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Structural health monitoring of offshore wind turbines: A review through the Statistical Pattern Recognition Paradigm

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ABSTRACT

Offshore Wind has become the most profitable renewable energy source due to the remarkable development it has experienced in Europe over the last decade. In this paper, a review of Structural Health Monitoring Systems (SHMS) for offshore wind turbines (OWT) has been carried out considering the topic as a Statistical Pattern Recognition problem. Therefore, each one of the stages of this paradigm has been reviewed focusing on OWT application. These stages are: Operational Evaluation; Data Acquisition, Normalization and Cleansing; Feature Extraction and Information Condensation; and Statistical Model Development. It is expected that optimizing each stage, SHMS can contribute to the development of efficient Condition-Based Maintenance Strategies. Optimizing this strategy will help reduce labor costs of OWTs' inspection, avoid unnecessary maintenance, identify design weaknesses before failure, improve the availability of power production while preventing wind turbines' overloading, therefore, maximizing the investments' return. In the forthcoming years, a growing interest in SHM technologies for OWT is expected, enhancing the potential of offshore wind farm deployments further offshore. Increasing efficiency in operational management will contribute towards achieving UK's 2020 and 2050 targets, through ultimately reducing the Levelised Cost of Energy (LCOE).

Contents

Abbreviations: AE, Acoustic Emission; OM, Operational Management; CB, Carbon Fiber; OMA, Operational Modal Analysis; CM, Condition Monitoring; OWF, Offshore Wind Farm; EOC, Environmental and Operational Conditions; OWT, Offshore Wind Turbine; EU, European Union; O&M, Operations and Maintenance; FBG, Fiber Bragg Grating; RSA, Response Surface Analysis; FEA, Finite Element Analysis; SHMS, Structural Health Monitoring Systems; FMECA, Failure Mode, Effects and Criticality Analysis; SVM, Support Vector Machines; LCOE, Levelised Cost of Energy; WF, Wind Farm; MEMS, micro-electromechanical system; WSN, Wireless Sensor Network; NN, Neural Networks; WT, Wind Turbine

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1. Introduction

Over the past 15 years, Wind Energy has experienced a remarkable growth in the European Union (EU). While in 2000 wind energy contributed 2.4% of the EU's electricity demand, by 2015 this percentage raised to 11.4%, or in absolute numbers, 12.9 GW of installed capacity became 141.6 GW. This rapid development is not only due to the targets set by the EU in 2006 for all Member States [1], but also due to the scalability of wind energy with units of larger capacity been deployed in larger farms, further offshore [2]. According to Renewable UK, Offshore Wind (OW) has officially become the most profitable renewable energy source since, it can produce more renewable energy than all of the other sources combined [3]. In Europe, including sites under construction, there are 84 Offshore Wind Farms (OWF) in 11 countries as of the end of 2015. Furthermore, 3,230 turbines are now installed and operational, reaching a cumulative installed capacity of 11,027 MW. In 2015 only, a grid-connected capacity of 3,019 MW, was added, accounting for almost double of the capacity added in 2014 [4]. Moreover, due to the increased deployment of 4–6 MW turbines in 2015, the average Offshore Wind Turbine (OWT) size became 4.2 MW, constituting a 13% increase over 2014.

Considering wind energy as a mature technology, allows developers and operators to gain confidence to include this energy technology within their mainstream portfolios. Increasing availability of farms and reliability of units, decreasing unscheduled maintenance and eliminating unexpected catastrophic failures, are the targets that attract focus towards deploying the next generation of wind farms. Structural Health Monitoring Systems (SHMS) can contribute significantly towards enhancing OWT's profitability, reliability and sustainability through more systematic operational management approaches. SHM represents the procedure of implementing a damage detection strategy for engineering infrastructures related to aerospace, civil and mechanical engineering [5], being damage referring to the variations in material and/or geometric properties of these systems [6]. Some of the most known structural damage roots are: moisture absorption, fatigue, wind gusts [7], thermal stress, corrosion [8], fire and lightning strikes [9]. Usually, there are two critical aspects that influence SHMS development: the sensing technology (and the associated signal analysis), and the interpretation algorithm [10].

Damage identification is performed through five similar disciplines [11]: SHM, Condition Monitoring (CM) [12], Non-Destructive Evaluation [13], Statistical Process Control [14], and Damage Prognosis [15,16]. Apart from the CM of rotating machines, SHM for OWT remains a research topic which is slowly getting into the field deployment stage. This is due to the early stage of the technology's deployment, the additional challenge that offshore environments pose to these technologies, and associated costs to operators for hardware installation and data processing.

Farrar and Sohn [17] were the first to introduce the Statistical Pattern Recognition Paradigm in the SHM field. This methodology follows four stages:

1) *Operational evaluation:* This stage tries to set the boundaries of the problem by replying to four questions concerning the implementation of the Damage Identification Facility. Questions are related to: the motivation and economic justification for implementing the SHMS, the different Systems' damage definitions, the Environmental and Operational Conditions (EOC) in which the SHMS are used, and the data acquisition limitations in the operational environment.
2) *Data acquisition, normalization and cleansing:* Data Acquisition refers to the selection of the excitation methods, type, quantity and location of sensors, and the Data Acquisition/Storage/Transmittal Hardware [18]. Data Normalization is another crucial aspect for the Damage Identification Process, as there are numerous conditions in which measurements can be taken [19]. Therefore, this Normalization constitutes the procedure of separating variations in sensor readings produced by damage, from those produced by the variation in EOC. Data Cleansing is the procedure of selecting data which is passing on to or rejecting from the Feature Selection procedure [11]. Two examples of Data Cleansing processes are filtering and resampling, which constitute Signal Processing Techniques [20].
3) *Feature extraction and information condensation:* This is the aspect of the SHMS that attracts most attention, as these features allow the distinction between damaged and non-damaged structures [21,22]. Data Condensation is essential when analogue feature sets acquired along the structure's lifetime are envisioned. Due to the extraction of data from a structure during long periods of time, robust data reduction techniques have to be developed to preserve feature sensitivity to the changes of interest.
4) *Statistical model development:* It is related with the implementation of the algorithms that work with the extracted features and calculate the extent of the damage to the structure. These algorithms can be divided into the two categories that are shown in Fig. 1 [23–25]. All of these algorithms assess statistical distributions of the measured or derived features, to enhance the damage identification process.

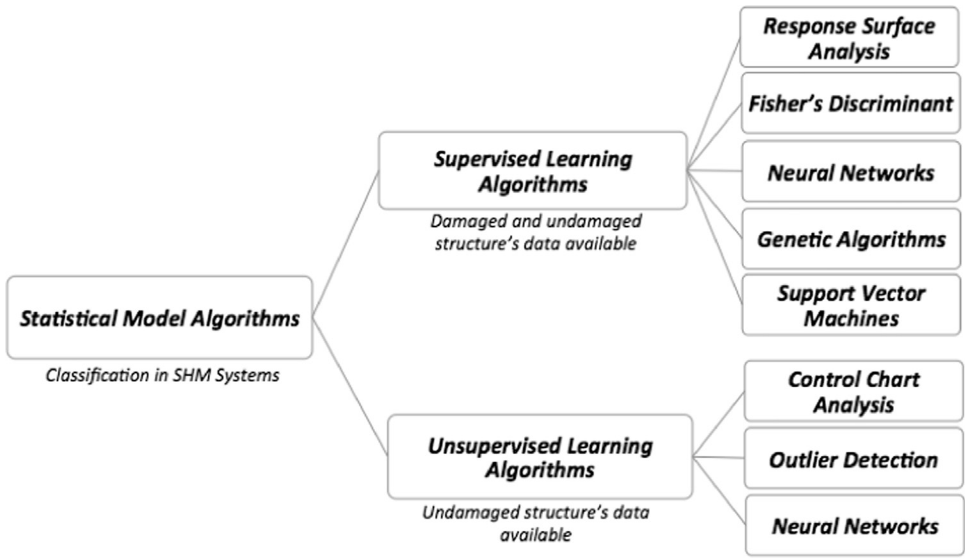

Fig. 1. Algorithms classification for Statistical Model Development.

This paper constitutes a comprehensive review of SHMS of OWT following the process of the Statistical Pattern Recognition Paradigm. The paper has been divided in eight sections. In Section 2, a comprehensive review of the SHMS for OWTs is carried out, presenting the history and evolution of SHMS and the different technologies that can be employed to OW. Each one of the framework's stages abovementioned has been reviewed in greater detail focusing on OWTs applications (Sections 3–6). Discussions of the capabilities and limitations of SHMS, the most used methods in the OW Industry and current technology gaps are presented in Section 7, followed by conclusions in Section 8.

2. Structural health monitoring systems for offshore wind turbines

2.1. History and evolution

The identification of changes in the dynamic response of systems has been carried out qualitatively, since practice has introduced tools by employing acoustic techniques [26,27]. Lately the emergence of SHM techniques has come together with the evolution, miniaturization and cost reduction of digital computing hardware [11]. Depending on the sector, this evolution took place sooner or later. For example, CM Systems for rotating machines constituted one of the first developed systems, whilst SHMS for the OW industry are currently an emerging research topic.

Nowadays, CM of rotating machines constitutes the most prosperous application of SHM Technology in terms of profitability, reliability and level of development. The failure identification process is based on pattern recognition related to displacement, velocity or acceleration time histories, commonly located at one point on the housing or shafts of the machinery during standard-operating conditions and start-up or shut-down transients [28]. Commercial software integrated with measurement hardware is marketed to help the user systematically apply this technology to the operating equipment [11]. These facts mentioned above, supposed the transition of SHMS in this field from a research topic to a common industry practice. A good example of this is the US Navy's Integrated Condition Assessment System [29].

The aerospace sector started studying the use of vibration-based Damage Identification during the late 70 s and early 80 s in conjunction with the development of the space shuttle programs [11]. That effort carried out on other applications that are being investigated for the National Aeronautics and Space Administration's Space Station [5]. Some of the most widely used technologies in this field are: fastener monitoring [30], blade tip clearance [31], and fatigue monitoring [32]. The Civil Engineering community has researched on vibration-based Damage Identification of bridges and buildings since the 80 s [33,34]. This research is currently being applied to offshore structures due to the similarities across industries.

During the 70 s and 80 s, the Oil and Gas industry carried out extensive research to develop vibration-based Damage Identification Techniques for offshore platforms [35]. Related to this technique, one of the research objectives was the detection of near-failing drilling equipment and the prevention of expensive oil pumps from becoming inoperable [36]. Unfortunately, most efforts were not successful, as this problem is fundamentally different to that of the rotating machines due to the impossibility of predicting where damage will occur and the structure's inaccessibility for data acquisition purposes. Besides, numerous practical issues were found apart from measurement acquisition difficulties, occasioned by platform noise, instrumentation difficulties in hostile environments, changing mass caused by marine growth, varying fluid storage levels, temporal variability of foundation conditions and the inability of wave motion to excite higher vibration modes [11]. However, different applications could finally overcome these issues and be implemented. For example, fatigue gauges are commonly employed for fatigue monitoring by measuring the crack-growth proportional to the cumulative fatigue damage for welded joints [37]. This approach was reviewed by [38] and [39]. Another example is presented in [40], where different techniques for corrosion monitoring are introduced and the application of flexible ultrasonic thin-film piezoelectric transducer arrays is described. Lastly, [41] suggests a methodology to enhance the reliability of SHM for flexible risers, which are widely used in offshore oil exploration facilities and are essentially composite structures consisting of several metal armours and polymeric layers.

Most of the Wind Farms (WF) are either at the beginning or in the middle of their service life and, currently, the trend is to build these WFs much further offshore. Therefore, special consideration due to extreme weather conditions and complex dynamics, such as sensor tolerance and endurance, data acquisition and transmission, among others, have to be accounted for [42,43] and [44]. As this sector grows, business economics currently demands management of OPEX and CAPEX costs [45]. For example, considering a 750 kW turbine with an expected 20-year service life, the operations and maintenance (O&M) costs account for between 25% and 30% of the overall energy generation cost or 75–90% of the investment costs [46].

Some of the technologies employed in OW differ from those employed by the Civil or the Oil and Gas Industries in aspects of accessibility, severity of the environmental conditions and more complex loading due to excessive operational loads. Due to these differences, further development and research in these technologies has been prioritized in the past years aiming to adapt them to OW applications. In order to make wind power competitive with other sources of energy, some of the performance indicators, such as availability, reliability, efficiency and integrity of turbines, still have to be improved [45]. In the following section, a review of the current SHM techniques used in the OW Industry is presented.

2.2. SHM technologies

SHMS of OWTs are becoming very much in demand now that machines are growing in size and OWF are being developed further from the coasts. In order to decrease the power generation costs and, therefore, the Levelized Cost of Energy, WT mass of components need to be optimized without compromising the structure's integrity. This can be achieved through making the turbines more structurally flexible, which directly affects their modal parameters, i.e. the resonance frequency [47]. Another important aspect is that OWTs' inspection and maintenance is considerably more expensive than onshore turbines'. Therefore, SHMS which are able to predict structural changes are becoming crucial to diminish operation and maintenance (O&M) costs and to assess the remaining lifetime of these structures. An example of a good application of SHMS to an onshore WT is presented in [48], where a life-cycle management framework for online monitoring and performance assessment is applied to WT.

SHMS have become a useful method to enhance Operational Management (OM) and optimize maintenance activities of modern infrastructure [35], as the information gathered can be employed in the development of a tailored, condition-based maintenance program [49]. This program aims to reduce the necessary downtime due to components inspection, prevent unnecessary replacements and failures, and increase availability. Furthermore, due to the capacity of monitoring the structure's integrity, design improvements can be implemented such as selection of lighter blades that will enhance performance with less conservative margins of safety [50] and which will adapt quicker to the wind's variability, capturing more energy [51].

General reviews of SHM can be found in [52] and [26,53] where assessment of the different methodologies was carried out. SHM techniques for WT were reviewed by [7], however, the majority of that review was based on bridges and civil infrastructures. A wide overview of how the EOC affects SHM techniques and the normalization of the data that needs to be carried out for compensating these variations is given in [24]. A discussion between SHM and CM costs can be found in [54].

Within this section, the different SHM techniques and especially those suitable for OWT blades, tower and foundation, are explained.

2.2.1. Acoustic emission monitoring

Failure mechanisms such as cracking, excessive deformation, debonding, delamination, impacts, crushing, among others, all provoke transient changes in stored elastic energy in particular points of a structure. This energy release can be effectively used to monitor WTs and, particularly, their blades. As Ciang mentioned in [5], Acoustic Emission (AE) is a very effective technique that detects failure mechanisms up to the microscale. However, this technique is less effective when it comes to damage characterization and assessment in the case that an appropriate algorithm is not available. Complex damage mechanisms in WT blades have been better understood since AE monitoring was carried out in a blade during loading, enhancing the ability to assess damage during testing [55–57]. Also during a certification test, the damaged area due to cracking in the blade was located due to the sound of the cracking mechanism [56]. Fatigue tests can also be monitored, as [58] presents; such as the sound produced due to stress released waves or energy dissipation using piezoelectric sensors [59,60].

AE signals are defined by their amplitude and energy [61]. As [59] explains, AE events will occur around a particular point, at a structure under certain loading. That particular point will be the one at which the structure will fail at some point, being the feature extremely useful in locating the failure. Even though most of the relevant literature is related to tests in WT blades, a few cases explain how the technique has been applied to a WT blade during operation [62], by using a broadband radio to send the AE data from the rotating frame to the ground with no signal resolution loss. Even though the previously collected data had acceptable levels of noise in low to moderate wind speeds, verification of the fact that the noise does not increase with wind speeds and the feasibility of those signals to be filtered, has to be assessed.

2.2.2. Thermal imaging method

This method aims to detect defects or anomalies in the material beneath the surface and it is based on the subsurface's temperature gradients. Thermal imaging can be applied to a WT blade by installing infrared cameras [63]. Irregularity of or damage to material is detected due to a change in the thermal diffusivity. Moreover, this technique can be divided in two categories depending on the thermal excitation method used: active or passive. The passive thermal imaging method aims to investigate materials at different temperatures, other than the ambient, and therefore, it is not normally used in SHMS of OWTs; the active approach has an external stimulus source (i.e. optical flash lamps, or heat lamps).

A particular type of active thermal imaging method is called the thermoelastic stress method and it is based on the thermoelastic effect, which consists of the change in temperature of an elastic solid produced by a change of stress [64]. As explained in [65], in the damaged or abnormal region, different heat conduction, higher acoustical damping, and stress concentration take place. This technique has been proven to be useful in WT blades fatigue tests [61,66], as stress concentrations during the test can be observed before damage in the surface can be appreciated. A promising variation of this methodology involves applying high power ultrasounds [67], or oscillating stresses with a mechanical shaker, to the surface that is being tested [65]. This technique is called vibro-thermographic and is able to locate and assess crack dimensions, as [67] states. Furthermore, it can be used for assessing voids and stress concentration in composites. Nevertheless, this method has the potential to become a promising SHM technique for WTs, and more research needs to be carried out in order to reduce the sensitivity to temperature variations [61].

2.2.3. Ultrasonic methods

Ultrasound is a method commonly used for assessing the inner structures of solid objects [68]. It has also turned out to be very useful with composite structures. The basic principle of this technique is that ultrasonic waves, emitted by a transmitter, pass through the tested material and are reflected and/or mode converted by a flaw or anomaly. This modified signal is picked up by a receiver once it has passed through the material (if not reflected). In the simplest arrangement, transmitter and receiver are placed on opposite surfaces of the material [69]. The aim of this technique is to reveal planar cracks that take place perpendicularly to the sound wave propagation direction [70]. An advantage of this method is that it can detect cracks of just a few millimeters.

2.2.4. Fatigue and modal properties monitoring

Fatigue and Modal Properties Monitoring are among the most important SHM techniques for OWT structures, as the consequences of structural damage may be catastrophic. These methods are very simple to implement on structures of any size as they are based in another CM technique, which is the most mature and successful methodology for rotating machinery monitoring; the vibration-based inspection method [35,71].

Modal Properties Monitoring is based on the principle that modal parameters, such as resonance frequency, damping coefficient and modal curvatures, among others, experience certain variations due to a change in different physical properties (i.e. reduction in mass or stiffness) [72,73]. Due to these changes, the structure is considered to be damaged; that damage being identifiable by comparison between the structure's modal parameters before and after an event. In other words, due to the fact that modal properties changes are considered as damage indicators, this SHM technique is categorised as a pattern recognition problem [53].

In order to be able to analyze the structure's dynamic response by studying its mode shapes, several accelerometers must be installed. Other analyses that can be carried out are curvature mode shapes and wavelet maps. These analyses are particularly relevant when they are carried out in service conditions [74]. However, performing these analyses accurately to a full scale OWT during operation is extremely difficult due to the high number of uncertainties which the offshore environment presents [47] and, therefore, special effort has been given to solve this issue in the past years [75]. One reason that makes this analysis difficult is the fact that wind and wave loading applied to the structure cannot be measured accurately in a continuous manner. This introduces the difficulty of having to employ Operational Modal Analysis (OMA) for calculating the modal parameters based on the assumption that the structure is subjected to unknown random loads [76–79]. OMA methods are based on the principle that in the analyzed time interval, the system is linear and does not vary with time. One issue pointed out in [80], is that most of the research regarding data variability due to changes in EOC was carried out in laboratories, where basic signal processing techniques were enough to solve the damage detection problem [81]. Unfortunately, these techniques are not considered enough to be employed in an OWT during operation.

Scour effect on the natural frequency of OWT was studied in [82], where it was proved that while scour increases, the natural frequencies of the support structure, and therefore the WT, decreases. This phenomenon represents a threat for the turbine as the natural frequency gets closer to the rotor's frequency of rotation [47]. Therefore, continuous monitoring of WTs' dynamics variations due to scour is recommended as it is expected to be a useful tool for developing maintenance plans regarding scour protection [82].

Another type of modal monitoring called resistance-based damage detection method has been found to be revolutionary due to the fact that it has the capability of detecting local damage. It uses piezoelectric materials which, by monitoring their electrical impedance, can detect the presence of structural damage. According to [83], only local response of the structure will be transmitted to the sensor in case the excitation frequency is big enough. Damage detection using this monitoring technique has been proven to be effective in different types of structures, including composite structures [84,85].

2.2.5. Strain monitoring

Strain monitoring is the technique that detects microscopic length variations in a component at pre-established locations, which does not necessarily mean damage detection. However, these length variations are known to be directly related to stresses and loads applied to the material [86]. Due to the fact that total deformations of large components, i.e. WT blades, are large because they are the sum of all the local deformations, they give no indication of local damage. For that reason, strain sensors have to be positioned at points of particular interest, where large deformations are expected. This limits their applicability to overall component damage sensing applications [87]. Strain monitoring has been proven to be useful in continuous operational WT monitoring as it was successfully employed in a 4.5 MW turbine [88]. However, in order to predict WT failures in blades, tower and foundation, prior knowledge of their component's stress field is required so that sensors can be mounted in critical areas.

Another SHM technology for strain monitoring is the Strain Memory Alloys Method, which relies on an irreversible crystallographic transformation for their smart properties. The transformation consists of the change, due to the strain, from one crystal state to another. The parent austenitic crystal structure is paramagnetic, while the product martensitic phase is ferromagnetic. Any SHMS related to this group of smart materials is considered as a passive system, as both full-time power supply and data storage facilities are not necessary. Instead, power is only needed during the sensor's interrogation, being the actual reading stored within the sensor element itself [89].

3. Operational evaluation

3.1. Offshore wind turbines damage definition and detection

Damage definition constitutes a very important stage of the Statistical Pattern Recognition Paradigm as the boundaries of the problem are defined within it. Moreover, damage features have high variability among fields and structures. Therefore, identification of damage causes, consequences and features must be carried out at the beginning of any SHMS design phase. Several risk analysis techniques can be employed, Failure Mode, Effects and Criticality Analysis (FMECA) being considered one of the most relevant for this particular case [90] [91]. Different reviews of OWT failure modes have been made in [5,46,92].

One of the main concerns regarding OWT damage detection is to identify the best way to detect structural damage. Usually the change in modal properties is used for this purpose [35]. However determining the best methodology constitutes a much broader field than what can be expected at first sight, as numerous different choices are available. Proof of this is the review of damage detection methods through the change in modal properties presented in [26]. The relevant method are: Natural Frequency Based Methods [93], Mode Shape Based Methods [94–98], Mode Shape Curvature Based Methods [99–103], Strain Mode Shape Based Methods [71,104–108], Dynamically Measured Flexibility Based Methods [109–111], and Neural Network Based Methods [112–117].

Damage definition in OWT blades is closely related to the one that anisotropic reinforced laminated composites have. Delamination is one of the most common failure modes in composites [118], which is responsible for causing stiffness reduction, variation in resonant frequency, and decrease in buckling capacity. Such defects might be caused by poor process control during manufacturing, impact loading, or other hazardous service environments [119].

There are many other failure mechanisms for carbon–fiber composites, such as fiber breakage, matrix cracking, fiber splitting, and delamination, as listed in [120].

The most probable failure mechanisms that an OWT's tower and foundation can experience are corrosion and fatigue due to combined wind and wave loading [121,122]. Failure of these structures due to the accelerated fatigue produced by the increase of stresses, when natural frequencies are found to be similar to the rotor's frequency, can lead to catastrophic consequences which must be avoided. This phenomenon, known as resonance, has to be dealt early in the design stage of these structures taking into account all operation stages through a structure's service life [123]. In the particular case of pile-foundations, scouring and reduction in the foundation's integrity over time can be problematic. Scour reduces the fundamental structural resonances of the support structure. Therefore, it can be considered a damage indicator as it can be correlated to a change in the natural frequency of the tower and an increase in the fatigue damage [79,82,124].

3.2. Variation in environmental and operational conditions

According to [125], the system's integrity state is a stochastic function of the initial system's integrity (quality), influenced by the acting loads (e.g. extreme loads, cyclic loads, environmental conditions). Even though a structure is considered to be damaged when at least one of its physical properties (mass, stiffness, etc.) varies, changes in EOC might induce variations in these properties without necessarily meaning that damage exists [80]. In fact, in the majority of the situations, it is extremely difficult to assess whether or not EOC cause sensitive variations in the SHMS measurements [126]. For this reason, this topic has been recognized as an important issue in SHMS and has been identified as a key concern across the research community [17].

SHMS for OWT are particularly relevant in the design phase, during shipping, installation and operation. The application of SHMS in harsh environments is a particularly challenging task. The reasons are not only because these systems need to be prepared to withstand the severity of the environment for a long period, and the ease of installation, ruggedness and reliability of equipment is essential in providing key information about the tower's structural integrity, but also because OWFs are being developed further than ever before from coasts, which is making their Operational Management critical [127].

The consequences that the variations in the EOC have on the dynamic behavior of structures were assessed in different studies [119,128]. For example, a statistical methodology that propagates variability in measured Frequency Response Function data and calculates the level of uncertainty of the modal properties is explained in [129]. A good example of the effect of the variation in the EOC is presented in [80], where the turbulence suffered by the rotor affected the operational WT Control System. Other important factors that strongly influence SHMS signals are extreme events, such as earthquakes. SHM technologies are known to have an accurate characterization of input excitations. Seismic excitations are transient in nature, constituting an issue that limits the performance of most SHMS due to the fact that these technologies are based on the stationary stochastic-excitation assumption [27]. Further information regarding this issue can be found in [130]. To conclude, any methodology employed has to be able to distinguish between EOC that affect signals and damage features in order to allow the SHMS to detect only damages in the structure.

4. Data acquisition, normalization and cleansing

4.1. Sensors types

As previously mentioned, SHMS for OWT can be used to detect damage in blades, tower and support structure. This section aims to introduce the different types of sensors and technologies which are used and in which subsystem. From the top to the base of the OWT, blades constitute a difficult element to integrate SHMS due to the high variety of failure modes that can develop, the high strains they experience, the fact that they are rotating components, and the high variability in their operating conditions [80]. Different sensors can be used in blades, as confirmed by different reviews [131]. Two approaches are followed: active and passive sensing technologies, whereby active sensing, but not passive, needs an external excitation [80].

Tower and Foundation constitute two key elements of OWT as they are not replaceable unless a significant cost is assumed. These are components that, once the turbine is installed, should sustain associated loads and their partial failure would carry catastrophic consequences. Therefore, early in the design stage, the intended turbine's service life and the possibility of extending it or repowering it with a new nacelle, must be taken into account [132]. Furthermore, due to the difficulty and sensitivity of fatigue analysis, SHMS should be installed in order to be able to verify the accuracy of the design calculations and implement an optimal Operational Management Strategy. These SHMS will mainly consist of fatigue and modal properties monitoring (such as resonance frequency or modal curvatures), corrosion and scour monitoring. It should be noted that regarding SHMS for operating WTs, not much progress has been made in developing robust applications, especially for OWT blades [133].

Some of the methods that were introduced in Section 2 [125,133–136] include vibration monitoring-based methods (accelerometers, piezo or micro-electromechanical systems (MEMS)), strain (strain gauge or fiber optic cables), ultrasonic waves which are widely applied in composite structures (piezoelectric transducer), acoustic emissions (usually barrel sensors), impedance techniques, laser vibrometry, impedance tomography, thermography (infrared cameras), laser ultrasound, nanosensors, and buckling health monitoring. The necessary sensors for implementation of these techniques are described below.

Structural dynamic responses are usually monitored by embedded strain gauges, piezoceramics or accelerometers [137]. Accelerometers are relatively simple devices whereby the operating principle is the comparison of the acceleration they experience with the acceleration due to gravity. They are commonly provided as MEMS which are very small devices with computing capability. These devices are commonly used for modal parameters and vibration monitoring of blades, tower and foundation of the WT. There are various types of accelerometers available, such as piezoelectric, optical, laser, capacitive, and servo. The selection of an accelerometer for a specific application depends on a number of factors, such as amplitude and frequency range of the response, sensitivity, resolution, etc. [37]. The SHM of civil engineering structures using plastic optical-fiber based accelerometers for estimating the natural frequencies by measuring the dynamic response was carried out in [138]. Other types of sensors that can be used to analyze modal parameters are piezoelectric patches, which were used in [51] at critical locations with the aim of comparing their natural frequency. Velocimeters, on the other hand, operate based on a principle similar to interferometry. In SHM these devices are primarily used to measure displacement by integrating acceleration or velocity measurements of the structural members they are attached to [139].

Two popular sensor groups exist for the purpose of strain measurement: traditional electrical and relatively modern fiber optic [86]. Electrical strain gauges have become so widely applied that they dominate the entire field except for special applications. They are, along with electrical resistances, the most popular types of sensors [140], closely followed by Fiber Bragg Grating (FBG) sensors, which recently have experienced considerable improvements [141].

Several electrical sensor types exist including capacitance, inductance, semiconductor and resistance. Each is sensitive to a differing electrical property [140]. Resistance strain gauges record the resistance variation of an electrically conductive wire relative to displacement. This resistance variation occurs due to a change in the cross sectional area and length of the wire as the specimen is elongated. Electrical resistances are generally used for identifying cracks in composite materials and joints. The most suitable material for monitoring using this method is carbon fiber (CB) polymer-matrix composites as their electrical properties are affected by structural damage. This material is commonly used due to its strong, super-elastic, and piezoresistive properties [142]. These sensors can also be used for identifying failures in conductive bolted joints. A novel method for analyzing the structural health of alumina nanocomposites, by the change in electrical conductivities after indentation, is proposed in [143]. The utility of the electrical resistance method for locating barely visible impact damage in carbon fiber composite structures was explained in [144].

Piezoelectric materials, when subjected to stress, produce an electric field and vice versa when subjected to an electric field. Furthermore, changes in the fundamental properties of the structure, such as mass, stiffness and damping, directly make the mechanical impedance vary, this variation being a clear damage indicator [145]. Damage detection using changes in the electro-mechanical impedance of piezoelectric wafer active sensors can easily be done by attaching them to the structure [146].

Even though piezoelectric materials are the most common sensor type for stress monitoring, there are many other sensors that can also be applied to this aim, such as: thin film sensors, piezoelectric composite materials, rolling sensors, and optic-based sensors [69]. However, an important drawback this technology has, is temperature and ambient vibrations effects in the piezoelectric sensors' performance in composites, as explained in [27]. Temperature effect in blades must be compensated in the results, as they are made from this material. In fact, [147] explained how a rise in temperature and vibrations can jeopardise the detection of the delamination caused by impacts. Other common drawbacks that strain gauges might experience are described in [86]: non-linearity, hysteresis and zero shift due to cold work [140].

Cracks and displacements can also be monitored by fiber-optic sensors which usually are: spectrometric, interferometric or intensity-modulated. An optical fiber is a glass or plastic fiber designed to guide light along its length. Moreover, FBGs were also proved to be useful as a corrosion transducer and temperature sensor simply by adding a metal coating to one segment of the fiber [148]; as a pH-sensitive corrosion detector [149] and good at delamination identification [150]. Furthermore, fiber-optic sensors are employed in SHMS for OWT in various forms:

1) Plastic fiber-optics can be attached, for example, to the blade of a WT to measure loads it bears. This measurement is carried out by the reduction of the light source's power that takes place in the plastic fiber-optic depending on the strain to which it is subjected [151]. This concept is used to sense strains in a structure. When loads increase, the measured optical power is reduced being damage detectable due to the fact that the normalized optical power decreases linearly as the strain increases, and drastically once the crack density in a composite laminate specimen increases [151].
2) FBG is made by illuminating the core of an optical fiber with a spatially varying pattern of intense Ultraviolet laser lights that have sufficient energy to break the highly stable silicon–oxygen bonds, which will raise, to some degree, the refractive index [152]. Although the main use of FBG consists of measuring strains crack evolution [151], impact damage can be detected by distributing FBG over the structure [137,138,153,154].
3) Optical fuses transversally positioned in laminated composites have been proven to be useful in damage detection [155]. For example, if short length optical fibers are embedded through the thickness of a graphite/epoxy laminate during the manufacturing process, the fibers act as optical fuses, which will break in areas of low energy impact damage [156].

4.2. Data collection and storage

It is widely recognized that dynamic data acquisition is a complex, tedious and costly process [157]. The recent development of wireless monitoring has brought a big advance in SHM and Infrastructure Asset Management [34] as it integrates wireless communications and mobile computing with sensors. The result is a more economic sensor platform that has three aims: acquisition of structural response data, local interrogation of collected measurement data, and wireless transmission of that data or analysis results to a Wireless Sensor Network (WSN), which comprises other wireless sensing units [34]. As explained in [158], a WSN is composed of four mean stages: communication, data acquisition, processing, and fusion stages. Moreover, WSNs encompass many fields: wireless communication, network technology, integrated circuits, sensor technology, MEMS, among many others. WSNs are composed of data acquisition systems which have numerous design parameters: a number of channels, a maximum sampling rate, and resolution, among others; a computational core, where all the data acquired are stored and which possess processing capabilities; and the wireless communication channel.

A real WSN application is presented in [157], where three WTs in operation, instrumented with WSN, proved their efficacy in operational conditions. While in the first turbine instrumented, the aim was to prove the accuracy in the collection and transmission of vibrational data from the turbine's tower, in the second turbine instrumented, several strain gauges were also included at its base. In both, wireless communication channels, performance was assessed and their data used for offline output-only towers modal analysis.

The acquired data from WTs contain key features for future developments in the Wind Energy Industry. For that reason, operators are starting to appreciate the importance of investing in SHMS [159]. However, even though monitoring has many proven advantages, it is expensive and its costs are the cause why only a few operational turbines have extensive sensor instrumentation [157]. An assumption usually made, is that traditional cable based monitoring systems are cheaper and easier to install. Nevertheless, this technology is not only more costly to install, but also introduces difficulties in the installation process due to the cables. On the contrary, wireless sensors are substantially cheaper and easier to install than traditional cable-based systems [160]. In the case of turbine blades, wireless communication eliminates the necessity of moving data through a slip ring interface, which is difficult and costly.

Wireless sensors are not, exactly, cable-based sensor replacements; without wires, wireless sensors usually depend on internally stored power for operation. Inefficient use of wireless sensors will deplete this precious energy source rapidly, making frequent battery replacement necessary. Among the three different types of WSN topologies (Star, Cluster tree, and Mesh [158]) there are several important issues for WSN use in SHMS. These were summarized in [157]: compatibility issues between different types of sensors, their sampling frequencies, the problem of transmission bandwidth and real-time ability variance, the selection of a wireless transmission frequency, topology choice, data fusion method, and the contrast between the energy consumption requirements of different applications to that of each different device.

Even though WSN have been proven to be applicable to OWFs [80], they have the disadvantage of the high amount of power needed by the sensors, which had been tried to be diminished with an increased interest in data telemetry with energy harvesting [161,162]. In order to provide enough power to the sensors without using batteries, piezoelectric, thermoelectric and photovoltaic energy harvesting techniques were assessed in [163], on a cross section of a CX-100 WT blade. The aim was to determine the feasibility of powering individual nodes that would compose the sensor network. In another study [164], a 4-channel AE wireless node was powered by structural vibration and wind energy harvesting modules.

4.3. Data normalization and cleansing

The ability to normalize the measured data with respect to varying EOC is a key aspect of a SHMS in order to avoid false positive indications of damage [19]. One example of the normalization process is carried out to the measured inputs when modal parameters are being extracted. Two strategies can be employed for normalizing these data: when the EOC are available and are not available.

The most important aspect regarding accuracy of data normalization comes with the damage sensitive features that must be extracted from these data. Those damage sensitive features must not be lost or diluted by the normalization process. There are different data normalization techniques. Some examples are: the subtraction of the mean value of a measured time history for direct current off-sets removal from the signal, the division by the standard deviation of the signal for normalizing varying amplitudes in the signal, curve fitting of analytical forms of the frequency response function to measured frequency response functions in experimental modal analysis, among others. If the structure is linear, this normalization procedure removes the influence of the input from the parameter estimation procedure.

Data normalization constitutes a very important part of the damage identification process as it affects significantly Neural Network (NN) performance [165]. Even though not all sources of variability in the data acquisition mechanism can be eliminated, they need to be identified and minimized as much as possible [166]. Therefore, appropriate measurements need to be carried out in order that such sources of variability can be statistically quantified [19]. An example of data normalization in OWT is explained in [167], where a non-linear regression model to perform data normalization was used in real-life data obtained from the monopile of an OWT. Further research on this topic will be carried out in the future because, in order to achieve successful SHM goals, data normalization procedures able to discriminate whether measurement variations are motivated by damage in the structure, or by changes in the EOCs [168].

Data cleansing is the procedure of selectively choosing data to pass on or to reject from the feature selection process or, in other words, is the procedure of selectively discarding data that might not represent the system's behavior [11]. Data cleansing is a difficult process due to the fact that it is commonly based on experts' knowledge gained in previous data acquisition processes. An example of data cleansing could be when a sensor is discovered to be loose and, therefore, based on the judgment of the experts; the measurements carried out by that sensor are not accurate and can jeopardise the accuracy of the data set. For this reason, the whole set might be discarded from the feature selection process. Signal processing techniques, such as filtering and resampling, can also be thought of as data cleansing procedures [24,34,169,170].

5. Feature extraction and information condensation

Feature extraction constitutes the methodology that refers to the identification of the damage sensitive physical characteristics. It is usually determined by the data obtained from the structure and is application specific [171]. Many methods can be used for damage feature identification, the most basic one being comparison of SHMS output data with similar data obtained when the same structure has experienced a damaging event. This methodology is based on the fact that damaging events have already occurred. Another process for feature identification is the numeric simulation of the damaged system's response to postulated inputs, which is currently the most used technique in several industries, e.g. the automotive industry. Another option for recognizing these sensitive features would be testing the structure or a representative specimen in a laboratory, introducing the expected damage. Damage-accumulation testing, during which structural components of the system under study are subjected to a realistic loading, can be used also to identify appropriate features [119]. As Farrar and Worden explain in [11], this methodology might involve induced-damage testing, fatigue testing, corrosion growth or temperature cycling to accumulate certain types of damage. As such, numerous articles in this theme issue are devoted to the feature extraction portion of SHM [18,20–22].

Data Condensation constitutes an inherent part of the Feature Extraction procedure. The different types and quantity of sensors needed to make any SHMS work efficiently and accurately usually produce huge amounts of data. Therefore, data condensation is, most of the time, a necessary stage occurring before the analysis of the extracted data through the statistical models. One possibility of data condensation is to summarize all the damage sensitive features in their adimensional form into feature vectors of small dimension. This constitutes an accurate way of estimating the feature's statistical distribution [119]. Moreover, data condensation is not only beneficial due to the savings in computational power, but also necessary in case of comparisons of many data sets over the lifetime of the structure. Even though the more data condensation is achieved, the more computational power is saved; the sensitivity of the chosen features to the structural changes under a certain level of variability in the EOC has to be ensured by the employment of robust data reduction techniques (such as, Principal Components Analysis [172], Discriminant Analysis [173], Regression Analysis [174], etc. [175]).

Another option for data condensation in AE is proposed in several studies [5,176]. This technique is based on the use of Structural Neural Systems, a highly distributed sensor concept that mimics the signal processing in the biological neural system [50]. This methodology is employed in situations when a great level of accuracy in the damage evaluation is needed, as both the number of sensors and the amount of power needed for condensing and processing the data increase considerably. Moreover, an improvement in this technology is presented in [177] by the connection in series or array pattern of multiple piezoceramic patches. This connection decreases the amount of channels necessary for data collection of AEs or high strains.

6. Statistical model development

Statistical Model Development is the Pattern Recognition section that addresses the applicability of the algorithms that operate on the extracted features, identifying and quantifying damage in a structure. There are two main types of algorithms: supervised and unsupervised learning [23–25]. These categories of algorithms correspond to SHMS that do contain and do not contain data from the damaged structure, respectively. Supervised learning approaches are preferable, as by their application, damage can be classified and quantified, while damage identification is the further level of damage, according to Rytter's Damage States of a System [178], that unsupervised learning algorithms allow [119].

6.1. Supervised learning

When supervised learning approaches are employed, very high demand of data is associated with them, as data from every conceivable damage situation must be available [179]. The two possible sources of damage data come from: physics-based modelling (i.e. from Finite Element Analysis (FEA)), and experiments. Difficulty in obtaining these data in some fields jeopardises the applicability of this approach (e.g. aviation). Moreover, to accumulate enough training data, copies of the system of interest that can be intentionally damaged in different ways, might be necessary. The different analyses that can be categorised as supervised learning algorithms are introduced below.

6.1.1. Response surface analysis (RSA)

The RSA obtains the approximation relationship between the resonance frequencies and other damage parameters (i.e. damage location, and size). An example of this technique is explained in [180], where damages were satisfactorily identified in beams and plates made of CB reinforced plastic. The technique was applied to data simulated in analytical models. Nevertheless, the applicability of this technique, experimentally, is low as numerous data from various damage conditions are required.

6.1.2. Fisher's discriminant

This method introduces a linear transformation of the original multivariate distributions into univariate distributions whose means are as far apart as possible, while the variances of those transformed distributions are as small as possible [119]. It was satisfactorily applied in [6] where linear and quadratic discrimination methodologies were implemented to measurements taken from a concrete bridge column subjected to static and dynamic testing. No relevant applications of this methodology have been found for OW; however in [181] a new co-training algorithm based on modified Fisher's Linear Discriminant Analysis was proposed for semi-supervised learning, which is meant to be very useful in applications such as brain-computer interface design.

6.1.3. Neural networks (NN)

NN are commonly used in SHMS for identifying, locating, and quantifying damage in structures. This methodology is nowadays very well known as substantial textbooks and monograph accounts exist [182]. NN are the group of statistical learning models inspired by biological NN. The reason NN are extremely useful in SHM applications is the fact that they are used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown [179].

Some of the studies that have employed NN in the past for assessing structural damage include: the evaluation of two NNs for damage assessment, namely the Multilayer Perceptron Network and the Radial Basis Function Network [183]; and the damage detection and location in a numerical simulation of a two-dimensional truss structure by using a feed-forward NN [184]. Other studies employed NN for assessing the integrity of bridges as the auto-associative NN employed in [185] or in [186] where NN were trained with FEA data of the bridge.

NNs were also used for structural damage detection in plate truss structures, where damage was assessed by evaluating different learning rates, network types, reduction techniques of network topologies, and dimension analysis [187]. Different reports [188–190] assess the benefits and drawbacks of using sensors and NN to detect impact in composite materials, which could be a possibility for SHM of OWT blades.

6.1.4. Genetic algorithms

Ruotolo and Surace did most of the research related to this field between 1996 and 2001 [191–194]. In 1997 they formulated a problem for choosing the location and depth of cracks in beams employing measured modal parameters, which afterwards will be optimized by a genetic algorithm [192,195] and [191]. Nevertheless, there are some practical issues because, as the structure's complexity increases either size or geometry, the optimization becomes prohibitive [27]. The same authors carried out a similar study in 1998 where genetic algorithms, simulated annealing, and eigensensitivity analyses were compared in order to identify several damage scenarios in a FEA of a frame structure [196]. Similar studies were carried out in [197] for detecting damage in a composite beam.

6.1.5. Support vector machine (SVM)

The SVM constitutes a powerful framework for general classification and regression problems; as many different types of discriminant functions, such as linear, nonlinear, neural network, and radial-basis discriminant functions, can be put in this tool with no real modifications [198]. While in [199], a SVM is applied to damage classification problems in ball bearings and truss structures, in [168], nonlinear principal component analysis based on the unsupervised support vector machine is introduced and incorporated for data normalization.

6.2. Unsupervised learning

Unsupervised Learning constitutes an alternative to Supervised Learning when no damage state data are available. However, the drawback Unsupervised Learning algorithms have, is that they can only be used for detection and possibly locating the damage [200]. For that reason, they have perhaps received less attention than Supervised Learning approaches. A common type of Unsupervised Learning algorithms is known as novelty detection or anomaly detection method [201–203]. The idea of novelty detection is that only training data from the normal EOC of the structure or system are used to establish the diagnostic. To do so, a model of the normal EOC is created with the aim of comparing it with the one made with the newly acquired data. When significant deviations are detected, the algorithm indicates novelty, which means that the system has departed from the normal condition and, therefore, acquired damage. Unsupervised Learning algorithms can be roughly categorized into three groups, i.e. Control Chart Analysis, Outlier Detection, and Neural Networks.

6.2.1. Control chart analysis

This methodology continuously monitors the features extracted from the measurements, for anomalies. When the observations fluctuate outside the control limits, the monitoring system alarms the abnormality of the system's condition [27]. In [6], Control Chart Analysis for monitoring a reinforced concrete bridge column was used. It has also been frequently used for process control of chemical plants, manufacturing facilities, and nuclear power plants.

6.2.2. Outlier detection

Outlier, or novelty detection, is the primary class of algorithms applied in unsupervised learning applications. These algorithms assess statistical distributions of the measured or derived features to enhance the damage identification process [204]. When applied in an Unsupervised Learning mode, statistical models are typically used to answer questions regarding the existence and location of damage. When applied in a Supervised Learning mode and coupled with analytical models, the statistical procedures can be used to better determine the type of damage, the extent of damage and remaining useful life of the structure. The statistical models are also used to minimize false indications of damage (both false-positive and false-negative), as these are undesirable.

Outlier Detection Methodologies use changes in the rank of a matrix as a damage indicator [196]. Firstly, a matrix is composed by putting the feature vectors in columns, measured during various EOC of a structure, without any damage state. Singular value decomposition is used to estimate the rank of this matrix. After that, the same matrix is increased by adding an additional column containing a new feature vector, this time corresponding to a potential damage state of the structure. In case this new feature vector corresponds to a damaged structure, it will be independent from the previously measured vectors and, therefore, the rank of the matrix will increase [205].

The basic principle of novelty detection is that a model of the system is built using training data only acquired from normal EOC of the structure. While the monitoring of the structure takes place, newly acquired data are compared with the model. In the case that significant deviations are found, the algorithm indicates novelty, which means that the system has deviated from the normal condition and, therefore, is damaged [206]. Three different novelty indices to detect damage in composite plates where introduced in

Table 1
Technology assessment: capabilities and limitations.

Technology	Capabilities	Limitations
Acoustic emission monitoring Type of sensors: - Piezoelectric transducers	• Very effective detecting failure mechanisms up to microscale. • Allows a simple, rapid and cost-effective inspection or monitoring of a structure. • Good response at low frequencies. • Multifunctional character of piezoelectric sensors.	• Limited application offshore • Variable damage characterization and assessment effectiveness depending on the algorithm. • Optimization of data processing needed as it still takes up much time and computational effort. • High sensitivity to background noise. • AE systems can only qualitatively gauge how much damage is contained in a structure. • Determining acoustic signature of the structure is very difficult
Thermal imaging method Type of sensors: - Impedance tomography - Thermography (infrared cameras)	• Fast. • Cost effective. • Trials using drones are currently being conducted, which will detect cracks up to 0.3 mm based on technology limitations, avoid the necessity of having personnel inside the turbine and be even more cost effective. Moreover, time required would be less than traditional sensors.	• Limited implementation in offshore structures. • Camera resolution for detecting cracks • Laborious Image processing • Cracks detection needs more automation from footage.
Ultrasonic methods Type of sensors: - Piezoelectric transducers	• It is sensitive to both surface and subsurface discontinuities. • The depth of penetration for flaw detection or measurement is superior to other NDT methods. • Only single-sided access is needed when the pulse-echo technique is used. • It is highly accurate in determining reflector position and estimating size and shape. • Minimal preparation is required. • Electronic equipment provides instantaneous results. • Detailed images can be produced with automated systems. • It has other uses, such as thickness measurement, in addition to flaw detection.	• Surface must be accessible to transmit ultrasound. • Skill and training required is more extensive than other methods. • Coupling medium to promote the transfer of sound energy into the test specimen is required. • Difficulty of inspection of rough, irregular, very small, exceptionally thin or not homogeneous materials. • Difficulty of inspection of cast iron and other coarse grained materials. • Linear defects oriented parallel to the sound beam may go undetected. • Reference standards are required for both equipment calibration and the characterization of flaws.
Fatigue and modal properties monitoring Type of sensors: - Accelerometers. - MEMS. - Plastic optical-fiber based accelerometers. - Velocimeters.	• High reliability, mature technology • Easy installation. • There are many different techniques available for this purpose. • Recent developments in Operational Modal Analysis solve some limitations. • Stable performance.	• Difficult analysis in operating conditions. • High number of uncertainties when applied in the offshore environment. • Environmental and Operational Conditions changes have to be accounted in the results. • Difficulties in wind and wave loads measuring.
Strain monitoring Type of sensors: - Strain gauge (capacitance, inductance, semiconductor and resistance). - Fiber optic cables. - Fiber Bragg Grating (FBG).	• Easy installation process once appropriate training has been undertaken. • Mature technology. • Optical fiber might be the future of strain monitoring as it is less prone to fatigue, eliminates wiring issues and allows more points to be monitored with the same cable.	• Not very robust system. • The installation is very sensitive to misalignments. • Reduced service life. • Distance between the sensor and the Data Acquisition System influences accuracy and limits sensor location. • Mechanical properties limitations • Can be affected by EMI noise.

[207]. Thus, a stochastic subspace approach to determine damage existence in a structure was used in [208].

6.2.3. Neural networks

NN in the Unsupervised Learning mode work in the same way as in the Supervised, apart from the fact that no data from damaging events are available. A good example is the adaptive NN model proposed in [209]. In the model, data obtained from FEA simulations are used to train the NN; being the modal parameters from the FEA simulations used as inputs. The NN output will consist of structural parameters. Once modal parameters from the actual structure become available, the NN is used to calculate the associated structural parameters. Finally, the FEA model is updated using these new structural parameters, calculating the associated modal parameters. Training will stop when the measured modal parameters are acceptably not so different from those calculated from the FEA model. In [210] a discussion of delamination detection within composites applying a similar methodology can be found. Good agreement between experimental and analytical results was achieved. In [48], synthetic damage patterns are introduced in the FEA models. These models' structural responses to the damage patterns are calculated, analyzed, and archived in a "damage catalogue" which was used for posterior deteriorations and damage assessment of the WT structure, in near real time. The most recent NN application to WT blades is explained in [81], where the different NN types that can be used are identified.

7. Discussion

Previous sections have reviewed the different SHM technologies that could be employed for OWTs. A summary of related critical aspects, such as cost/effectiveness, capabilities and limitations can be found in Table 1, based on a structured survey aiming to map current practice within the industry. Responses have indicated high levels of interest and engagement in this topic obtaining responses from multiple industrial stakeholders including sensor providers, equipment providers, consultancies and designers, and developers/operators.

Some of the conclusions derived from the data collection process can be summarized below:

- First generation of wind farms were equipped with sensors after their deployment. The technologies mostly used were strain and fatigue and modal properties monitoring.
- The percentage of instrumented turbines within a wind farm is between 3% and 12%, showing a wide discrepancy in best practice.
- Strain gauges, accelerometers and inclinometers are the technologies mostly used for Structural Health Monitoring. LVDTs (Linear Variable Differential Transducer) are of interest as they can measure displacements with high reliability and accuracy, however at the expense of cost.
- To date, natural frequency analysis is considered to be the most commonly applied practice for detecting deviations from the design intent in wind turbine foundations, as other techniques are either very expensive, low maturity or of low accuracy.
- Fiber optics technology for strain measurement is considered a promising future technology due to the numerous benefits it brings. However, this option has not been costed or implemented in any case and installation needs to be carefully assessed.
- A necessity of the development of new methodologies to collect, review, purify and analyze the data collected by CM and SHM solutions has been pointed out by most of the interviewees.

8. Conclusions

In this paper, a review of the Statistical Pattern Recognition Paradigm for SHMS for OWT has been carried out. It is expected that by the assessment of each one of the stages present in this paradigm, SHMS can contribute in the development of an appropriate Condition Based Maintenance Strategy. The optimization of this strategy will lead to reducing labor costs of WT inspection, preventing unnecessary replacement of components, discovering design weaknesses before failure, improving the availability of power while preventing WTs overloading, and maximizing return in wind farm investments [50]. Increasing efficiency in operational management will contribute towards achieving UK's 2020 and 2050 targets, through ultimately reducing the Levelised Cost of Energy (LCOE) [211].

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