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Review article

Digital tools for floating offshore wind turbines (FOWT): A state of the art

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A B S T R A C T

Operations and installation on offshore wind and especially floating are complex and difficult actions due to site accessibility and equipment availability. In this regard, digitalization is disrupting the wind section thanks to the development of advanced sensors, automated equipment, computational power, among other. All these allow to optimize and simplify different parts of the offshore wind power plant development (i.e. design, planning, installation, O&M, etc.). This fact is of special interest on maintenance, since the early detection of failures or malfunctions lead to reduced costly corrective maintenance. This paper presents a literature review of current state-of-the-art on the application of digitalization activities which can be applied for floating wind, including typical component failures, monitoring techniques and advanced digital tools as Digital Twin concept and Building Information Models (BIM). Finally, the review paper provides an analysis of existing gaps, needs and challenges of the sector to provide guides on research and innovation to foster offshore wind sector.

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1. Introduction

Floating offshore wind is a sector which is rapidly evolving aiming to become a key market player in the coming years as reinforced by the European Commission on their Offshore Renewable Energy Strategy published in 2020 (Comission, 2020). Currently, there are just a few floating wind farms in operation (e.g. Hywind, Kinkardine, etc.) which most of them are pilots; however new projects are planned worldwide (Umoh and Lemon, 2020).

Due to its floating nature, FOWT presents new and additional dynamics to bottom fixed offshore wind turbines due to hydrodynamic and aerodynamic motions which have an impact on wind turbine accelerations and generation Proskovics et al. (2013).

From the economic perspective, the cost of wind energy is quite different depending on its location and technology required being onshore the cheapest (45-87€/MWh), bottom-fixed offshore (67-110€/MWh) and floating (above 150€/MWh) (Blanco, 2009). As presented before, floating wind is gaining attention. In this regard and focusing on both offshore concepts, the cost breakdown can be seen in Fig. 1.

Also, due to the extreme sea conditions, reduced site access and higher cost of transport, there is increased difficulty to perform site operations (commissioning and decommissioning, O&M, etc.). Particularly, these difficulties include reduced time windows to carry out maintenance activities. For this reason, the down times in case of failed components can be much higher than in the case of an onshore wind turbine. Having increased knowledge regarding the state of health of the wind farm as a whole and its components and detecting failures at an early stage, through online continuous monitoring is very important, because any small failure may lead to large amount of energy and money loss. The system failure may be prevented and the down time reduced by scheduling the maintenance earlier. For this reason, there is an increased need in the development of Digital Twins (Sivalingam et al., 2018; Blanco, 2009; Kim et al., 2019; Kim and Kim, 2015, 2016; Tong, 1998; Santos et al., 2016; Umoh and Lemon, 2020) based on artificial intelligence tools for predictive maintenance, data obtained from additional sensors for monitoring in real-time as well as BIM for increased control and uncertainty reduction during the whole commissioning, design, etc. process.

There are different types of floating foundations (Fig. 2). The typical floating foundations can be categorized by the following four classes: spar class (e.g. Hywind Scotland Pilot Park), semisubmersible class (e.g. Windfloat EDP (2018)), TLP (Tension Leg Platform) class (e.g. Pelastar Beattie, 2019) and barge class (e.g. Saitec Saitec, 2019) (Enterprise, 2021; Umoh and Lemon, 2020; Henderson et al., 2010).

Fig. 3 shows the number of installed units by concept category. It also shows that the spar-buoy and semi-submersible types are the most popular.

The platforms that are more stable can be towed into port for long-term maintenance. They have lower maintenance and installation costs compared to the TLP and spar-buoy systems that are more difficult to float back to shore (Butterfield et al., 2007).

Details about the wind farms components and their typical failures are presented in the next section.

The research performed in this paper presents the current status of digitalization for floating wind systems. The work has provided an overview of different technologies (sensors) and methodologies (processes) that may help to increase the whole efficiency of the operation and maintenance of floating wind; thus, reducing its costs. The paper has also provided some review of typical failure rates of different components in order to ensure proper technology prioritization in order to minimize its risk and increase system reliability. In addition, advanced digital techniques as DigitalTwin and BIM has been presented as potential drivers of a successful and advanced digitalization of floating wind, including advanced modelling, data acquisition, data treatment, operation and increased knowledge. In addition, the paper has identified the current challenges, research gaps and has provided recommendations for proper research lines.

Table 1
Critical components ranked by risk priority number as based on (Sivalingam et al., 2018).

Assembly	Risk Priority Number (RPN)
Frequency converter	38.3
Pitch	33.9
Yaw system	30.8
GearBox	30.1
Nacelle auxiliaries	29
Control & Comm. systems	28.1
Generator	27.6
Main shaft set	27
Tower	26
Power electrical system	25
Foundation	24.6
Cable	24
Blade	21
Hydraulic system	18
Auxiliary electrical system	17.8
Transition piece	17.3
Nacelle structure	16
Hub	12

2. Typical failures of an offshore wind farm

Due to the reduced periods to perform O&M activities in offshore locations, it is of relevance to identify the most critical elements/components (the systems more likely to fail) of wind turbines and other elements on the whole wind farm installed offshore. In this regard, the analysis of typical failures is provided in this section as well as monitoring technologies and techniques are explained later on.

In this regard, it is worth noting that there is clear gap on existing/available data regarding failures on offshore wind and even less for floating. Thus, in order to provide good and valuable information inputs from different references and technologies including onshore cases are considered.

In Fig. 4, the annual failure rates and corresponding down times for offshore wind turbines are provided. From the figure, it can be seen how certain components have larger failure rates, although they are easier to repair/substitute; and others present a low failure rate but the required time to solve the issue is larger (up to 8 days) and represent critical elements leading to large energy losses. Thus, early detection is required and of great value (Rolfes et al., 2014).

Table 1 shows the components of a floating offshore wind turbine that are most prone to failure. The most critical one is the frequency or power converter, which also has an important impact on power generation, making it a relevant element to consider and monitor.

Other critical components are the pitch and hydraulic systems, which make up approximately 13% of the overall failure rate, as determined by Carroll et al. (2016) The authors made an analysis on approximately 350 offshore wind turbines located in

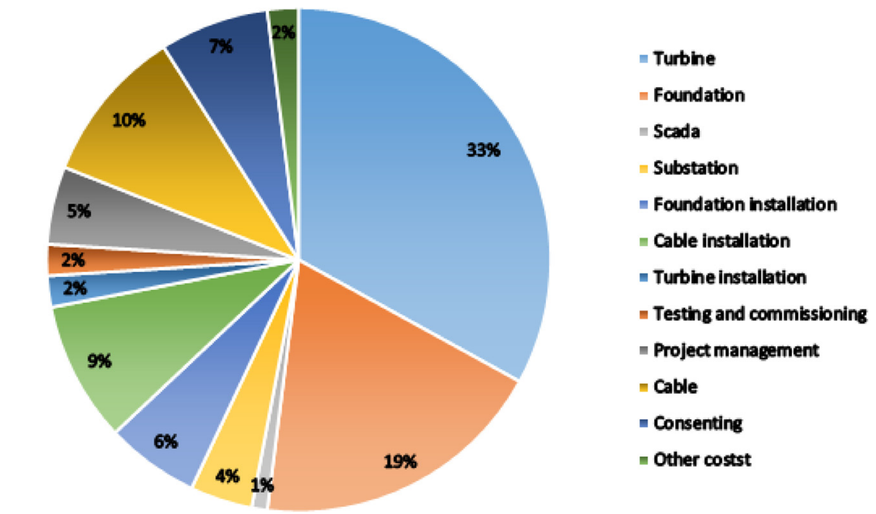

Fig. 1. Estimate of capital cost breakdown for an offshore wind farm as based on Blanco (2009).

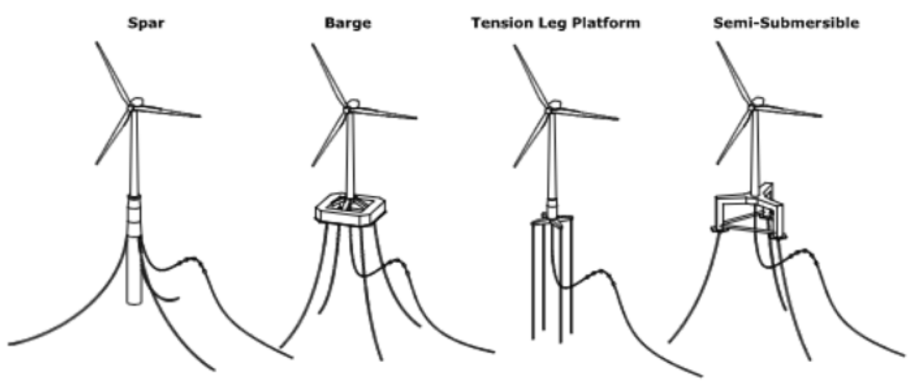

Fig. 2. Illustration of various categories of floating foundation Scheu et al. (2018).

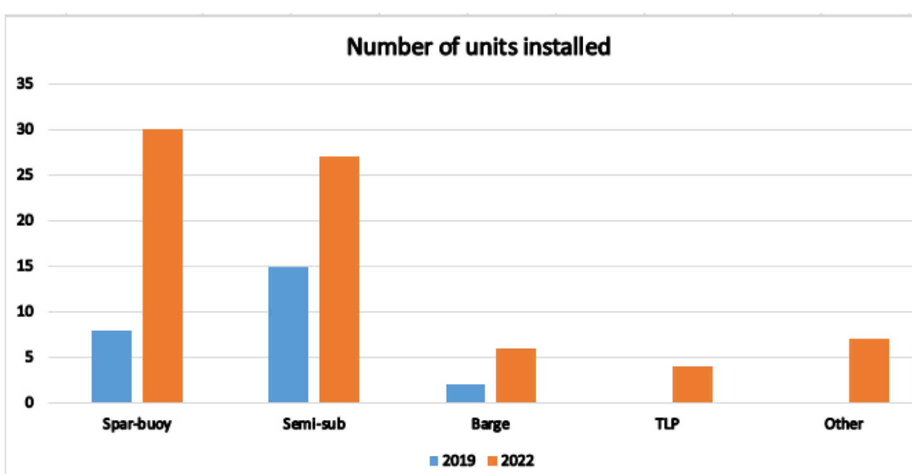

Fig. 3. Installed and expected number of units by concept category as based on Enterprise (2021).

Europe and provided failure rates for the wind turbine and its components. It has been determined that the average failure rate for an offshore wind farm is 8.3 failures per turbine per year, out of which 6.2 are minor repairs, 1.1 major repairs and 0.3 major replacements.

However, it is required to keep in mind that floating wind is quite different from onshore and bottom-fixed technologies, not from the wind turbine perspective but from the support, connection, foundations, etc. In this regard, the FOWT consists of 5 systems: the support system, pitch system, gearbox, generator, and auxiliary system (Fig. 5) (Li et al., 2020).

Details on floating wind turbine's components, typical failures and the sensors used for monitoring are briefly presented in the following.

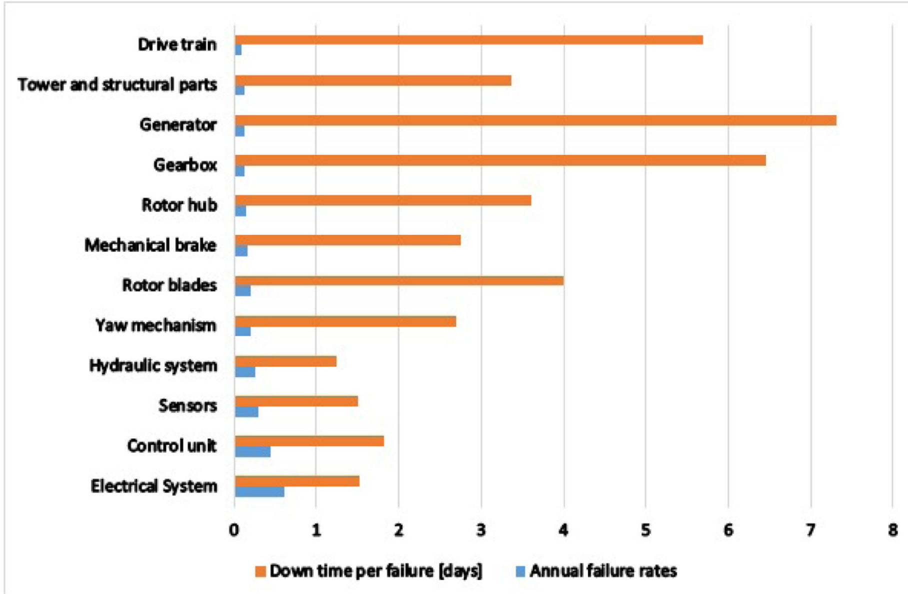

Fig. 4. Annual failure rates of offshore wind turbine parts and corresponding down time (in days) as based on Rolfes et al. (2014).

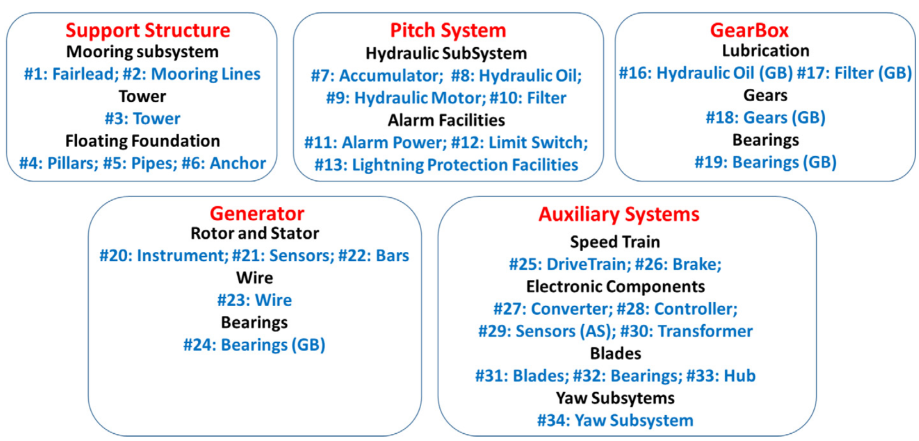

Fig. 5. The structure of FOWT (GB: Gearbox; GE: Generator; AS: Auxiliary system) as based on Li et al. (2020).

The support system of FOWT consists of a tower, cabin, floating foundation and mooring system. The mooring subsystem and the floating foundation provide stable buoyancy for the upper structures. The main causes of the support structure failure are fatigue, corrosion, welding cracking and hull collision. At extreme sea conditions, the floating foundation, the mooring lines and the tower vibrate intensely which can cause severe accidents like tower fracture, mooring system failure and blades damage (Kang et al., 2017; Li et al., 2020; Kang et al., 2019; Tillenburg, 2021).

Mooring lines. Mooring lines connect a floating structure to its anchor on the seabed. They are made of different material combinations such as wire, fibre ropes and steel chains. There are different types of mooring systems, as the catenary based, taut-leg and semi-taut (Enterprise, 2021).

The offshore floating wind sector is still immature, therefore information about mooring failure and its consequences is not wide enough. From oil and gas experience, Ma et al. (2013) calculated a failure rate about 0.03 obtained from 300 permanent moorings during 10 years. From the results obtained by Fontaine et al. (2014), 0.2 fails per platform during its life span can be expected.

Anchors. Anchors have the role of securing the mooring system to the seabed (Fig. 6).

Fig. 7 shows the prevalent failure modes of mooring systems. It can be seen that tension is attributed to only 1% of failures while fatigue is responsible for 24% (Enterprise, 2021).

The most common mechanisms that contribute to mooring line failure are detailed below (Intermoor, 2016; Pham et al., 2019; Decurey et al., 2020):

- Fatigue damage - can be due to the repetitive axial and bending stress;
- Corrosion - due to the contact of the material with the surrounding environment, chemical reactions, bio-colonization (aggregates of marine organisms like seaweed and mussels on mooring lines) can occur; this can lead to corrosion and as a consequence, to the constant reduction of diameter of chain links, material loss and modified mooring responses. The corrosion observed in the catenary mooring lines of a meteocean buoy operated at the Ecole Centrale Nantes/SEM-REV sea test site is illustrated in Fig. 8 and the marine species colonization in Fig. 9. The colonization of mussels on a mooring chain can be seen in Fig. 10.

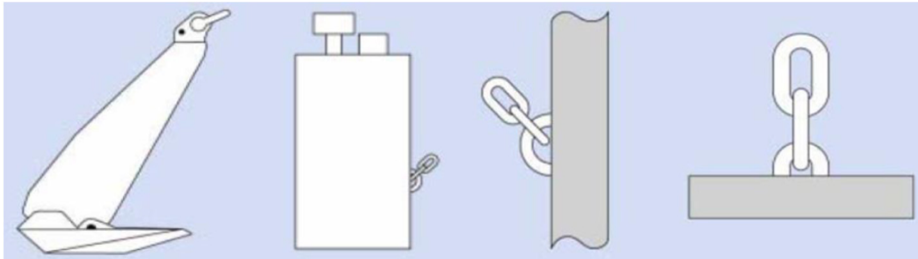

Fig. 6. Selection of anchors typically used in offshore energy projects. From the left; Drag-embedded, driven pile, suction and gravity anchor (James and Ros, 2015).

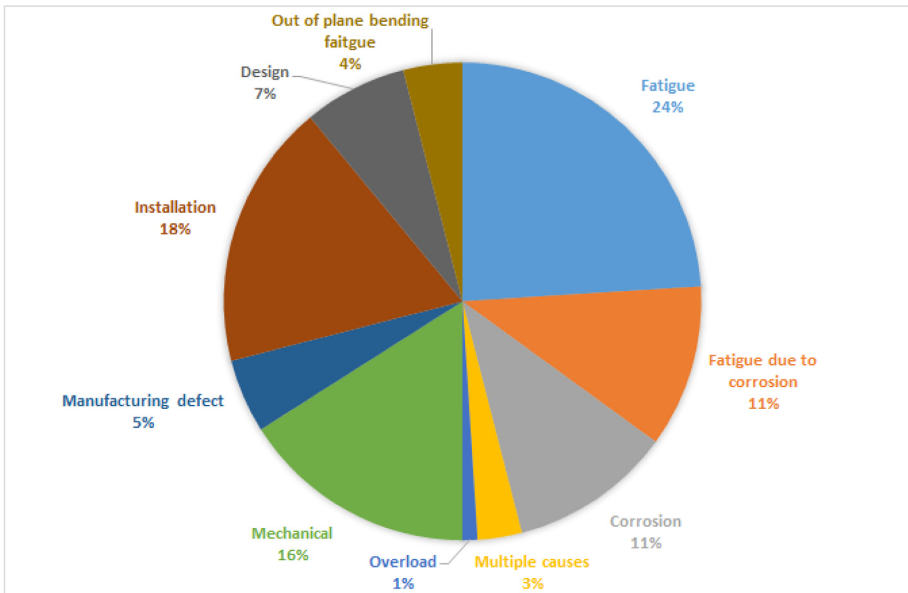

Fig. 7. Pie chart of prevalent failure modes in mooring systems as based on Enterprise (2021).

Fig. 8. Corrosion observed in catenary mooring lines for FOWT (Pham et al., 2019).

- Mechanical damage - can occur during installation or inspection operations and can lead to mooring lines damage;
- Excessive tension - the more severe environmental conditions like storms and hurricanes, can lead to excessive tension in the mooring lines.

The mooring lines can be monitored with underwater cameras, and by measuring the mooring line tension, diameter and frequency response (Butterfield et al., 2007; Decurey et al., 2020).

2.1. The yaw and pitch system

The yaw and pitch system turns the blade or part of the blade, adjusting it according to the angle of attack of the wind. The yaw subsystem is designed for turning the rotor directly facing the wind. The failure of the yaw and pitch control system represents one of the main causes for blades failure. Also, the hydraulic system failure, hydraulic oil failure, lightning protection failure, limit switch failure, oil leakage and overpressure can lead to the

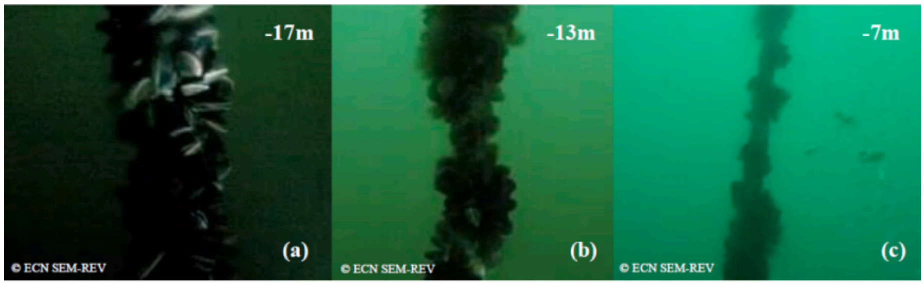

Fig. 9. Marine species colonization on mooring lines for FOWT (Pham et al., 2019).

Fig. 10. Colonization of mussels on a mooring chain Decurey et al. (2020).

pitch system failure (Kang et al., 2017; Santos et al., 2016; Li et al., 2020).

2.2. The auxiliary system

The auxiliary system's components are the following: speed train, electrical components, lightning protection system, hydraulic system, cooling system. The electronic components (controllers, sensors, transformer, etc.) ensure the efficiency of the energy production. The electronic components failure represent 61% of the auxiliary system failures (Kang et al., 2017; Li et al., 2020; Kang et al., 2019).

2.3. The power converter

The Power Converter, which is usually working on a back-to-back configuration, is a critical element on wind turbine systems, since it is the responsible of controlling and managing the electric power generated. It is worth noting that the most common failure occurs on the active switching component (e.g.IGBTs, Insulated Gate Bipolar Transistors); this failure may come due to electrical overloading which translates to thermal issues. In addition, it must be pointed out that the impact of the failure of the converter can vary depending on the wind turbine technology applied (e.g. DFIG, PMSG,etc.). However, in offshore locations the technology typically applied is permanent magnets synchronous generation which implies a full-rated converter. This means that if the converter fails all generation is lost. Some failure rates on power converters are illustrated in Fig. 11. Fig. 12 shows the diagram of a power converter and IGBT structural cross section view. In both onshore and offshore environment, wind speed and temperature variation lead to overload on the power converter, and consequently, to high failure rates. The main cause is the thermal driven failure due to the different coefficients of thermal expansion of adjacent materials layers in the IGBT during thermal cycles (Sivalingam et al., 2018). The onshore vs offshore converter failure rates are illustrated in Fig. 11.

2.4. Generator

The generator is the electrical machine responsible for transforming the mechanical energy into electrical energy. The generator faults can have electrical (open-circuits, short-circuit, etc.) or mechanical (due to corrosion and dirt) causes (Kang et al., 2017; Santos et al., 2016; Li et al., 2020; Tillenburg, 2021).

Fig. 13 shows a comparison between the failure rates of an onshore and offshore generator. The higher failure rate for offshore wind turbines could be due to higher average wind speeds in offshore sites.

2.5. Gearbox

The gearbox is a mechanical device that increases/decreases the torque by increasing/decreasing the speed. Not all wind turbines have a gearbox. The gearbox failures are usually caused by bearings failure (mainly due to corrosion), gears failure and lubrication failure, while the gears failure are caused by abnormal vibration (Li et al., 2020; Ghane et al., 2016).

3. Sensors for monitoring

There are different monitoring techniques used for different components of the turbine: condition monitoring (CM) which is performed on rotating machinery and electrical components ($f<50$ Hz); Structural health monitoring (SHM) is performed on the support structure and blades and it can be divided into global (vibration-based) monitoring and local monitoring of specific wind turbine parts ($f<5$ Hz); SCADA (supervisory control and data acquisition) ensures the monitoring of environmental and

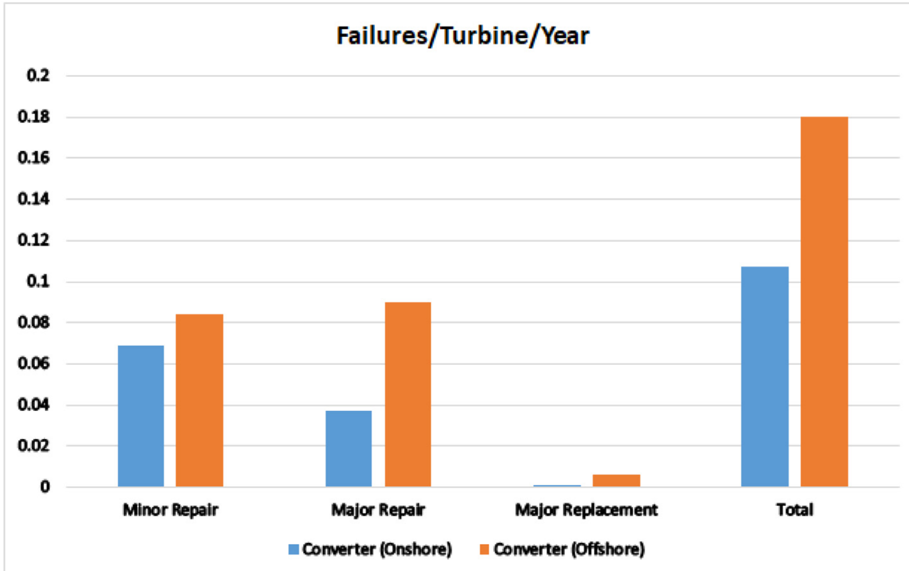

Fig. 11. Onshore vs. offshore converter failure rates as based on Carroll et al. (2016).

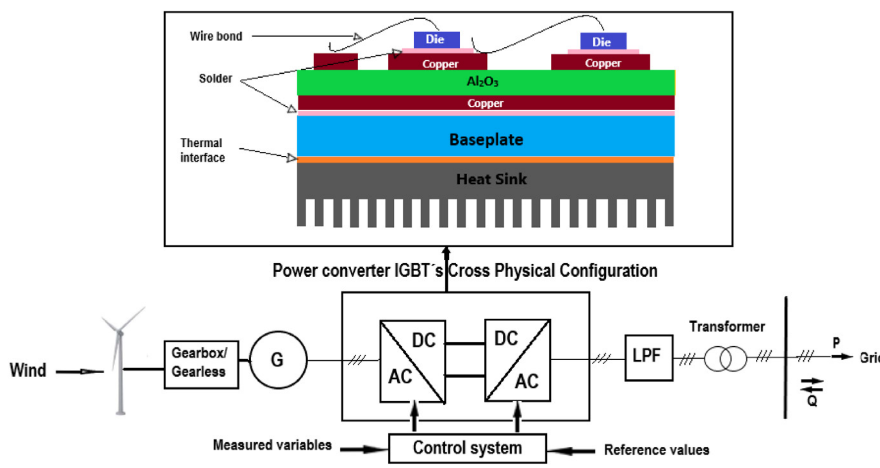

Fig. 12. Schematic diagram of full scale power converter and IGBT structural cross section view as based on Sivalingam et al. (2018).

operational conditions (f<0.002 Hz). Electrical system monitoring, rotating machine monitoring, and blade and pitch monitoring is performed with accelerometers, proximeters and by analysing the particles in oil (Rolfes et al., 2014).

In Kim et al. (2019) a structural health monitoring for floating offshore wind turbines is suggested and tested using operational modal analysis (OMA) with numerical-sensor signals. The numerical sensor signals are simulated using a time-domain turbine-floater-mooring fully-coupled dynamic simulation computer program. The operational modal analysis is a method which consists of analysing the sensors signals responses of the tower or blade. The magnitude of the difference in modal characteristics between intact and damaged conditions shows how big the structural damages are Di Lorenzo et al. (2016).

Di Lorenzo et al. (2016) detected blade damage by using the vibration-based SHM.

In Li et al. (2012) Middlegrunden and Horns Rev offshore wind farms in Denmark were simulated as case studies using an underwater network simulation tool.

Some of the most known structural damage causes are: moisture absorption, fatigue, wind gusts, thermal stress, corrosion, fire and lightning strikes (Martinez-Luengo et al., 2016).

3.1. Vibration based damage detection

Vibration analysis is a monitoring technique that can early detect failures in mechanical components. Any changes to the natural frequency of a structure could indicate changes of its characteristics or geometry. For this reason, by analysing the Eigen-frequency, mode-shapes and modal curvature important information about the structural integrity of the wind turbine can be obtained. It is applied to wind turbine components like shafts, bearings, gearboxes and blades. High frequency local modes could indicate the small damages and the global modes characterize large damages and structural changes (Li et al., 2012; Rolfes et al., 2014; Santos et al., 2016; Kolios et al., 2021). Often this method has to be supplemented by finite element analyses to locate and quantify the damage. The sensors required for vibration analysis are accelerometers, piezoelectric sensors, or microelectromechanical systems (MEMS). When a component presents a local defect, this will generate a pulse of very short duration. This pulse produces vibration and noise which can be monitored (Rolfes et al., 2014; Tandon and Choudhury, 1999).

Fig. 14 shows the measurement setup of a bearing in a wind turbine gearbox.

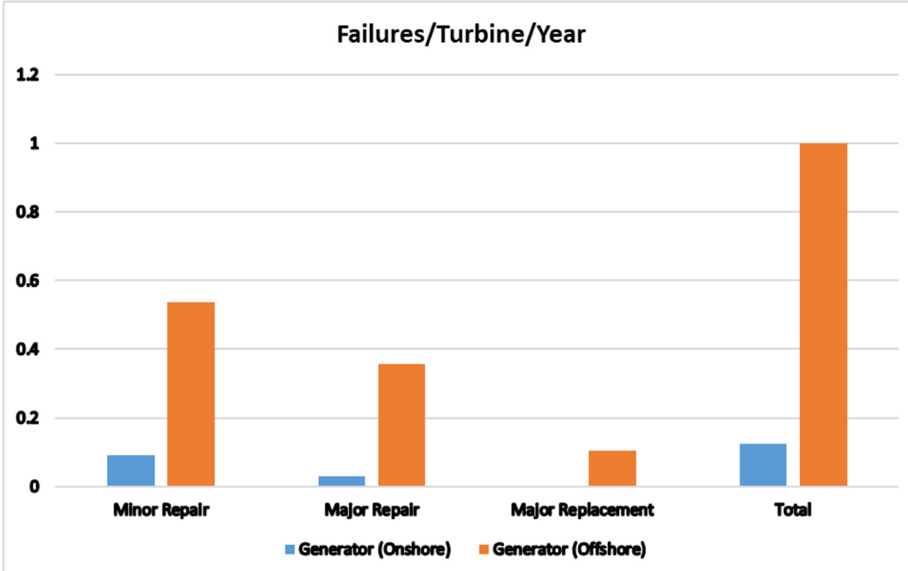

Fig. 13. Onshore vs. offshore generator failure rates as based on Carroll et al. (2016).

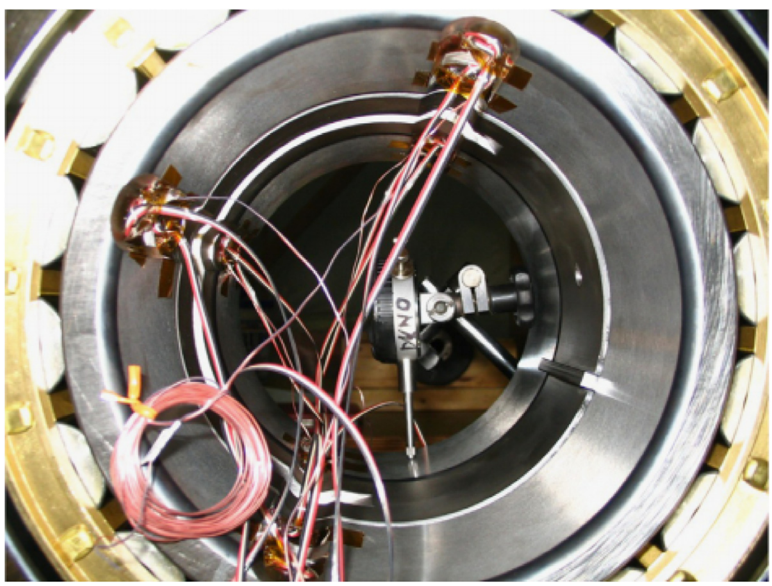

Fig. 14. Instrumentation of a gearbox bearing. Wymore et al. (2015).

In Tandon and Choudhury (1999) a review of vibration and acoustic measurement methods for the detection of defects in rolling element bearings is presented.

A single-mode vibration model has been developed by McFadden and Smith (1984) to explain the appearance of various spectral lines corresponding to different defect locations in the spectrum. Fig. 15 illustrates a typical spectrum obtained from a rolling element bearing with an inner race defect.

3.2. Acoustic emission

The acoustic emission (AE) technique is usually applied for fault detection in gearboxes, bearings, shafts and blades. By classifying the acoustic signals according to amplitude and energy, information about the type of damage can be obtained (such as cracking, excessive deformation, debonding, delamination, etc.). The acoustic emissions can be captured with piezoelectric sensors, which have high sensitivity, and many types of damage can be detected and located even before they become visible (<1 cm). Fatigue tests can also be monitored, as the sound produced due to energy dissipation can be captured using piezoelectric sensors (Li et al., 2012; Rolfes et al., 2014; Martinez-Luengo et al., 2016).

Gomez Munoz and Garcia Marquez (2016) collected acoustic emission signals applying macro-fibre composite (MFC) sensors to detect and locate cracks on the surface of the blades. The blade section with the placement of the sensors is illustrated in Fig. 16.

3.3. Oil analysis

Oil and valve issues represent about 30% of the overall pitch/hydraulic failures. Oil issues consist of failures like leaks, unscheduled oil changes and unscheduled oil top ups (Carroll et al., 2016).

Oil analysis typically involves the following main tests: viscosity analysis, oxidation analysis, water content or acid content

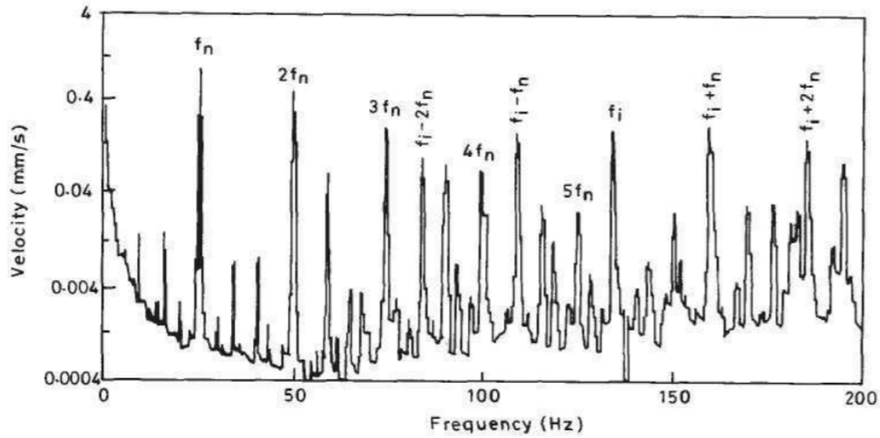

Fig. 15. A typical spectrum obtained from a rolling element bearing with an inner race defect (Tandon and Choudhury, 1999).

Fig. 16. Blade section with sensors for acoustic emission location Gomez Munoz and Garcia Marquez (2016).

analysis, particle count, machine wear, temperature. Oil monitoring has the purpose to measure the quality of the oil, which prevents damage from operation with poor quality oil, and also to measure the wear on the machinery. The presence of an excessive amount of particles can indicate failure or abnormal wear conditions. This type of detailed analysis is typically performed offline. Online real-time monitoring is more efficient for detecting failures that develop rapidly or when the accessibility is limited. Online detection technologies can be the following: electromagnetic sensing, flow or pressure drop and optical debris sensing. Internal gearbox failures can only be detected by oil analysis (Santos et al., 2016; Wymore et al., 2015).

3.4. Temperature measurement

Temperature measurement is used to detect potential failures through the changes in temperature for components like bearings, oil, generator windings, etc. Generally, temperature measurement is used along with other monitoring methods (Santos et al., 2016).

The thermal imaging method is used in detecting defects or anomalies in the material beneath the surface and is based on the subsurface's temperature gradients. By installing thermal cameras, damages to the material can be detected due to a change in the thermal diffusivity (Martinez-Luengo et al., 2016).

3.5. Strain measurement

Strain measurement is a technique used for SHM of blades and towers. The sensors used are typically foil strain gauges, fibre optical strain (FOS) gauges and LVDTs (Linear Variable Differential Transducers) that are placed in critical areas. The insensitivity of FOS gauges to lightning has led lately to an increase in their use (Li et al., 2012; Rolfes et al., 2014; Santos et al., 2016). LVDTs are reliable and accurate displacement sensors. They are robust and immune to the large magnetic fields surrounding the high voltage cables coiled in the foundation, but they are expensive (Kolios et al., 2021; Martinez-Luengo et al., 2016; Currie et al., 2015).

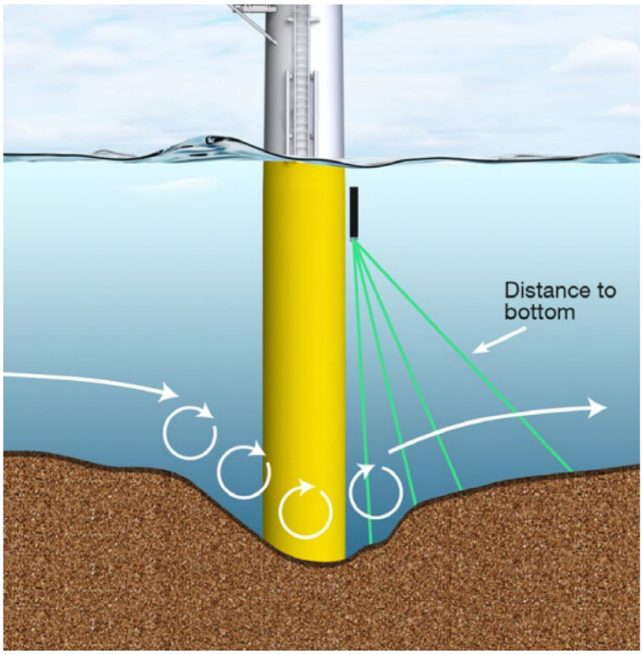

Fig. 17. Nortek scour monitoring system (Nortek, 2013).

Strainstall monitoring systems that are available on the market are consisting of strain gauges, displacement sensors and accelerometers placed between the monopole and transition piece to measure displacement and strain, and on the main tower to measure bending, torque and axial load (Kolios et al., 2021; Martinez-Luengo et al., 2016; Faulkner et al., 2012).

3.6. Optical fibre monitoring

Optical fibre monitoring is a technique that is used for the SHM of the wind turbines. The optical fibres can be placed on the surface or embedded into the components that are going to be monitored. This technique is expensive when compared to other monitoring methods (Santos et al., 2016).

3.7. Ultrasonic testing technique

Ultrasound is a method commonly used for the structural assessment of towers and blades and avoids sending ROVs (remotely operated vehicles) or divers on-site. The basic principle of this technique is that ultrasonic waves, emitted by a transmitter, pass through the tested material and are reflected by a flaw or anomaly. This signal is picked up by a receiver, if it was not reflected. The laminate and dry glass fibres and delamination can be checked below the surface with ultrasound scanning. There are different techniques for this analysis: pulse-echo, through transmission, and pitch-catch. An advantage of this method is that it detects cracks of just a few millimeters (Santos et al., 2016; Martinez-Luengo et al., 2016; Kolios et al., 2021).

Floating offshore wind turbines can be weakened by scour around their base. Scour holes are generated by storms or strong currents. This is more typical for fixed structures and less for floating structures. For this reason, Nortek developed an acoustic scour monitoring system that uses four narrow acoustic beams to detect the along-beam distance from the sensor to the seabed at four points away from the structure (Fig. 17) (Nortek, 2013; Kolios et al., 2021).

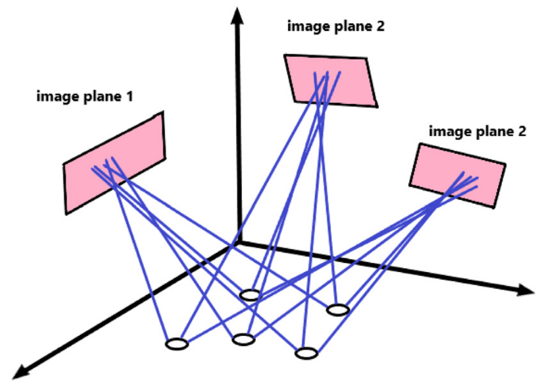

Fig. 18. Simultaneous process of 2D images taken from different locations as based on Ozbek et al. (2010).

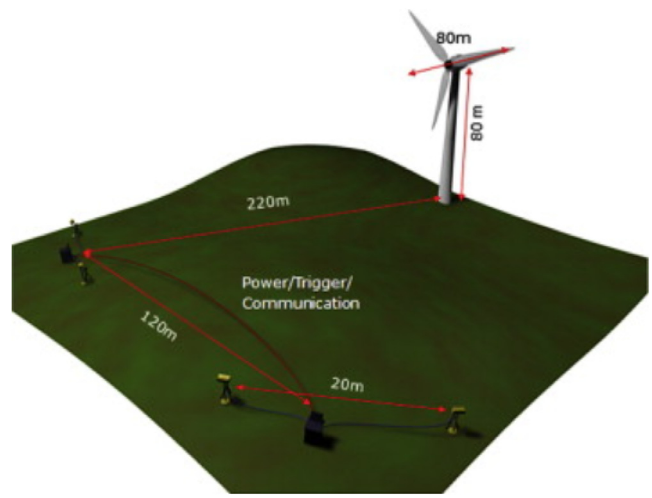

Fig. 19. The measurement setup and camera locations (Ozbek et al., 2010).

3.8. Photogrammetry

Nowadays there are cameras and diagnostic software available in the market for online monitoring.

Photogrammetry is a measurement technique where 3D coordinates or displacements of an object can be obtained by using the 2D images taken from different locations and orientations (Fig. 18) (Ozbek et al., 2010).

Ozbek et al. (2010) performed infield tests on a 2.5 MW - 80 m diameter - wind turbine using photogrammetry technique. The 3D dynamic response of the rotor was captured at 33 different locations simultaneously by using 4 CCD (charge coupled device) cameras while the turbine was rotating. Fig. 19 shows the measurement setup and camera locations.

By placing markers that are made up of retro-reflective materials on the wind turbine and having the camera systems follow the motion of these markers from different orientations, the 3D deformation vectors were constructed (Fig. 20).

3.9. Mooring system monitoring

From oil&gas experience we may conclude that mooring system monitoring may become an important issue to prevent costly O&M activities. Moreover, oil&gas experience on mooring system is very significant but not directly replicable in floating offshore wind. Uncertainties related with fatigue, corrosion-fatigue, snap loading or extreme events need to be understood in depth based

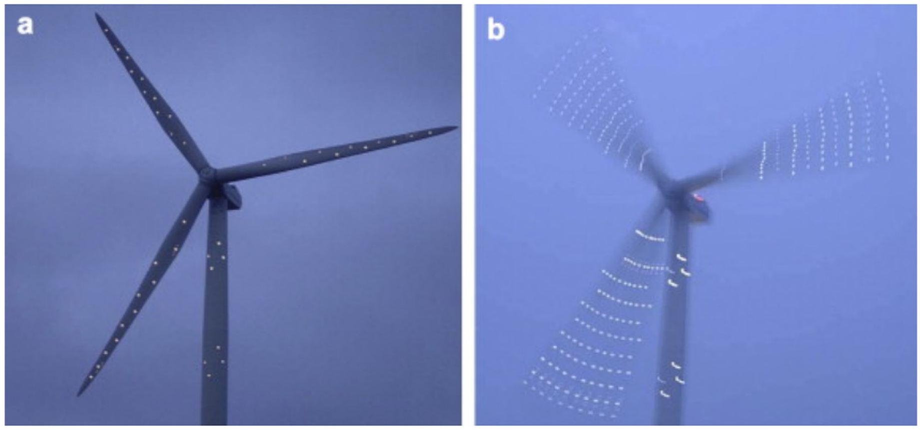

Fig. 20. The Layout of markers on the turbine (Ozbek et al., 2010).

Fig. 21. Idermar METEO Project - 100Tons Load cell (Guanche et al., 2011).

not only in laboratory and numerical data but also on field experience. Because of that monitoring of mooring lines is key to deep into the dynamics of those systems to reduce current and future risk failures, as well as to ensure mooring line integrity.

Mooring lines monitoring may be used for: (1) monitoring mooring line loads to deep into the mooring line dynamics and (2) breaking detection. The mooring loads monitoring may be conducted by direct measurements by means of load cells (Fig. 21) or load shackles (Fig. 22). These two types of gauges have been proven on under water activities and harsh environment (i.e. Hywind Scotland offshorewind.biz (2021)).

Both technical solutions share the same working principle. They include a strain gauge that measures changes in electrical resistance when forces induce some deformation over a specific piece. The main advantage of load cells is that it is a relatively simple and robust system, proved on marine environment, which provide accurate measurements. On the other hand, because it is direct measurement it needs to be included on the mooring system. Therefore, it must be compliant with the design requirements of the mooring system and the usually required high level standards.

Other measuring techniques have been derived directly from the shape of the mooring line detection. They are based on measuring the inclination of the mooring line close to the fairlead or at different locations of the mooring line (Wang et al., 2016) or by means of sonar techniques (Lugsdin, 2012). Both cases are indirect measurements which are mainly applicable to catenary mooring lines (quasi-static approach) and useful for mooring line integrity.

Real-Time movement measurements, by means of GPS systems, have been used quite often to evaluate potential mooring failures (Hageman et al., 2019). Abnormal changes of the offset of the floating offshore wind platform for a given environmental loads may highlight a potential failure of a mooring line. Based on time domain numerical models and more advanced systems including Neural networks or Artificial Intelligence systems. More recently activities have evidenced the capabilities of

Fig. 22. 75 Tons Load Shackle DOVICAIM Project (Meneses et al., 2018).

Artificial Neural Networks to predict mooring dynamics and more specifically mooring failure in floating structures (Kwon et al., 2020).

3.10. Platform movements monitoring

Monitoring the dynamics (i.e. position, velocities and accelerations) are crucial for floating offshore wind platforms. Nowadays, there is a significant availability of high-resolution geolocation systems (GNSS – Global Navigation Satellite systems) which show improved robustness and accuracy improvements (GSA, 2017), that can be combined with other kind of sensors (i.e. IMUs) for a better performance and increased output rate. Thanks to that, new group of services are being developed to increase reliability, improve the management of a wide variety of offshore assets, or to go beyond already existing alert systems.

GNSS technologies track and process the broadcasted signals in space by the different satellites' constellations. GNSS receivers determine the user position, velocity, and precise time (PVT) by processing the signals broadcasted by satellites. ESA (2018). Nowadays, there are four GNSS technologies available: GPS (USA), GLONASS (RF), BeiDou (PRC) and Galileo (EU). It is important to notice that a GNSS receiver operates at a low sampling rate with inferior accuracy and with a time delay from the communication and computation. The impact of low sampling rates and the time delay effects over slow dynamic systems is insignificant. Something which might be the case of the average positioning of moored structures. However, wave-induced motions over a wind turbine foundation is not a slow dynamic response. Part of the wave energy will be exciting natural periods, which in the case of pitch or heave motion of a typical floating offshore wind semi-sub are in the range of 20 to 30 s, but part of the energy will be exciting motions in the range of wave frequency (from 4 to 20 s). Therefore, the motion estimator must consider the receiver singularities (time delay, etc.) (Ren et al., 2019).

Apart from geolocation systems, Inertial Measurement Units (IMU), consisting of accelerometers and gyroscopes, are being used to estimate, not the position of the structure but the acceleration and/or tilts and headings of the device (Fossen, 2011).

Some examples can be found on the floating wind industry where coupled GNSS systems and IMUs have been used to analyse the positioning of a floating structure with the highest level of accuracy, like IDERMAR, Dovicaim and Saitec (Guanche et al., 2011).

The company ACORDE Technologies developed a motion measurement technology based on Novatel and OXTS technology (see Fig. 23). Based on it a motion compensation system was developed (Guanche et al., 2016) to evaluate linear velocity at the locations of the different anemometers along the met mast (see Fig. 24).

3.11. Conclusions

Both acoustic emissions analysis and strain measurement require a large number of sensors to localize damage. Another disadvantage is the background noise caused by a WT in operation which introduces difficulties to the signal processing and the association of the signals to damage types. The sensors for acoustic emissions are very cheap, while the optical fibre measurement is a more expensive monitoring method. Table 2 presents a summary of the most common monitoring methods for wind turbines and the sensors that are being used (Rolfes et al., 2014).

4. Digital twin

First, it is important to indicate that the concept digital twin is used by several people considering different meanings. The most common background on any of such definitions can be understood as a model-based representation of a real asset trained or developed using real-data. In this regard, this model can be used and trained with very different objectives (LeBlanc and Ferreira, 2020).

In Glaessgen and Stargel (2012), Glassgen and Stargel state that a DigitalTwin comprises 3 main parts: Real System, Virtual System and information sharing among the previous .

According to literature, to properly develop a Digital Twin, three steps must be followed (Gambhava and Gräfe, 2021):

- Data acquisition
- Model creation and/or model update/validation
- Real asset and model integration

Through such steps, an integrated-validated digital twin allowing comparison for both real time monitoring and offline planning can be properly created. In this regard, one of the main issues for such development is data availability (i.e. historical data); this is of special relevance for online monitoring and control, but to continuous model fitting for offline applications is not a critical issue, since it is being trained online.

Fig. 23. Idermar Metmast – GNSS Antenna (Novatel - system).

Fig. 24. Idermar position monitoring system.

Table 2
Monitoring methods and sensors (Rolfes et al., 2014; Yang et al., 2014).

Method	Sensors	WT components	Advantages	Disadvantages
Vibration analysis	Accelerometers, piezoelectric sensors (cheaper with high sensitivity), microelectromechanical systems (MEMS) - more expensive	Main shaft; main bearing; gearbox; nacelle; tower; foundation;	Indicates small damages, as well as large damages; the sensors can be very cheap with high sensitivity	Often this method has to be supplemented by FE method
Acoustic emissions	Piezoelectric sensors	Blade; main bearing; gearbox; generator; tower;	Damage can be detected and located before it becomes visible; fatigue tests can be performed with this technique;	Large number of sensors required; big number of outputs and cabling; the cost is high; appropriate for smaller structures;
Ultrasonic testing technique	Piezoelectric wafer; actuators/ transmitters and receivers (cheap, accurate and sensitive);	Tower; blades;	Can be used for SHM, as well as for detecting surface defects like delamination; detects cracks of just a few millimeters from long distance; the cost is low to medium	Damage localization is difficult;
Strain measurement	Typical foil strain gauges; FOS (insensitive to lightning); LVDTs (expensive and accurate);	Blades	The sensors are reliable and accurate; can be also used for mooring system monitoring	Detection of small damages is difficult; the cost is very high; requires a large number of sensors;
GNSS technologies	GNSS receivers	Platform	It is a useful method for monitoring platform movements	Is more accurate if used with IMUs;

An example of a model calibration is presented in Tygesen et al. (2018) and an example of model updating can be found in LeBlanc and Ferreira (2020). A series of tests were performed on a H-style vertical axis wind turbine in order to ensure the digital twin finite element models correctly match reality. Experimental Modal Analysis with impact testing was performed. It consists of

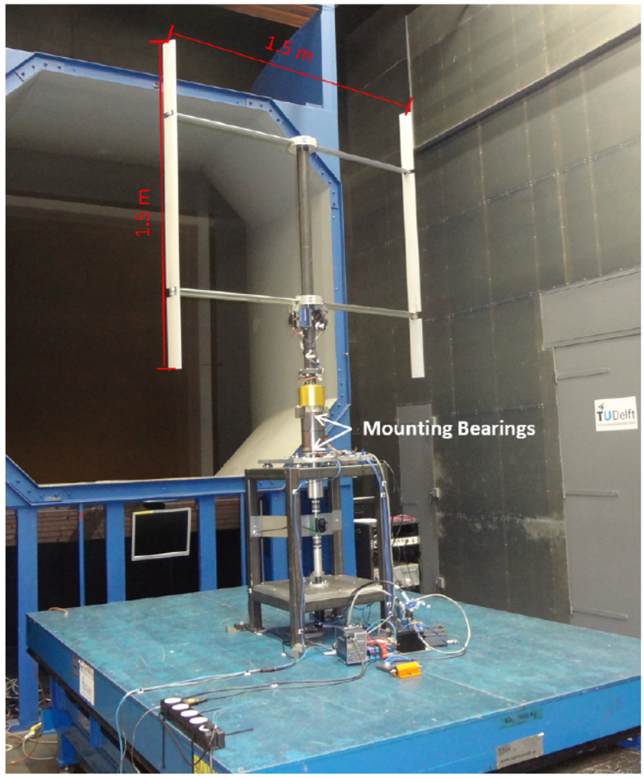

Fig. 25. Pitch vertical axis wind turbine (LeBlanc and Ferreira, 2020).

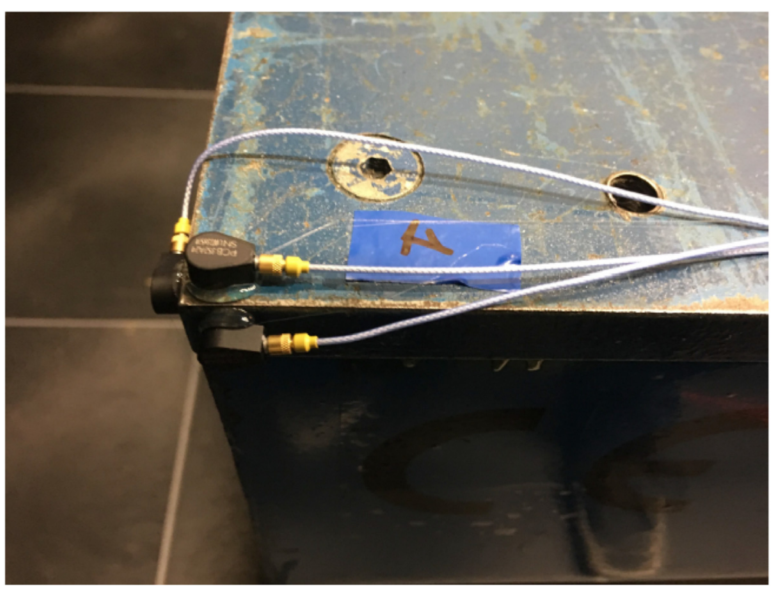

Fig. 26. Accelerometers on platform (LeBlanc and Ferreira, 2020).

measuring a series of excitation and response between degrees of freedom of the structure. Six accelerometers placed in the X, Y and Z directions of the corner of the platform and the X, Y and Z directions on the bottom of the first blade (Fig. 26) were used to measure the response of the structure and the frequency response function was obtained. The structure is presented in Fig. 25. A comparison between the synthesized FRFS and the measured one is illustrated in Fig. 27.

In Pimenta et al. (2020) a digital twin of an onshore wind turbine using monitoring data was developed. The bending moments on the tower section (on which strain gauges were placed 6.5 m above tower base) from both experimental and numerical data can be seen in Fig. 28.

Ramboll has developed its digital twin methodology to create a digital duplicate of offshore wind assets, called "True Digital Twin". Their approach consists in creating a digital copy of the real assets, which can be used to update the numerical model, visualize and monitor their condition Gambhava and Gräfe (2021).

Pargmann et al. (2018) developed a digital twin for wind farm monitoring by using cloud technologies, IoT (Internet of

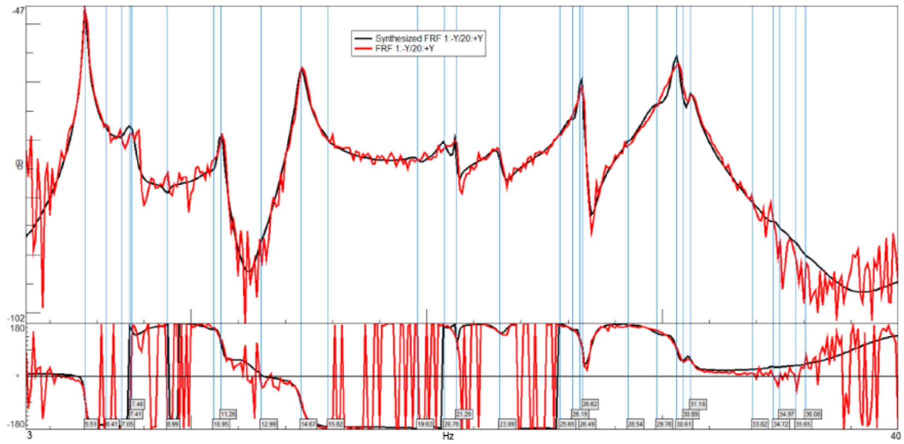

Fig. 27. Example of a synthesized FRF(black) with a measured FRF(red) from the fit mode shapes(blue vertical lines) (LeBlanc and Ferreira, 2020).

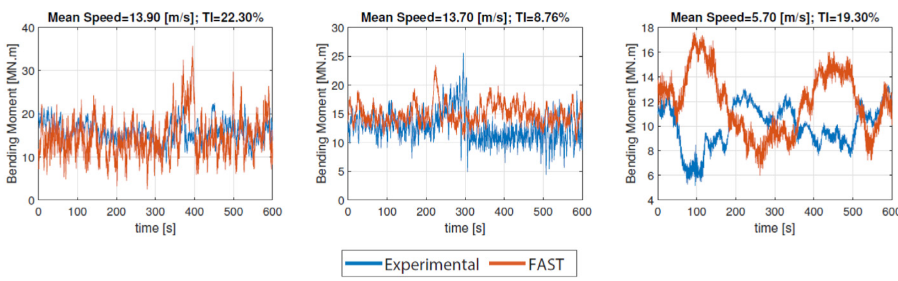

Fig. 28. Comparison between numerical and experimental bending moment (Pimenta et al., 2020).

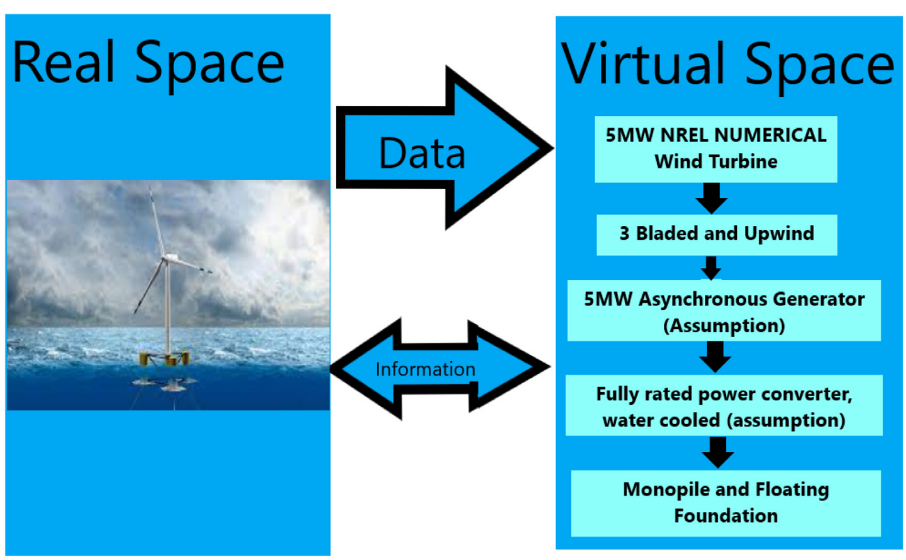

Fig. 29. 5MW Wind turbine configuration for fixed and floating application as based on Sivalingam et al. (2018).

Things) and a new user interface based on augmented reality. Wind turbines were equipped with various sensors which provided continuous data streams by continuously measuring parameters like wind speed, humidity, vibration or spindle temperature. Raspberry Pi - computers were implemented on each wind turbine to gather data streams from those sensors The data can be visualized for monitoring and analysis by using smart glasses.

Sivalingam et al. (2018) developed a digital twin of offshore fixed and floating wind turbine power converter by using 5MW NREL virtual wind turbine. Wind and ambient profiles were imported from SCADA data and loading profile was used in the Aero-Elastic-Servo-Control model (FAST) to generate torque and speed for the generator model input. The power loss was estimated from the SCADA data power values. Python was used to predict the junction temperatures of IGBTs and diodes together with junction temperature. Fig. 29 illustrates the 5MW NREL numerical turbine that was used in virtual space for digital twin technology framework.

Under the digital twin platform, virtual sensors have been used for locations in the structure without strain gauges. The virtual sensor details are shown in Fig. 30.

This methodology was successfully implemented to predict damage accumulation and RUL accurately for fixed and floating

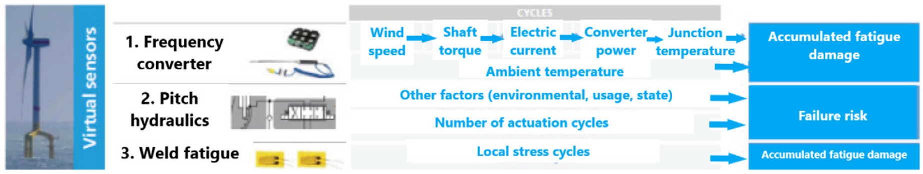

Fig. 30. Virtual sensor details in digital twin technology platform as based on Sivalingam et al. (2018).

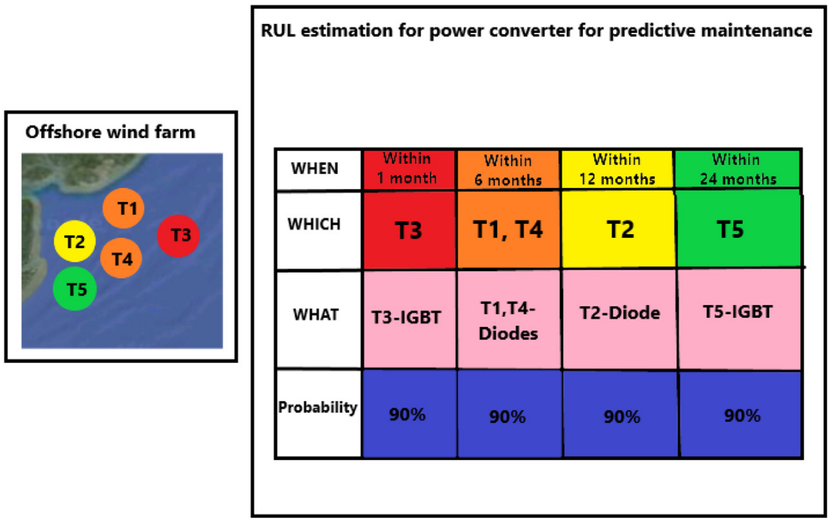

Fig. 31. Output for wind farm level case of power converter RUL module in digital twin platform for O&M strategy planning as based on Sivalingam et al. (2018).

offshore wind turbine power converter. Fig. 31 shows the output in digital wind platform.

Currently different researchers and companies have started to develop their own Digital Twins by taking advantage of Artificial Intelligence techniques, as Machine Learning or Deep Learning, with different main objectives. From the research perspective, the application of artificial intelligence techniques with main focus on fault-detection, operation and maintenance (Arcos Jiménez et al., 2020) and condition monitoring is gaining and attracting more interest in the last years. In Stetco et al. (2019), a review of machine learning techniques with focus on condition monitoring of wind turbines. The paper Helbing and Ritter (2018) presents a deep learning technique application for fault location of wind turbines, and Xiao et al. (2021), is specifically focused on power converter. However, very low research at the moment is provided for floating wind yet for these purposes (Kane, 2020).

From the industry perspective, General Electric has the so-called GE DigitalWindFarm, taking advantage of already existing data from the wind turbines to optimize the wind farm operation, such development has been patented (Tao et al., 2018; Lund et al., 2018a,b) and can be seen in Fig. 32 (Tao et al., 2018; Energy, 2016).

DNV-GL also has developed WindGemini which aims to evaluate wind turbine performance and state-of-health of components by estimating the remaining life and the failures, by using different measurements as temperatures and frequency analysis for structural health (GL, 2019). This can be seen in Fig. 33. Additionally, Siemens developed its own Digital Twin with the aim of enhancing planning, operation and maintenance of the power systems by using grid data and GIS information. This aims to ensure grid security and reliability (Siemens, 2017).

Building a digital twin for the floating offshore wind turbines could facilitate monitoring and diagnosis in real time from a longer distance. Besides the data obtained from the sensors, the wind turbine architectural-geometry data is also important for structural health monitoring. By creating a 3D model of the FOWT and modelling the sensors, the installed equipment and the components with Building Information Modelling technology (BIM), a better image about the wind turbine condition could be obtained.

5. Building information modelling (BIM)

BIM (Building Information Modelling) is a process for generating and operating the digital 3D model with additional information of a physical asset. BIM is widely applied in construction sector, since it allows to have a wider control and knowledge of the whole development from an early stage of the project. With the help of a set of software tools and processes, the digital representation of the physical and functional characteristics of a floating wind turbine can be created, although not yet typically implemented. In this regard, with the BIM methodology, a 3D model of an object, can also be a repository of project data. BIM combines technology, people and processes.

With the help of smart built environment(SBE) technology, which refers to built environment that has been embedded with smart objects, such as sensors and actuators, making the environment sufficiently "smart" to interact intelligently with, a 3D model of the floating wind turbines could be created in order to facilitate the monitoring and diagnosis processes. BIM also contains the following data: the physical information of smart objects, their hardware information and their installation locations (which can be documented and visualized in 3D).

BIM methodology can generate and maintain information produced during the whole lifecycle of a building project, from design to maintenance, in a centralized BIM model. BIM methodology can achieve different dimensions starting from 3D until high-complex, high-information 7D model (Sampaio, 2018). Also BIM application can be extended for the life cycle management of

Fig. 32. GE digital infrastructure of a 2MW (left) and a 3MW (right) wind farm (Energy, 2016).

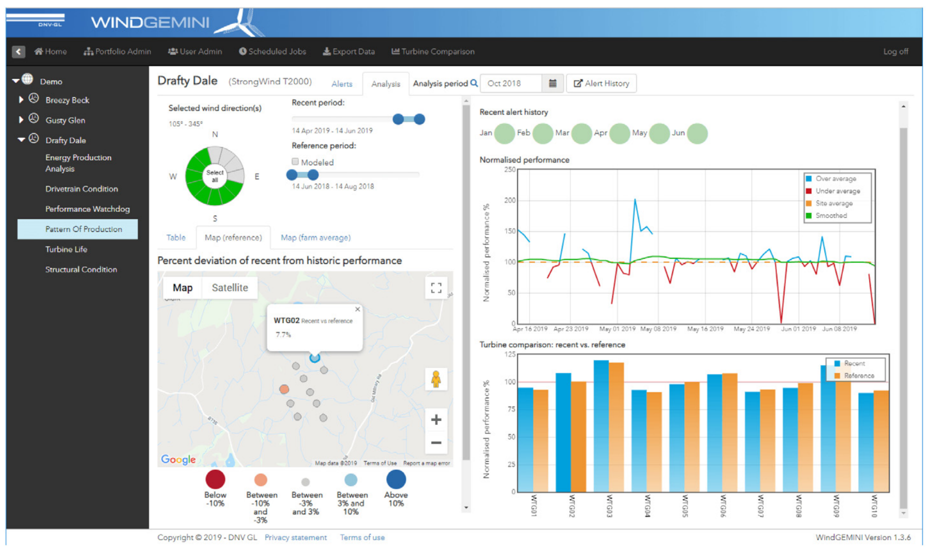

Fig. 33. Software interface for the digital twin for wind turbines from DNV GL (GL, 2019).

the offshore wind farm. It can be implemented from the beginning of the development phase until the decommissioning phase of an offshore wind farm. As previously indicated, BIM concept is being further developed by increasing the existing dimensions by providing additional information to complete all project needs. Such dimensions can be described as follows: 3D (integrated and models of all components), 4D (adding construction planning and control), 5D (including a cost evaluation of the whole project), 6D (the analysis of energy and sustainability indices), 7D (O&M operations and global management). It is worth noting that in the 7th dimension or in a new one, the information and details for information sharing and data acquisition from sensors are available. The most popular BIM software is the Revit suite from Autodesk and Archicad from Graphisoft. Autodesk research group integrated BIM with sensors and meters to provide 3D visualization of building performance and life-cycle operation. When conducting a building performance analysis, for example a floating offshore wind turbine, not only the information from sensors is important, but also the wind turbine nacelle&structure layout/geometry data (Zhang et al., 2015; Sampaio, 2018; Gambhava and Gräfe, 2021; Murphy, 2016).

The offshore wind industry needs to adopt advance BIM level & functionalities. Due to the complexity and duration of such a project, there are potential barriers that could impede the adoption of BIM, like timeline required to develop and execute an offshore wind project, the lack of information due to the competitive environment, contractual and legal constrains, etc. However, there are powerful examples of projects with similar challenges that have successfully adopted BIM (Murphy, 2016).

BIM model can be classified according to the level of detail it contains. There are three maturity levels, from level 0 to 3, that are illustrated in Fig. 34. Currently, the offshore wind industry is situated at Level 1.

Zhang et al. (2015) proposed a three-layer verification framework to assist BIM users in identifying possible defects in their SBE design. The produced BIM model was exported as an International Foundation Class (IFC) file, so that other BIM tools could share the information. The authors created an SBE design using Revit, which was modelled as a smart house with sensors, actuators, smart meters, PV panel and wind turbine.

The authors managed to perform energy management and analysis in BIM software using real-time data from the distributed energy resources, smart meters and sensors for a smart building. Fig. 35 shows an instance from a living room sensor displayed to the user.

In O'Shea and Murphy (2020) a method of integrating sensors to enhance the visualization of structural health monitoring through BIM is developed. The study describes how monitoring data can be integrated within the BIM of an offshore lighthouse. Its purpose was to identify how a proposed SHM system on an existing offshore structure can be represented in BIM format. The sensor monitoring includes vibration monitoring (with accelerometers and geophones), pressure monitoring (with a boroscope and pressure gauge, environmental monitoring (Lidar sensors and anemometers located on the helipad safety netting providing wind speed and direction) —including wave, tide, wind, air pressure and temperature. An in-situ measurement of incident wave height and water was performed. The sensors were modelled in Revit as illustrated in Fig. 36.

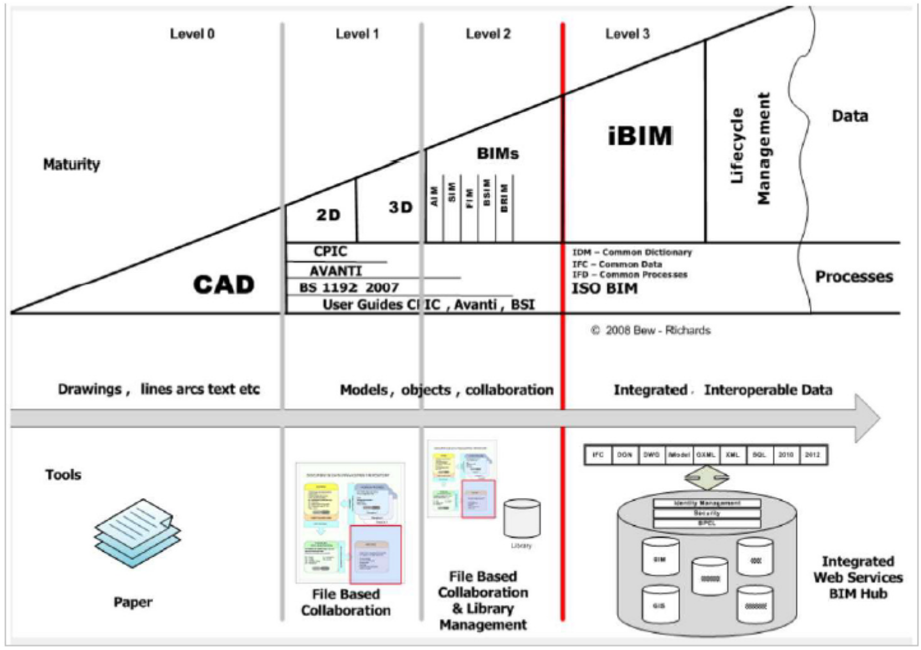

Fig. 34. Levels of BIM (Gambhava and Gräfe, 2021).

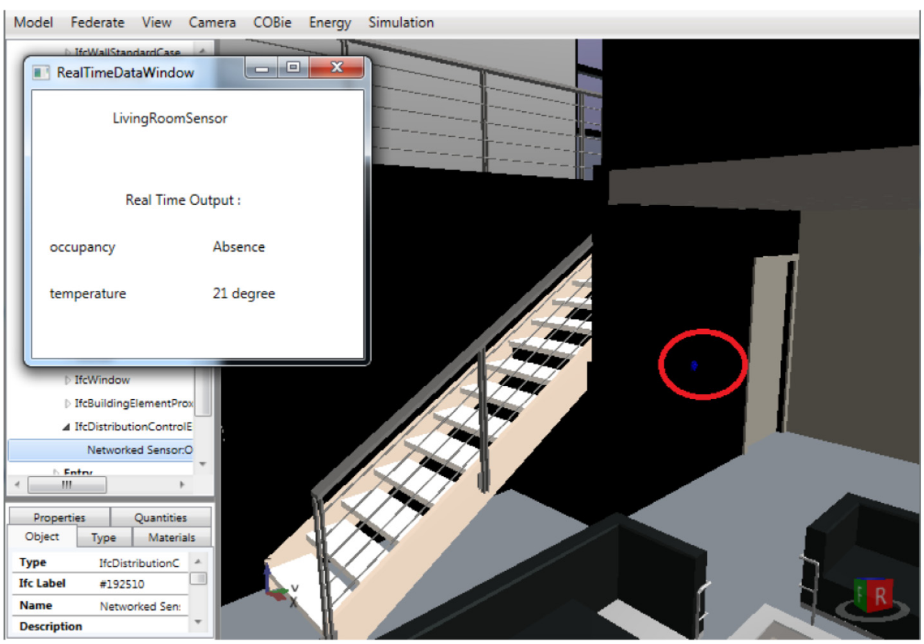

Fig. 35. Real-time monitoring data display to the user (Zhang et al., 2015).

An analysis of the light houses responses to large storms as predicted with sea level rise was simulated in finite element analysis (FEA) validated with data collection and visualized within BIM. Important information about the light house structural behaviour was extracted from the sensor data, like the natural frequency modes of the structure. The results of the analysis were compared to simulated frequency modes derived in FEA through the BIM environment.

Alvarez-Anton et al. (2016) developed a new design of a wind turbine tower by using BIM methodology/design approach. The "hybrid[2] towers" consist of four prefabricated quarter-circle-shaped concrete elements in the cross-section which are connected by a framework. A side view of the concrete tower is illustrated in Fig. 37.

RamView360 is a web-based BIM model visualization tool. It provides a 360-degree view from the specified viewing location (called annotation points) in the 3D environment. The tool uses the BIM method to represent the 3D model with overlaid technical information like the component information/KPIs. The BIM approach provides user-friendly navigation to visualize the specific overlayed information in the 3D virtual model (Figs. 38 and 39). This tool gives a wide range of functions to visualize the 3D model as per user requirements e.g. BIM visualizer, CFD simulation model, CAD model and point cloud model generated from LiDAR scanning. RamView360 uses 360-degree photos as input from detailed 3D modelling software or a point-cloud dataset from the LiDAR scanner to generate BIM model (Gambhava and Gräfe, 2021).

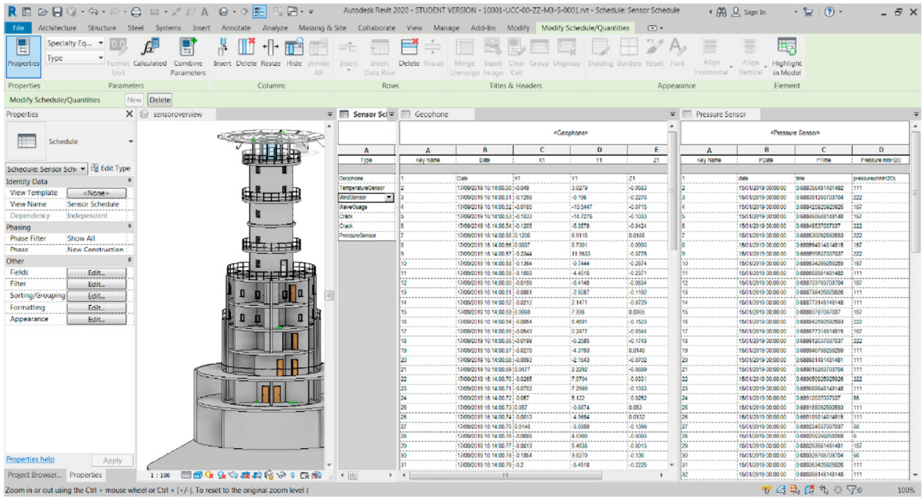

Fig. 36. Sensor data displayed within Revit (O'Shea and Murphy, 2020).

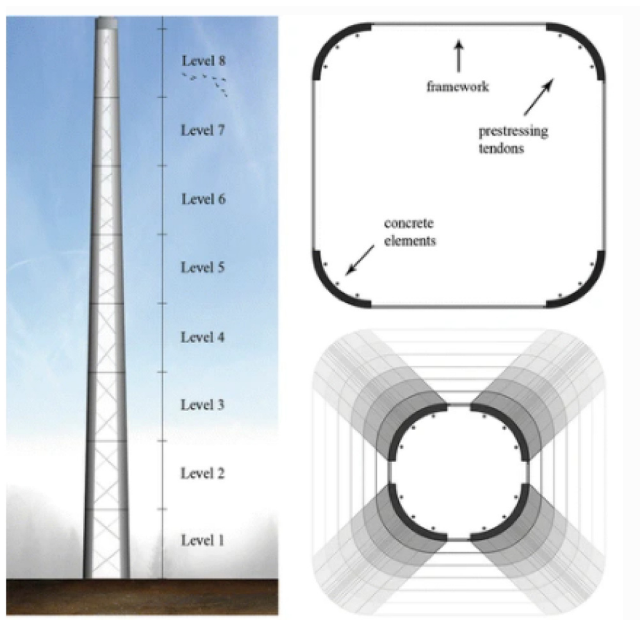

Fig. 37. Side-view of the tower (left); lower and upper cross-sections of the tower (right) (Alvarez-Anton et al., 2016).

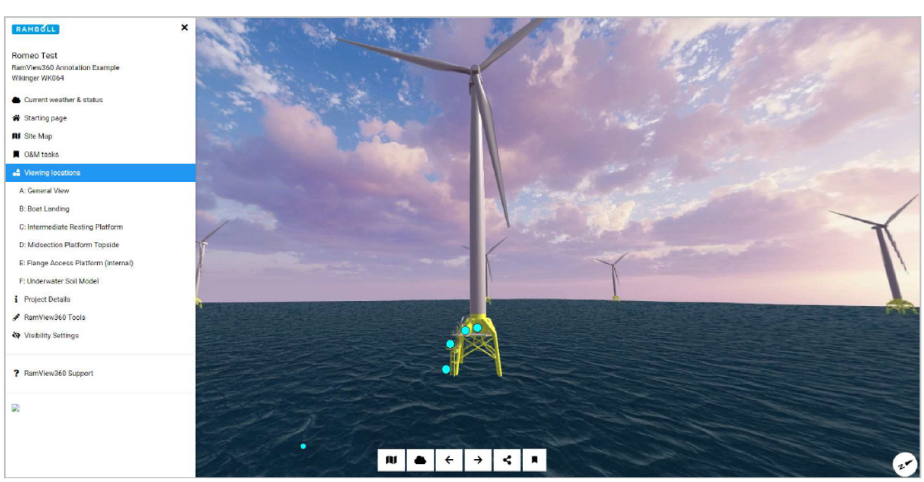

Fig. 38. RamView360 desk panel (Gambhava and Gräfe, 2021).

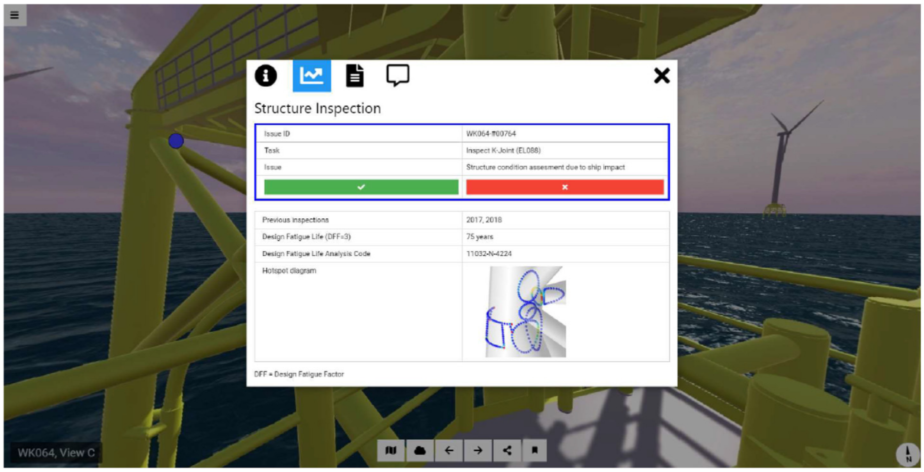

Fig. 39. Structure inspection example in RamView360 (Gambhava and Gräfe, 2021).

Even though several researchers have successfully applied BIM technology in obtaining digital representations of the physical and functional characteristics of buildings, there is a clear research gap in applying this technology for onshore and offshore wind turbines.

6. Research gaps and challenges

In this section, the key needs and challenges that floating wind development is facing are briefly summarized.

From the sensors point of view:

- Obtaining more accurate and quantitative data from working offshore wind turbines by using sensors that attenuate the interferences;
- Evaluate which sensors are the best for each component/part and purpose;

In order to develop a digital twin:

- Developing a reliable offshore wind turbine numerical model which can then be used to simulate the structure response and test alternative monitoring strategies algorithms for data processing, overcoming the lack of experimental data available for this type of structures;
- Development of condition monitoring systems towards intelligent machine health management, i.e. to intelligent software algorithms and automated analysis;
- Developing sensors specifically for FOWT (e.g. for underwater cables or other parts of the floating substructures);
- Placing physical sensors on a floating offshore wind turbine and gather all the data. By comparing the data gathered from the sensors with the simulated data of the FOWT, a digital twin can be created;

For Building Information Models:

- Define potential BIM use-cases as per the stakeholder knowledge maturity level;
- With the digital representation of the floating wind turbine, and by integrating the data coming from the sensors with BIM, a 3D visualization of the FOWT performance and life-cycle operation can be obtained. This could offer a better image of the wind turbine state and facilitate the monitoring and diagnosis processes;
- Taking advantage of BIM capabilities and benefits beyond 3D visualization.

7. Conclusions

Due to the growing support for the transition away from traditional energy generation towards green energy, during the last years, there has been an increasing interest in floating offshore wind turbines.

Even though the floating offshore wind turbines are more suitable for deep waters than the fixed wind turbines, it is very difficult to perform O&M operations. In case of a storm, the down time of a faulty component can last for weeks. For this reason, and because the detection of a subsystem failure may prevent the system failure, it is important to detect failures at an early stage, through online continuous monitoring. This can be achieved by placing different sensors (for vibrations, temperature measurement, etc.) on the FOWT and acquire the data in real time. By using this data, along with simulated data, a digital representation of the floating offshore wind turbine, called a digital twin, can be created. Building a digital twin for the floating offshore wind turbines could facilitate monitoring and diagnosis in real time remotely.

This paper presented the typical failures of a FOWT, the most prone to failure components and the most common monitoring and diagnosis techniques along with the required sensors. Also, the stages of a digital twin development and some examples of digital twins already available on the market were taken into consideration.

When conducting a building performance analysis, for example a floating offshore wind turbine, not only the information from sensors is important, but also the wind turbine architectural/geometry data. By creating a 3D model of the wind turbine, and integrating the WT's sensors data to enhance the visualization of structural health monitoring through BIM, a clear image of the FOWT performance and life-cycle operation can be obtained.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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