10.1115/1.1286601
Moghaddam BT, Hamedany AM, Mehmanparast A, Brennan F, Nikbin K, Davies CM (2019) Numerical analysis of pitting corrosion fatigue in floating offshore wind turbine foundations. Procedia Structural Integrity 17: 64-71. https://doi.org/10.1016/j.prostr.2019.08.010.
Moghaddam BT, Hamedany AM, Taylor J, Mehmanparast A, Brennan F, Davies CM, Nikbin K (2020) Structural integrity assessment of floating offshore wind turbine support structures. Ocean Engineering 208: 107487. https://doi.org/10.1016/j.oceaneng.2020.107487
Momber A (2011) Corrosion and corrosion protection of support structures for offshore wind energy devices (OWEA). Materials and Corrosion 62(5): 391-404. https://doi.org/10.1002/maco.201005691
Mrsnik M, Slavic J, Boltezar M (2013). Frequency-domain methods for a vibration-fatigue-life estimation - Application to real data. International Journal of Fatigue 47: 8-17. https://doi.org/10.1016/j.ijfatigue.2012.07.005
Nasiri S, Khosravani MR, Weinberg K (2017) Fracture mechanics and mechanical fault detection by artificial intelligence methods: A review. Engineering Failure Analysis 81: 270-293. https://doi.org/10.1016/j.engfailanal.2017.07.011
Nguyen TAT, Chou S-Y (2018) Maintenance strategy selection for improving cost-effectiveness of offshore wind systems. Energy conversion and management 157: 86-95. https://doi.org/10.1016/j.enconman.2017.11.090
Nielsen JS, Sørensen JD (2021) Risk-based derivation of target reliability levels for life extension of wind turbine structural components. Wind Energy 24(9): 939-956. https://doi.org/10.1002/we.2610
Niemi E, Fricke W, Maddox S (2004) Structural Stress Approach to Fatigue Analysis of Welded Components - Designer´s Guide
Niemi E, Fricke W, Maddox SJ (2018a) The Structural Hot-Spot Stress Approach to Fatigue Analysis. Structural Hot-Spot Stress Approach to Fatigue Analysis of Welded Components: Designer's Guide, 5-12. https://doi.org/10.1007/978-981-10-5568-3_2
Niemi E, Fricke W, Maddox SJ (2018b) Structural Hot-Spot Stress Determination Using Finite Element Analysis. Structural Hot-Spot Stress Approach to Fatigue Analysis of Welded Components: Designer's Guide, 17-31. https://doi.org/10.1007/978-981-10-5568-3_4
Nøhr-Nielsen L (2018) Corrosion Protection of Offshore Wind Power Plants. GfKORR, Gesellschaft für Korrosionsschutz, ANNUAL CONFERENCE 2018

Ok D, Pu Y, Incecik A (2007) Artificial neural networks and their application to assessment of ultimate strength of plates with pitting corrosion. Ocean Engineering 34(17-18): 2222-2230. https://doi.org/10.1016/j.oceaneng.2007.06.007

Okasha NM, Frangopol DM (2009) Lifetime-oriented multi-objective optimization of structural maintenance considering system reliability, redundancy and life-cycle cost using GA. Structural Safety 31(6): 460-474. https://doi.org/10.1016/j.strusafe.2009.06.005

Onoufriou T (1999) Reliability based inspection planning of offshore structures. Marine structures 12(7): 521-539. https://doi.org/10.1016/S0951-8339(99)00030-1

Oritz K, Chen NK (1987) Fatigue damage prediction for stationary wide-band stresses. 5th International Conference on the Applications of Statistics and Probability in Civil Engineering

Ossai CI, Boswell B, Davies IJ (2016) A Markovian approach for modelling the effects of maintenance on downtime and failure risk of wind turbine components. Renewable energy 96: 775-783. https://doi.org/10.1016/j.renene.2016.05.022

Papadrakakis M, Papadopoulos V, Lagaros ND (1996) Structural reliability analyis of elastic-plastic structures using neural networks and Monte Carlo simulation. Computer methods in applied mechanics and engineering 136(1-2): 145-163. https://doi.org/10.1016/0045-7825(96)01011-0

Papadrakakis M, Lagaros ND (2002) Reliability-based structural optimization using neural networks and Monte Carlo simulation. Computer methods in applied mechanics and engineering 191 (32): 3491-3507. https://doi.org/10.1016/S0045-7825(02)00287-6

Paris P, Erdogan F (1963) A critical analysis of crack propagation laws. Journal of Basic Engineering 85: 528-534. https://doi.org/10.1115/1.3656900

Paris PC, Gomez MP, Anderson WE (1961) A rational analytic theory of fatigue. The Trend in Engineering 13: 9-14

Pidaparti RMV, Palakal MJ (1995) Neural network approach to fatigue-crack-growth predictions under aircraft spectrum loadings. Journal of Aircraft 32(4): 825-831. https://doi.org/10.2514/3.46797

Postma EO, van den Herik HJ, van der Maaten LJ (2009) Dimensionality reduction: a comparative review. Journal of Machine Learning Research 10(1-41): 66-71

Price SJ, Figueira RB (2017) Corrosion protection systems and fatigue corrosion in offshore wind structures: current status and future perspectives. Coatings 7(2): 25. https://doi.org/10.3390/coatings7020025

Ramberg W, Osgood WR (1943) Description of stress-strain curves by three parameters. National Advisory Committee for Aeronautics, Washington DC

Ramos S, Diaz H, Silva D, Guedes Soares C (2021) Levelized cost of energy of offshore floating wind turbines in different case scenarios of the Madeira Islands. Developments in Maritime Technology and Engineering, 627-637

Ray T, Gokarn RP, Sha OP (1996) Neural network applications in naval architecture and marine engineering. Artificial Intelligence in Engineering 10(3): 213-226. https://doi.org/10.1016/0954-1810(95)00030-5

Ricles JM, Bruin WM, Sooi TK, Hebor MF, Schonwetter PC (1995) Residual strength assessment and repair of damaged offshore tubulars. Proceedings of 27th Offshore Technology Conference

Riera-Guasp M, Antonino-Daviu JA, Capolino G-A (2014) Advances in electrical machine, power electronic, and drive condition monitoring and fault detection: state of the art. IEEE Transactions on Industrial Electronics 62(3): 1746-1759. https://doi.org/10.1109/TIE.2014.2375853

Rokhlin SI, Kim J-Y, Nagy H, Zoofan B (1999) Effect of pitting corrosion on fatigue crack initiation and fatigue life. Engineering Fracture Mechanics 62(4-5): 425-444. https://doi.org/10.1016/S0013-7944(98)00101-5

Rouhan A, Schoefs F (2003) Probabilistic modeling of inspection results for offshore structures. Structural safety 25(4): 379-399. https://doi.org/10.1016/S0167-4730(03)00016-X

Rubert T, McMillan D, Niewczas P (2018) A decision support tool to assist with lifetime extension of wind turbines. Renewable energy 120: 423-433. https://doi.org/10.1016/j.renene.2017.12.064

Rychlik I (1987) A New Definition of the Rainflow Cycle Counting Method. International Journal of Fatigue 9(2): 119-121. https://doi.org/10.1016/0142-1123(87)90054-5

Sadananda K, Vasudevan AK, Holtz RL, Lee EU (1999) Analysis of overload effects and related phenomena. International Journal of Fatigue 21: S233-S246. https://doi.org/10.1016/S0142-1123(99)00094-8

Santos F, Teixeira A, Guedes Soares C (2015a) Review of wind turbine accident and failure data. Renewable Energies Offshore, 953-959

Santos P, Villa LF, Reñones A, Bustillo A, Maudes J (2015b) An SVM-based solution for fault detection in wind turbines. Sensors 15(3): 5627-5648. https://doi.org/10.3390/s150305627

Schijve J (2001) Fatigue of structures and materials. Kluwer Academic

Schillings C, Wanderer T, Cameron L, van der Wal JT, Jacquemin J, Veum K (2012) A decision support system for assessing offshore wind energy potential in the North Sea. Energy Policy 49: 541-551. https://doi.org/10.1016/j.enpol.2012.06.056

Shabakhty N, Boonstra H, van Gelder P (2003) System reliability of jack-up structures based on fatigue degradation. Safety and Reliability, 1437-1445

Shafiee M, Finkelstein M, Bérenguer C (2015) An opportunistic condition-based maintenance policy for offshore wind turbine blades subjected to degradation and environmental shocks. Reliability Engineering & System Safety 142: 463-471. https://doi.org/10.1016/j.ress.2015.05.001

Shi C, Gong Y, Yang Z-G, Tong Q (2019) Peridynamic investigation of stress corrosion cracking in carbon steel pipes. Engineering Fracture Mechanics 219: 106604. https://doi.org/10.1016/j.engfracmech.2019.106604

Shittu AA, Mehmanparast A, Shafiee M, Kolios A, Hart P, Pilario K (2020) Structural reliability assessment of offshore wind turbine support structures subjected to pitting corrosion-fatigue: A damage tolerance modelling approach. Wind Energy 23(11): 2004-2026. https://doi.org/10.1002/we.2542

Shittu AA, Mehmanparast A, Hart P, Kolios A (2021) Comparative study between SN and fracture mechanics approach on reliability assessment of offshore wind turbine jacket foundations. Reliability Engineering & System Safety 215: 107838. https://doi.org/10.1016/j.ress.2021.107838

Silva JE, Garbatov Y, Guedes Soares C (2013) Ultimate strength assessment of rectangular steel plates subjected to a random localised corrosion degradation. Engineering Structures 52: 295-305. https://doi.org/10.1016/j.engstruct.2013.02.013

Singha KL, Ranganatha VR (2007) Cycle counting using rainflow algorithm for fatigue analysis. National Seminar on Aerospace Structure, 301-306

Skinn DA, Gallagher JP, Berens AP, Huber PD, Smith J (1994) Damage Tolerant Design (Data) Handbook. Wright Laboratory, Air Force Materiel Command

Smith SW, Newman JA, Piascik RS (2003) Simulation of fatigue crack initiation at corrosion pits with EDM notches, NASA/TM-2003-212166

Soliman M, Frangopol DM, Mondoro A (2016) A probabilistic approach for optimizing inspection, monitoring, and maintenance actions against fatigue of critical ship details. Structural Safety 60: 91-101. https://doi.org/10.1016/j.strusafe.2015.12.004

Song S, Li Q, Felder FA, Wang H, Coit DW (2018) Integrated optimization of offshore wind farm layout design and turbine opportunistic condition-based maintenance. Computers & Industrial Engineering 120: 288-297. https://doi.org/10.1016/j.cie.2018.04.051

Sørensen JD, Toft HS (2010) Probabilistic design of wind turbines. Energies 3(2): 241-257. https://doi.org/10.3390/en3020241

Sørensen JD, Tarp-Johansen NJ (2004) Cost-optimal structural reliability of offshore wind turbines. Special Topic Conference: The Science of Making Torque from Wind, Delft, 593-602

Sørensen JD, Tarp-Johansen NJ (2005) Optimal structural reliability of offshore wind turbines. 9th International Conference on Structural Safety and Reliability, ICOSSAR, 1423-1430

Sørensen JD (2012) Reliability-based calibration of fatigue safety factors for offshore wind turbines. International Journal of Offshore and Polar Engineering 22(3): 234-241

Sørensen JD (2006) Optimal reliability-based design of offshore wind turbine parks. Proceedings of the 2nd International Forum on Engineering Decision Making conference, Lake Louise, 1-12

Sørensen JD, Rackwitz R, Faber MH, Thoft-Christensen P (1991) Modelling in Optimal Inspection and Repair. International Conference on Offshore Mechanics and Arctic Engineering, Stavenger, 281-288

Stetco A, Dinmohammadi F, Zhao X, Robu V, Flynn D, Barnes M, Keane J, Nenadic G (2019) Machine learning methods for wind turbine condition monitoring: A review. Renewable energy 133: 620-635. https://doi.org/10.1016/j.renene.2018.10.047

Straub D, Goyet J, Sørensen JD, Faber MH (2006) Benefits of risk based inspection planning for offshore structures. 25th International Conference on Offshore Mechanics and Arctic Engineering, 59-68

Suresh S (1998) Fatigue of materials. Cambridge University Press, 313-342

Thoft-Christensen P, Murotsu Y (1986) Application of structural systems reliability theory. Springer

Thöns S, Faber MH, Rücker W (2013) Life Cycle Cost Optimized Monitoring Systems for Offshore Wind Turbine Structures. IRIS Industrial Safety and Life Cycle Engineering: Technologies/Standards/Applications, 75-90

Tian Z, Jin T, Wu B, Ding F (2011) Condition based maintenance optimization for wind power generation systems under continuous monitoring. Renewable Energy 36(5): 1502-1509. doi: https://doi.org/10.1016/j.renene.2010.10.028

Tunna JM (1986) Fatigue life Prediction for Gaussian Random Loads at the Design Stage. Fatigue and Fracture of Engineering Materials & Structures 9(3): 169-184. https://doi.org/10.1111/j.1460-2695.1986.tb00444.x

van der Tempel J, de Vries W (2005) Frequency domain calculations of offshore wind turbine response to wind and wave loads European Offshore Wind Conference & Exhibition

Votsis RA, Michailides C, Tantele EA, Onoufriou T (2018) Review of technologies for monitoring the performance of marine structures. The 28th International Ocean and Polar Engineering Conference, Sapporo

Wallace W, Hoeppner DW, Kandachar PV (1985) AGARD Corrosion Handbook. Volume 1. Aircraft Corrosion: Causes and Case Histories. Advisory group for aerospace research and development neuilly-sur-seine (France)

Wasim M, Djukic MB (2020) Hydrogen embrittlement of low carbon structural steel at macro-, micro-and nano-levels. International Journal of Hydrogen Energy 45(3): 2145-2156. https://doi.org/10.1016/j.ijhydene.2019.11.070

Weijtens W, Noppe N, Verbelen T, Iliopoulos A, Devriendt C (2016) Offshore wind turbine foundation monitoring, extrapolating fatigue measurements from fleet leaders to the entire wind farm. Journal of Physics: Conference Series 753(9): 092018. https://doi.org/10.1088/1742-6596/753/9/092018

Wheeler OE (1972) Spectrum Loading and Crack Growth. Journal Basic Engineering 94(D): 181. https://doi.org/10.1115/1.3425362

Willenborg J, Engle RM, Wood HA (1971) A Crack Growth Retardation Model Using an Effective Stress Concept. Air Force Flight Dynamic Laboratory, Wright-Patterson Air Force Base, USA

Wirsching PH (1980) Fatigue under wide band random Stress. Journal of Structural Division 98: 1593-1606. https://doi.org/10.1061/JSDEAG.0005477

Wu K, Ito K, Shinozaki I, Chivavibul P, Enoki M (2019) A Comparative Study of Localized Corrosion and Stress Corrosion Cracking of 13Cr Martensitic Stainless Steel Using Acoustic Emission and X-ray Computed Tomography. Materials 12(16): 2569. https://doi.org/10.3390/ma12162569

Wu K, Jung W-S, Byeon J-W (2016) In-situ monitoring of pitting corrosion on vertically positioned 304 stainless steel by analyzing acoustic-emission energy parameter. Corrosion science 105: 8-16. https://doi.org/10.1016/j.corsci.2015.12.010

Yang W, Jiang J (2011) Wind turbine condition monitoring and reliability analysis by SCADA information. Second International Conference on Mechanic Automation and Control Engineering, 1872-1875

Yeh C-H, Lin M-H, Lin C-H, Yu C-E, Chen M-J (2019) Machine learning for long cycle maintenance prediction of wind turbine. Sensors 19(7): 1671. https://doi.org/10.3390/s19071671

Yeter B, Garbatov Y (2022) Structural integrity assessment of fixed support structures for offshore wind turbines: A review. Ocean Engineering 244: 110271 https://doi.org/10.1016/j.oceaneng.2021.110271

Yeter B, Garbatov Y, Guedes Soares C (2021) Structural health monitoring data analysis for ageing fixed offshore wind turbines structures, OMAE2021-63007. Proceedings of the 40th International Conference on Ocean, Offshore and Arctic Engineering, OMAE21

Yeter B, Garbatov Y, Guedes Soares C (2014a) Spectral fatigue assessment of an offshore wind turbine structure under wave and wind loading. Developments in Maritime Transportation and Exploitation of Sea Resources 1: 425-433

Yeter B, Garbatov Y, Guedes Soares C (2014b) Fatigue damage analysis of a fixed offshore wind turbine supporting structure. Developments in Maritime Transportation and Exploitation of Sea Resources 1: 415-424

Yeter B, Garbatov Y, Guedes Soares C (2015a) Fatigue damage assessment of fi xed offshore wind turbine tripod support structures. Engineering Structures 101: 518-528. https://doi.org/10.1016/j.engstruct.2015.07.038

Yeter B, Garbatov Y, Guedes Soares C (2015b) Low cycle fatigue assessment of offshore wind turbine monopile supporting structure subjected to wave-induced loads. Towards Green Marine Technology and Transport, 287-294

Yeter B, Garbatov Y, Guedes Soares C (2015c) Fatigue crack growth analysis of a plate accounting for retardation effect. The Maritime Technology and Engineering, 585-594

Yeter B, Garbatov Y, Guedes Soares C (2015d) Assessment of the retardation of in-service cracks in offshore welded structures subjected to variable amplitude load. Renewable Energies Offshore, 855-863

Yeter B, Garbatov Y, Guedes Soares C (2015e) Fatigue reliability assessment of an offshore supporting structure. The Maritime Technology and Engineering, 671-680

Yeter B, Garbatov Y, Guedes Soares C (2015f) Fatigue reliability of an offshore wind turbine supporting structure accounting for inspection and repair. Analysis and Design of Marine Structures, 737-347

Yeter B, Garbatov Y, Guedes Soares C (2016a) Evaluation of fatigue damage models predictions for fixed offshore wind turbine support structures. International Journal of Fatigue 87: 71-80. https://doi.org/10.1016/j.ijfatigue.2016.01.007

Yeter B, Garbatov Y, Guedes Soares C (2016b) Reliability of Offshore Wind Turbine Support Structures Subjected to Extreme Wave-Induced Loads and Defects. Proceedings of the 35th International Conference on Ocean, Offshore and Arctic Engineering, OMAE16, V003T002A060

Yeter B, Garbatov Y, Guedes Soares C (2017a) System reliability of a jacket offshore wind turbine subjected to fatigue. Progress in the Analysis and Design of Marine Structures, 939-950

Yeter B, Garbatov Y, Guedes Soares C (2017b) Risk-based multi-objective optimisation of a monopile offshore wind turbine support structure, OMAE2017-61756. Proceedings of The 36th International Conference on Ocean, Offshore and Arctic Engineering, OMAE17

Yeter B, Garbatov Y, C. GS (2018) Failure assessment of transition piece of jacket offshore wind turbine. Progress in Maritime Technology and Engineering, 359-368

Yeter B, Garbatov Y, Guedes Soares C (2019a) Risk-based life-cycle assessment of offshore wind turbine support structures accounting for economic constraints. Structural Safety 81: 101867. https://doi.org/10.1016/j.strusafe.2019.06.001

Yeter B, Garbatov Y, Guedes Soares C (2019b) Ultimate strength assessment of jacket offshore wind turbine support structures subjected to progressive bending loading. Ships and Offshore Structures 14(2): 1-11. https://doi.org/10.1080/17445302.2018.1484030

Yeter B, Garbatov Y, Guedes Soares C (2020a) Strength assessment of jacket offshore wind turbine support structure accounting for rupture. Journal of Offshore Mechanics and Arctic Engineering 142(1): 011902. https://doi.org/10.1115/1.4044290

Yeter B, Garbatov Y, Guedes Soares C (2020b) Risk-based maintenance planning of offshore wind farms. Reliability Engineering and System Safety 202: 107062. https://doi.org/10.1016/j.ress.2020.107062

Yeter B, Garbatov Y (2021) Optimal Life Extension Management of Offshore Wind Farms Based on the Modern Portfolio Theory. Oceans 2(3): 566-582. https://doi.org/10.3390/oceans2030032

Yeter B, Garbatov Y, Guedes Soares C (2022a) Life-extension classification of offshore wind assets using unsupervised machine learning. Reliability Engineering & System Safety 219: 108229. https://doi.org/10.1016/j.ress.2021.108229

Yeter B, Garbatov Y, Guedes Soares C (2022b) Analysis of Life Extension Performance Metrics for Optimal Management of Offshore Wind Assets. Journal of Offshore Mechanics and Arctic Engineering 144(5). https://doi.org/10.1115/1.4054708

Yeter B, Garbatov Y, Guedes Soares C (2022c) Optimal management of offshore wind assets at different stages of life extension accounting for uncertainty propagation. Proceedings of the 41th International Conference on Ocean, Offshore and Arctic Engineering, OMAE22, Hamburg

Zhang W, Bao Z, Jiang S, He J (2016) An artificial neural network-based algorithm for evaluation of fatigue crack propagation considering nonlinear damage accumulation. Materials 9(6): 483. https://doi.org/10.3390/ma9060483

Zhao W, Baker MJ (1992) On the probability density function of rainfow stress range for statonary gaussian processes. International Journal of Fatigue 14(2): 121-135. https://doi.org/10.1016/0142-1123(92)90088-T

Ziegler L, Gonzalez E, Rubert T, Smolka U, Melero JJ (2018) Lifetime extension of onshore wind turbines: A review covering Germany, Spain, Denmark, and the UK. Renewable and Sustainable Energy Reviews 82: 1261-1271. https://doi.org/10.1016/j.rser.2017.09.100

Ziegler L, Schafhirt S, Scheu M, Muskulus M (2016) Effect of load sequence and weather seasonality on fatigue crack growth for monopile-based offshore wind turbines. Energy Procedia 94: 115-123. https://doi.org/10.1016/j.egypro.2016.09.204