Manuscript version
DOI original paper: 10.1016/j.rser.2016.05.083

Structural Health Management utilization for lifetime prognosis and advanced control strategy deployment of Wind Turbines: An overview

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***Abstract*—In this contribution, Wind turbine (WT) systems subjected to strong intermittent fluctuating load are considered. The challenge discussed, results from contradictions between requirements related to efficient operation with respect to energy production costs and those related to lifetime and maintenance. Especially pronounced in larger WT systems, structural loads contribute to lifetime shortening due to damage accumulation and damage-caused effects influencing other subsystems of the wind turbine. Continuous monitoring of the WT system concerning State-of-Health is necessitated to provide information about the condition of the system guaranteeing reliable and efficient operation, as well as efficient energy extraction. In recent years, structural health monitoring of WT systems is significantly improved through on-line automated fault detection and health or condition monitoring (CM) system integration. In this contribution the focus is given to hardware components (mainly sensor technologies) and methods used for change evaluation, damage detection, and damage accumulation estimation under an assumption of known fracture mechanics knowledge. Accordingly, this contribution comprises recent knowledge about methods and approaches of handling structural loads with emphasis on offshore wind turbine systems and applied sensing technologies (especially with respect to wind turbine blades, gearboxes, and bearings). Moreover, a brief sketch of an advanced concept is developed concerning fatigue load examination in terms of an influence of the operating conditions on the system's lifetime extension. Key idea of the introduced approach is to use the operating conditions to control and especially to extend system's lifetime. The review presents an actual state-of-the art and overview related to the use and application of SHM-related technologies and methods. Especially in combination with the briefly introduced lifetime extension concept, the contribution gives an outlook to upcoming technological options.**

***Index Terms*—Structural health monitoring, Wind turbine, diagnosis, prognosis, lifetime control, home limp modes.**

INTRODUCTION

As the demand on energy production from renewable sources constantly increases, recent developments in wind turbine design are enforced by changed requirements reflected in Wind Turbine (WT) size increase (harvesting more energy), applied advanced control strategies, and improved Structural Health Monitoring (SHM). Apart from aforementioned requirements, the costs of energy production have to be at least comparable with the costs of energy production from conventional sources to make wind turbine system commercially acceptable [1]. Wind turbine system is exposed to harsh environment and fluctuating load affecting system's performance and ultimately causing the loss of functionality. Not only the fluctuating load but also environmental conditions (humidity, salinity, changeable temperature, ice, etc.) have a strong impact on WT performance in terms of damage initialization/propagation and have to be considered. Due to changes in material properties occurring over the system usage and subsequently decreasing components reliability, continuous monitoring of critical wind turbine system parameters is inevitable targeting to detect system State-of-Health that differs from an initial (considered as undamaged) State-of-Health [2]. In these terms, fault is defined as a significant change of system parameters beyond acceptable/allowed limits reflected in the negative influence on overall system performance. As such, fault is closely related to damage occurred in the system [3] but still cannot be understood as system failure. Even the fault is present in a system, the impact on system performance can be tolerable. Contrary, system failure is defined as complete loss of functionality whereas the system is not in position to perform predefined functionalities [4]. As noted in [4], fault detection includes the statement about whether a fault in a system is present or not. Whenever the fault is occurred, fault diagnosis have to be carried out targeting to identify fault type, fault location, as well as fault criticality. Accordingly suitable maintenance action have to be applied. In these terms, continuous health monitoring of the system is indispensable.

The decision about suitable action according to detected fault belongs to one of the tasks of SHM systems. Depending on the fault and related criticality, the required action may include corrective maintenance intending to restore the system state to the previous (undamaged) state or emergency maintenance targeting to avoid failures with more critical consequences. Nevertheless if corrective or emergency maintenance is planned to be applied, an approach considers the maintenance decision made at the point of fault detection, but not before the fault is indicated. Conversely, it is possible to carry out preventive maintenance. Here, the action is required before the failure happens (for instance: preestablished maintenance interval or elapsed predefined service time) [5]. Structural health monitoring therefore plays an important role to avoid system premature breakdowns, as well as reduction of system downtimes [6] [7] possibly reducing at the same time operating and maintenance costs [8].

In spite of that, recent effort in SHM development focuses on condition-based and reliability-based maintenance. Decision to perform the maintenance in condition-based maintenance strategy is system specific and based on the system state observation as well as on fulfillment of predefined conditions (for instance predefined limit reached, high vibration index, temperature out of acceptable boundaries, etc.) [9] [10]. Contrary, reliability-based maintenance combines the knowledge of the current system health state with the previous health state to infer the probability of failure [11]; it includes the estimation of system reliability and prediction of system health state in terms of making decision on whether the maintenance action will be performed or postponed [12]. Remarkable benefits of reliability-based maintenance are especially pronounced in offshore WT systems concerning hampered approach to offshore site [13]. Regardless of applied maintenance strategies, SHM also aims to find a cost-effective solution for system operation/health monitoring. The importance of SHM development can be clearly seen from the fact that the maintenance costs contribute between 11% and 30% of the overall wind turbine costs [14]. From the other point of view, operation and maintenance costs are especially pronounced in offshore WT installments as individual costs of replacement and maintenance actions are in general higher compared to the associated costs for onshore installments. As an example, a feasibility study done for offshore wind farms in Germany inferring potential fields for improvements concerning Operation and Maintenance (O&M) costs reduction is discussed briefly [15]. An analysis in aforementioned study belongs primarily to an analysis of expected wind farm installment/operation costs in dependence on expected benefits and energy generation costs. Moreover, the feasibility study considers different wind farm configurations and locations, different commissioning times, as well as different possibilities for investment financing. With respect to energy generation costs, long-term cost saving may be achieved by increasing rotor size and by extension of wind farm lifetime to 25 years (instead of 20 years). If technical aspects of individual WT components are concerned, dominant cost savings may be achieved in: i) supporting structure costs (reduction of 5,5% up to 6,6%), ii) O&M costs (reduction of 5,4% up to 7,8%), iii) installation costs (reduction of 3,6% up to 5,0%). Concerning O&M costs, cost savings may be achieved by simultaneous maintenance and replacement of multiple components. From these results, high potential for cost savings in O&M field is clearly stated.

Sohn et al. [16] discuss the definition of SHM within a statistical pattern recognition framework. Structural health monitoring process, following the authors [16], represents statistical pattern recognition problem whereas SHM tasks can be solved through four successive steps. The first step regarding to Sohn et al. [16] is to establish a suitable technical awareness of the data acquirement limitations, operational and environmental conditions, system failure criterion, and also awareness about economical justification for SHM. As the second step, data acquisition and measurement chain involving selection of sensors, number and localization of sensors, as well as associated hardware/software modules have to be deployed. If necessary, the data from different sensors have to be fused and preprocessed (filtered, normalized, etc.). In the third step, the features from fused signals are extracted/selected. As the last fourth step, statistical model inferring to calculate statistical indicators of feature change has to be established. Hence, the damaged/undamaged state of the particular system is reflected in the deviation of statistical indicators in these states. Hence, Farrar et al. [17] discuss not only SHM in general framework but also point out the tasks to be solved and improved for efficient damage prediction: i) measurement chain and processing of measured data, ii) algorithms used for feature extraction, iii) establishment and validation of lifetime/damage prediction models, and iv) reliability and uncertainty analysis of the models.

Recent reviews about SHM methods and approaches applied to WT systems are given in [18] [19] [20]. The authors of [18] focus on nondestructive methods of SHM and structural health system requirements, detail the statistical results related to WT components most likely to fail, as well as the failure modes of WT components without comprehensive analysis of them. Further, in Lu et al. [19] a review about Condition Monitoring (CM) techniques applied to WT systems discussing them in a general framework along with the correlation of specific CM technique to a specific WT component is given. Additionally, the authors of [20] detail CM techniques considering their classification in two groups: i) intrusive and nonintrusive CM techniques, and ii) destructive and nondestructive CM techniques. Herein, different concepts are introduced targeting to detect as well as predict system failures based on signature analysis of data captured through Supervisory Control And Data Acquisition (SCADA) system [20]. In aforementioned reviews, sensing techniques used up to 2013 are detailed and existing shortcomings, accompanied to particular CM techniques, are pointed out. Possibilities for further improvements, namely online automated CM and development of data processing techniques adapted to real-time processing, are stated. Moreover, fatigue load analysis of WT and its integration in SHM are not considered.

Conversely, this contribution emphases SHM methodologies related to wind turbine blades and gearboxes/bearings additionally integrating the damage mechanisms and discussion on damage growth reduction. Corresponding damage mechanisms in relation to the structural loads in WT systems are pointed out and are aimed to be explained in detail. More attention is attracted to offshore WT system as the estimated installment, operation, and maintenance costs are higher in comparison with onshore installments as well as the deployment of SHM for those systems is more challenging due to more complex operating conditions as well as burdensome accessibility to the offshore WT systems. Moreover, SHM deployment for offshore WT systems requires the analysis of potential extreme values of wind and waves (changing instantaneously) [21], as well as the analysis of underwater measurements (sea currents) [22].

Accordingly, the contribution is organized as follows: i) in the first section, variable loads the WT is exposed to are stated, ii) hence, sensing methods and accompanying signal processing techniques with special emphasis on their advantages, disadvantages, and applicability to a particular system component are addressed in the second and third section, iii) afterwards the safety and reliability control engineering concept is described in the fourth section. At last, the contribution closes with the summary and conclusion.

I. Design for variable loads

A. Wind turbine inflow conditions

Estimation and monitoring of fatigue loads in WT systems is an important task, especially in offshore WT systems whereas additional information about surrounding area (landscape, sea waves/currents, etc.) are necessary [23] [24]. Aerodynamic loads like wind speed, wind direction and shear, seismic load, as well as the climate impacts resulting from ice, snow, humidity, air density, and thermal loads, are reflected in structural loads of both offshore and onshore WT systems. Beside the aerodynamic loads, the environmental loads in offshore WT systems are even more complex including hydrodynamic loads (surface waves and sea currents). Correspondingly, the consideration of hydrodynamic loads beyond the aerodynamic loads is necessary for fatigue analysis.

In [25], it is stated that the surface waves and ocean currents strongly affect the performance of WT. As noted in Luznik et al. [26], surface waves particularly affect WT blades loading and power production, but without significant impact on the power coefficient. Therefore, in order to reduce structural loads, to employ adequate WT design, and to adopt the operation management with respect to modeled/predicted environmental conditions, modeling of fluid dynamics as well as load prediction seems to be important [27], especially for the design process. Computational fluid dynamics (CFD) models are needed for inflow conditions prediction, control strategy adaption, as well as power loss prediction taking into consideration environmental conditions [28]. Judging on [28], modeling of wind and surface waves dynamics is mostly based on empirical knowledge and long-term measurement data. As mentioned in [29], the models providing an approximation of wind and sea waves dynamics are a "mixture of mathematical, probabilistic, empirical, and statistical" [29] models. Those models are in general based on long-term and short-term measurements collected from in-service WT systems. Independent from the applied models, modeling of fluid dynamics contributes to suitable WT design employment. Different WT designs (for instance floating support platform design) show different impact on the structural loads of offshore WT wherein established models can be used [30]. Qiu et al. [31] distinguish three methods for prediction of structural response behavior as well as load prediction, namely model tests, full-scale tests, and numerical modeling. The idea of load calculation and prediction, induced by wind, wave, currents, icing, etc., is also detailed in [32], whereas the analysis is dedicated to loads applied to ship structures, as well as offshore "floating cranes" [32] which can be correlated to WT systems. Judging on aforementioned contributions, environmental and operational loads are in most cases unknown and/or difficult to define whence the difficulty of loading profile prediction becomes understandably aggravated.

Hence, Leishman [33] discusses predictive analysis of wind turbine aerodynamics in terms of modeling and predicting wind speed, wind turbulence, blade/wake interactions, and wakes occurred close to wind turbine installments. Special emphasis in [33] is given to the modeling of velocity field occurred behind WT due to induced wakes and their mutual interaction with particular WT components. Unsteady and stochastic nature of those effects is identified as the most challenging task in deployment of dynamic inflow models, and in turn also as the most aggravating factor in accurate prediction of the same. The author points out necessity for further research in this field belonging in the first line to rotor wake and unsteady aerodynamic modeling [33].

Additionally, according to the results stated in [29], it is recognized that modeling of inflow characteristics without considering uncertainties assigned to the models and the measurement equipment can lead to ambiguous results. Uncertainties are not only associated to the models and measurement equipment but also to the environment, human factors, or fluid properties [31]. This is one of the upcoming research fields in the next years.

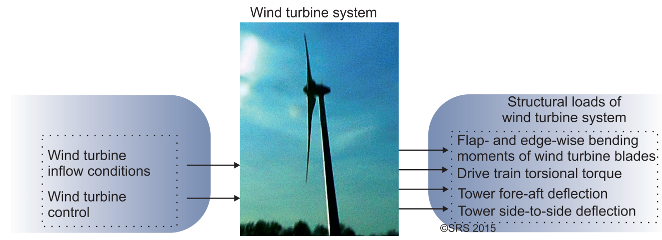

Fig. 1. Qualitative relations of structural loads (right side) to operating conditions (left side)

B. Effect of inflow conditions on WT fatigue growth and modeling

Both aerodynamic as well as hydrodynamic loads cause the fatigue damage leading to the system failure at the point at which the fatigue loads, quantified using tower fore-aft and side-to-side deflections, flap-wise and edge-wise bending moments of blades, as well as drive train torsional torque measurements as depicted in Fig. 1, become considerably huge [32]. Moreover, particular inflow condition (for instance: wave height) correlation to accumulated damage/damage rate or fatigue occurred in a structure [32] is indispensable in terms of structural loads reduction. In practice, fatigue analysis entail the usage of additional sensors for mechanical stress measurements (bending moments of blades, bending moments of tower, etc.) introducing uncertainties simultaneously increasing the costs of wind turbine installment. In case of mechanical stress measurements represented as time series data, the fatigue loads are related to system and operation parameters. Up to now, fatigue testing of particular components are mostly done under specific laboratory conditions which are realized in situ. According to [34] those conditions are not able to represent the dynamics of the load situation or related real conditions.

Some contributions [35] state that certainly measured signals from WT system such as generated power, pitch angles, generator speed can also be used to perform the fatigue load analysis as those parameters are affected by structural loads. In this case, the significance of other parameters that may also be used is not clarified and suitably inferred [36].

Probably the most widely used fatigue damage accumulation rule is Palmgren-Miner rule [37]. This well experienced and often applied technique acts as a model/system combining the fatigue load expressed by load parameters like stress and/or amplitudes in relation to the number of usages (frequency of their occurrence, cycles, or simple related usage parameters like hours, kilometers or similar). The often cited approach is used for damage evaluation and accumulation. The fatigue load representation in form of load amplitudes vs. frequency of their occurrence is necessary for damage accumulation rule application. This kind of load/stress-usage relations can - beside others - be achieved using Rainflow Counting Algorithm providing a prerequisite for an integration of aforementioned relationship in damage accumulation rule to calculate overall damage accumulated in the system [38]. Summarizing the aforementioned facts it can be stated that the limitations of Palmgren-Miner rule are following: i) with load representation in form of load amplitudes vs. frequency of their occurrence loading sequence is neglected, ii) loading under constant amplitude is considered, what is not case in practice [39]. Although identified shortcomings, Palmgren-Miner rule is still used owing to simplicity of application and existing fatigue databases related to gaining knowledge about material specific S-N curve [34].

Sevenois et al. [40] and Van Paepegem et al. [41] review existing fatigue damage modeling techniques for composite materials deployed over the last 15 years. In [40], the discussion about existing fatigue models is carried out through model classification in four groups, namely: ”fatigue life models”, ”residual strength models”, ”residual stiffness models”, and ”mechanistic models” [40], whilst similar classification is found also in [41]. Judging on [40], fatigue life models are used to predict remaining useful lifetime (RUL) using life cycles, stress, and laminate stiffness relations often achieved through the experiments. Contrary, residual stress models relate to prediction of residual strength, while residual stiffness models ”are also concerned with the prediction of deformation of the structure during fatigue process and the resulting stress redistribution” as stated in [40] (that are in the basis statistical and probabilistic models). At last, mechanistic models are related to particular physical deterioration mechanisms modeling.

Kong et al. [42] use the Goodman diagram, load spectrum along with S-N linear damage equation, as well as ”Spera's empirical formulae” [42] to determine fatigue life. Similarly, Marino et al. [43] discusses ”equivalent fatigue load” (EFL) as the constant stress amplitude applied over service time (overall life cycles) causing equivalent damage originating form originally applied varying amplitude stress.

It can be concluded that some of the aforementioned models require the usage of S-N curves or Goodman diagrams, while others rely on probabilistic/statistical theory. In these terms also Artificial Neural Networks (ANNs) can be used to model S-N curves based on carried out tests on CFRP materials. For instance, Zulaga-Ramirez [44] used linear damage accumulation rule whereas S-N curves are modeled using ANN based on the load history data represented by commonly used rainflow counts. Deployed ANN model shows good agreement with experimental data but do not have noticeable effect on overall prediction results. It is used within linear damage accumulation models. Contrary, An et al. [45] use Bayesian approach to predict lifetime. The authors of [45] state more accurate prediction results using Bayesian approach in comparison with commonly used damage accumulation models but identify also aggravating factors and limitations of Bayesian approach. This results from non-optimal choice of measured data, presence of noise, and uncertainties due to material properties and production processes or similar.

The estimation and prediction of fatigue loads are closely related to the system failure prediction, but may also require the monitoring of the predefined system parameters. Hence, SHM deployment with the emphasis on the blades and gearboxes/bearings, corresponding sensing techniques, as well as on further data conditioning (time based, frequency based, combined time-frequency based), and statistical analysis of measured signals is introduced in order to detect and classify the failure.

II. Structural health monitoring

Among all wind turbine components, rotating parts of wind turbines are the most relevant components to structural loads. In the first line, the WT rotor, gearboxes, and bearings have to be mentioned. In terms of structural loads it can be noted that different materials exhibit different characteristics concerning material/component aging, fatigue resistance, strength, etc. Accordingly, aforementioned material characteristics are the decisive factors in material selection to be used for component manufacturing and cannot be arbitrarily chosen. Not only for safety and operating parameters monitoring purposes, but also for purposes of gaining the knowledge about accumulated strain load in components along with forecasting the residual lifetime using the feedback got from sensors, SHM integration in wind turbine operation is justified [46].

Concerning wind turbine rotor blades, previously used steel and steel alloys have been almost completely phased out and replaced with different composite materials owing to their increased strength and fatigue resistance, retained stiffness, as well as less weight [47]. Nowadays WT blades are manufactured using epoxy, polyester, or vinylester reinforced material with carbon (Carbon Fiber Composites) or glass (Glass Fiber Composites) fibers [48] [49]. Composite materials moreover differ in fibre content, type of fabrication (fiber architecture), lay-up sequence, and fiber orientation. All of these properties affect the characteristics of composites [50] [47] [51] [52]. As outlined by Mandell et al. [53], ”Composite Materials Fatigue Database” based on constant stress amplitude test results made on wide range of composite materials (130 different composite materials) dates back in 1999. The most valuable finding disclosed by aforementioned tests is decreased fatigue resistance with fiber content increase beyond 45% [53]. In accordance with the database, by using an adequate combination of matrix as well as fiber type it is possible to achieve fatigue performance adapted to particular application. Additionally, steel, steel alloys, and iron are still predominant material for gearboxes, bearings, and wind turbine shafts production. These materials with emphasis on aging and consequent component/system reliability decrease are beyond the scope of this contribution.

A. Structural monitoring of blades - sensing techniques

Inadequate sensing techniques applied to particular component leads to ambiguous results concerning the measurements of relevant parameters as prerequisite for further analysis and data conditioning. Once the relevant system parameters are chosen, selection of sensors, sensor locations, and the choice of data acquisition/storage and transmission elements are responsible for successful condition monitoring [54]. The technical and partly theory-based decisions are strongly related to the knowledge about the physics of failures (failure modes) and other phenomena revealed in particular material (herein composites). Concerning WT blades, Ciang et al. [18] notes that critical spots in WT blades (where the damage is most likely to occur) are root section of blade and bonding/welded joints.

As outlined in [55] and [56], typical failure modes of blades are cracks, fiber breakage, fiber pulling out/lack of resin, delamination, and debonding. Delamination is defined as matrix layer separation [41] [57] while debonding is understood as losing the ability of materials to adhere to each other [58]. Especially in case of material-mixed compounds and composites, the surface where two materials meet each other (fiber/matrix interface) are the most susceptible to failures [59]. Thus, it is also worth to infer the ways of reducing the failure propagation rate. Discussed failure modes are detectable using suitable measurements got from continuous monitoring system. Concerning wind turbine blades, measurements of Acoustic Emission, ultrasound, vibration, infrared, or thermal signals as well as strain monitoring, visual inspection, radiographic, and eddy current testing are mainly applied targeting to correlate them to the damage process. Concerning existing technologies, aforementioned techniques are not capable of online monitoring of the blade during operation (and therefore loading) but prior or after. As outlined by Schubel et al. [46], Acoustic Emission and strain monitoring techniques are techniques that nowadays offer high potential for online implementation.

1) Acoustic Emission measurements: Inceptive steps towards research on Acoustic Emission phenomena date back to 1978 and are made by Drouillard [60]. Acoustic Emission (AE) is defined as an emission of elastic waves within the material subjected to deformation as a consequence of energy release in *Standard Terminology for Nondestructive Examinations* [61]. The Acoustic Emission technique is a passive NDT technique owing to sources of elastic waves emitted by examined object but not by additional excitation source [62]. Moreover, as one of rare nondestructive techniques (NDT) to be applied during system loading (not apriori or posteriori), those Reyleigh waves are often used monitored signals. Typical sources of elastic waves are micro structural changes in blades as crack initiation, fiber breakage, matrix cracking, debonding, and delamination [46]. Acoustic Emission wave is characterized by both low amplitude range and high frequency bandwidth (100 kHz to 1 MHz) [63]. Elastic waves are converted into electrical signal using surface-mounted piezoceramic sensors. Low amplitude range along with high frequency bandwidth aggravates the capture of waves and sets

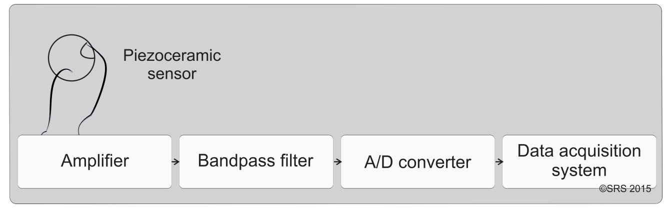

Fig. 2. Measurement chain/data acquisition module for AE signal capturing

additional requirements on measurement chain and sensors. Low amplitude signal have to be amplified whereby the amplification of signal reaches 100 to 1000 times. Along with signal amplification signal-to-noise ratio is changed as not only utilizable signal but also existing noise is amplified. To eliminate noise, frequency bandwidth is limited to range between several kHz to 1MHz whereas bandpass filter is used to cut of frequencies beyond aforementioned bandwidth [64]. At last, data acquisition have to be solved concerning A/D converters capable to work in high frequency bandwidth and development boards consisting of elements able to face with fast I/O throughput (FPGAs, CPU arrays, or similar). A typical AE measurement chain is depicted in Fig. 2. Event counts, rise time, peak amplitude, arrival time, duration, signal energy content, root mean square are used in the analysis of AE signals. Newest developments in the field of AE emission signal analysis shows that the distinction between different failure mechanisms is possible [65]. Recently, considerable attention has been also given to SHM using guided waves whereas elastic waves are induced and introduced into the structure serving as an active SHM method.

2) Structural monitoring using guided waves: Guided waves are ultrasonic elastic waves that propagate along structure guided by structure boundaries [78] [79]. Although the guided waves can be discussed in terms of ultrasonic inspecting methods, herein are discussed separately targeting to point out specifics of this technique, especially dedicated to lamb waves generation and their usage in internal structure inspection. Recently, guided waves are used to detect damage location, type, as well as severity of damage [80]. As active NDT technique, the excitation of structure using suitable transducers is required. Here, transducers and actuators are often integrated in the structure to be monitored. As transducers in guided waves technology comb transducers, electromagnetic, acoustic, piezoelectric transducers, as well as fiber optic transducers are used. To use guided waves in SHM, the healthy state of a structure has to be known in advance, so that it can be used as reference in comparison to the state being evaluated. Predefined features of reflected/received waves, namely amplitude, frequencies, response time, etc. are analyzed targeting to detect anomalies in a structure [81]. Among guided waves, the most attention is perhaps attracted to lamb waves generated and occurred in frequency range between 0.5 and 4MHz [3]. The lamb waves are generated using piezoelectric tentacles. This solution has main shortcoming in undesirable couplings of transducer and inspecting surface, whereas the proper media has to be found [82]. Therefore, noncontact techniques for lamb wave generation/sensing are developed affecting

TABLE I
OVERVIEW OF MONITORING TECHNIQUES FOR WIND TURBINE BLADES WITH ACCOMPANYING ADVANTAGES AND DISADVANTAGES

Condition monitoring method	Advantages	Disadvantages	Online applicability
Acoustic Emission measurements [60], [62], [46], [63]	- continuous monitoring during system loading - possibility for damage localization - high-sensitivity - no need for additional excitation source	- high requirements on measurement chain - no physical relation between Acoustic Emission and correlated damage - as often applied in noisy operating environments, the discrimination of AE signal difficult due to signal weakness	Yes
Guided waves [79], [3], [82], [83], [78], [81], [91], [3]	- high signal attenuation in high frequency range - damage localization	- active nondestructive technique - coupling between transducers and inspecting surface - laser based lamb waves generation and sensing as non-contact solution	Yes
Ultrasound measurements [72], [74], [73], [76], [77]	- detection of extremely small flaws in material - imaging of the size, shape, and orientation of flaws - automated image processing possible - high potential of noncontact optical and sound excitation sources	- additional excitation source necessary, inspected surface have to be accessible for the transducer - time-consuming technique	Yes
Strain measurements [67], [46], [69], [71], [68]	- continuous monitoring during in-service operation - tremendous potential of optical sensors and its integration in composite structures - suitable for component lifetime prediction	- requirement on the knowledge about the hot spots in advance - necessity for a huge number of sensors due to the fact that one sensor measures strain only at one point	Yes
Vibration measurements [85]	- nondestructive technique - indication of both the location and the criticality of damage	- difficult distinction of vibration signatures originating from normal usage and changes resulting from damage occurrence	No
Eddy current testing [87], [88], [86], [89]	- high accuracy of internal damage detection - high accuracy of damage localization - detection of the defect depth	- time-consuming processing - not applicable as in-service inspection method	No
Thermographic measurements [90], [91], [92]	- useful in fatigue testing - simplicity of application - short inspection interval (time consumption relatively low)	- high sensitivity to temperature variations - not applicable to continuous in-service testing - requirement on external excitation source in active thermal imaging method	No
Radioscopy/Radiography testing [93], [94], [95]	- detection of internal damages - mostly used in blade production quality testing - high accuracy concerning damage localization	- requirement on X-ray source and X-ray detector - long exposure time - not applicable to continuous in-service monitoring	No
Visual inspection [96], [97]	- used as supplement to other monitoring techniques - possibility to detect external damages such as cracks and scratches	- accuracy low - rarely used standalone - high computational requirements if performed using camera devices (image processing)	Yes

TABLE II
OVERVIEW OF MONITORING TECHNIQUES OF GEARBOXES/BEARINGS

Condition monitoring method	Advantages	Disadvantages	Online applicability
Vibration measurements [99], [100], [101], [102], [103]	- often used as combined inspecting technique with Acoustic Emission - low cost technique - detection of failure criticality not possible	- unsatisfactory results in detection of failures in gearboxes/bearings in early initiation phase - unsuccessful application to components rotating under low rotation speed (as usually occurs in the WT systems)	No
Acoustic Emission measurements [19], [104], [105]	- applicable in low rotation speed region - detectability of failure in early initiation phase	- monitoring under high sample rates - high requirements on measurement chain	Yes
Oil analysis [10], [11], [104], [106]	- applicable for online as well as offline monitoring - direct determination of State-of-Health	- cost intensive technique if applied online - mainly applicable offline due to high costs of online implementation - online implementation sets requirements on closed oil system of bearings/gearboxes	Yes
Shock pulse method [10], [108], [107], [109], [110]	- low cost technique - accurate detection as well as localization of failure occurrence in bearings (gearboxes) - often used combined with vibration technique	- low sensitivity to loading profile change = not useful in terms of fatigue analysis	No

the design of transducers. Recently developed approaches considers optical and laser-based lamb waves generation and sensing techniques avoiding thereby direct coupling between transducer and inspecting surfaces. As reported by Leong et al. [82], a possible problem solution is to use laser-based lamb wave generation and sensing. Aggravating circumstances in laser-based sensing are high costs and high noise along with low sensitivity due to a high signal attenuation [82]. Despite aforementioned limitation considering limited application to metallic structures and composites, the application of piezoceramic actuator for lamb wave generation, and scanning laser vibrometer for lamb wave sensing is discussed in [82]. According to [82], cracks detection inside metallic structures using aforementioned simple sensor-actuator combination is possible. Berger [83] applied fibre optical and piezoceramic sensors for onboard continuous monitoring of composite structures and pulled out some conclusions: fibre optical sensor measurements can easily be correlated to used/exhausted lifetime of the system, system of sensors have to be set as close as possible to the damaged element/source/position/component, outlay of application is pretty high. Contrary to fibre optic sensors, piezoceramic sensors can be positioned far away from the damage. The application is simplified, but does not offer an information about used lifetime of a structure.

3) Ultrasound measurements: Unlike passive AE monitoring methods as introduced before whereas AE waves are emitted by a concrete, ultrasound acoustic monitoring (UA) method requires both: an external excitation source for ultrasound wave generation which propagates and interact within concrete, and ultrasound receiver (active method). According to [72], the main challenge in ultrasound inspection technique is set to an automated in-service spatial scanning. Concerning WT blades, noncontact scanning laser vibrometers based on Doppler effect principle whereas the optical signals (frequency, phase difference) are analyzed in different ways, are introduced as an instrumentation device for measurement and imaging of vibration [73]. Park et al. [74] applied noncontact ultrasound laser imaging to a visualization of damage in composites like delamination and debonding. As excitation source pulse laser beam is used to generate ultrasonic waves. Wavefield imaging technique is successfully applied to GFRP and CFRP composites. Acoustic-laser vibrometer consisting of acoustic sources as excitation and scanning laser vibrometer as a transducer is discussed in [75] and [76] in a similar manner. Experiments are done under laboratory conditions with an aim to infer impact of different configurations and operational parameters on measured signal signatures. According to [75], acousto-laser vibrometer SHM method showed good results with respect to the detection of delamination and damages occurred at the boundaries between CFRP layers. Hence, combined AE and UA monitoring method is introduced in a study of Scheerer et al. [77]. Here, AE is used to localize the damage and UA to infer the shape and size of damage. Tests are done on two different types of specimens, namely pressure vessels overwrapped by a number of CFRP layers and Al-Li metallic panels. The contribution compares passive Acoustic Emission method with an active (ultrasound Acoustic Emission method). Summarized from [77], both methods are able to detect anomalies in both specimens, but passive Acoustic Emission method shows better results in damage severity estimation. Despite promising results reported in [77], additional studies are still necessary to make combined AE/UA technique commercially acceptable.

4) Strain measurements: Elastic deformation of material as well as change in length due to applied compressive or tensile stresses is quantitatively determined as strain and is proportional to applied stress. For suitable sensor positioning, the maximum tolerable strain level as well as the expected strain at blade hot spots (blade roots, blade bonded/welded joints) have to be known in advance to make failure/damage detection as well as failure propagation/prognosis possible. Aggravating factor in strain monitoring is the requirement on a number of sensors concerning the fact that one sensor measures the strain only at one point. In these terms, WT blade hot spots have to be covered by sensors as they sense ”the most cumulative damage” [66]. Blade deflection and root bending moments (flap-wise and side-to-side) as critical WT blade spots are measured mostly using traditional electrical strain gauges and commercially available fiber optical sensors [67]. Electrical strain gauges work on a principle of electrical parameter measurements (depending on a sensor type: resistance, capacitance, inductance). Fiber optical sensors, contrary to electrical strain gauges, correlate light intensity, light wavelength change, or light phase to strain whence the load history can be reconstructed and consequently component lifetime can be predicted.

Recently, optical Fibre Bragg Gratings (FBGs) have gained increasing interest. The principle on which FBGs work considers light wave propagation and reflection in exactly predefined manner. Light wave propagating thorough optical fiber is modified on such way that only well defined light wavelengths are propagated whilst the others are reflected. Reflection or propagation is adjustable through refraction index variation. Fibre Bragg Gratings (FBGs) serve as sensors especially adapted to WT blade monitoring due to advantages they offer: i) low long distance signal transmission with low signal attenuation, ii) insusceptibility to electro-magnetic interference, iii) hundred of sensors on one transmission line (number of sensors on one fiber-multiplexed sensors) each identified by specific wavelength [46]. Moreover, small dimension of FBGs makes them suitable for embedding in a structure [68] facilitating thereby continuous strain monitoring (through sensor integration into structure; smart WT blades, smart composites) [69] [70]. Considering smart composites, not only sensors can be embedded in a structure but also heater elements targeting to overtake the problem of icing/freezing during critical operating conditions. Implementations into composite structures introduces additional thermal stresses in composites and micro displacements that can be measured using shearing cameras. To infer those changes of surface strain under thermal loading, displacement gradients are analyzed (shearography) and afterwards correlated to ”in- and out-of-plane surface strain components” [71].

In [46], comparison between acoustic, ultrasonic, and strain monitoring methods is carried out targeting to introduce improvements into WT blade design. According to [46], acoustic and ultrasonic methods do not provide an information about internal structural stresses and require advanced signal processing techniques. Contrary, strain monitoring measurements are able to reveal accumulated strain loads at specified blade locations. Based on strain measurements at specified blade locations, blade lifetime estimation as well as replacement and maintenance actions is possible [46].

5) Vibration measurements: Intermittent changes of wind flow and turbulences the wind turbine is exposed to, cause vibrations primarily reflected in WT blades. In dependence of current State-of-Health, vibration signals contain different signatures that can be revealed using appropriate signal processing technique (time-based, frequency-based, time-frequency based. Thus, relationship between vibration signal signatures and the State-of-Health of WT blades also can be established [84]. Recent improvements in vibration method belong mostly to improvements in advanced signal processing techniques and algorithms targeting to provide fast, efficient, and online applicable approach.

However, vibration measurements are used for characterization of mechanical properties of composites (mostly natural frequency, mode shape, and damping) [85]. As outlined by Gibson [85], vibration measurements can be used to gain knowledge about the distribution of fibers, ”interlaminar fracture toughness” [85], an occurrence of damage, or the degradation within composites.

6) Eddy current testing: The physical principle lying behind eddy current testing is the variation of conductivity caused by material deterioration. Conductivity of material is measured using high-frequency eddy currents generated by electromagnetic induction. In case of damage, Eddy current density changes causing nonuniform heating of damaged and undamaged areas which can be captured by IR camera [86]. Afterwards, image analysis is necessary to extract those signatures which are related to damages. Eddy current is a NDT inspection method that can be applied to conductive materials. Although in the cases of relatively low conductivity of composites [87], it is still sufficient to apply Eddy current testing in order to detect different anomalies such as delamination, fiber break, matrix cracking, layer misalignments, and similar. For instance, Heuer et al. [88] applied eddy current testing to the detection of anomalies in Raw Carbon Fiber (RCF) and CFRP materials. From the results summarized in [88], it can be stated that the anomalies in the depth up to the fifth layer as well as anomalies of only a few millimeters are detectable using this technique. Beside good results in the detection of flaws in materials, excellent results can be obtained in the examination of quality indicators of manufacturing process (fiber distribution, orientation, density). Despite the fact that Eddy current techniques are one of the oldest applied NDT techniques, in recent years some advances are introduced. Here Eddy Current Pulsed Thermography (ECPT), Eddy Current Pulse Phased Thermography (ECPPT), and Eddy Current Lock-in Thermography (ECLT) should be mentioned. Eddy Current Pulsed Thermography uses magnetic field intensity along with conductivity analysis to distinguish different types of damage in composites. He et al. [89] made a comparative study on ECPT, shearography, and flash thermography whereas higher reliability as well as better accuracy in detection of damages positioned deep in a structure is shown by ECPT. The main shortcoming of ECPT is higher time consumption needed in comparison with shearography and flash thermography.

7) Thermographic measurements: Monitoring of temperature changes to detect internal and external surface anomalies is discussed in terms of both: i) as a passive monitoring method, whereas the ambient temperature is compared to material temperature, and ii) as an active monitoring method based on the use of thermoelastic effects (change of structure temperature caused by changed stress). While passive thermal imaging method is not often used in WT blade monitoring, active thermal imaging method requires an external excitation source such as flash or heat lamps [90]. Energy transferred to the material induces specific temperature distribution around damaged areas allowing damaged area detection and stress analysis. Internal damages as delamination, debonding, matrix cracking, and fiber pulling out can also be detected using thermographic measurement and even more in an early stage, before the damage is propagated to a critical level [91]. Thermal imaging is especially useful in fatigue testing, but still shows poor performance concerning operating WT (application during loading) as it is highly dependent on ambient temperature. Measurement chain has in its basis infrared (IR) camera as transducer and heating device as an external excitation source [92].

8) Radioscopy/Radiography testing: Contrary to thermal imaging, X-ray imaging is based on nonuniform absorption of X-rays inside damaged area. It offers the possibility to detect and localize internal damages as delamination, debonding, and matrix cracking [93]. It requires an X-ray source as well as an X-ray detector. As X-ray source, X-ray tubes providing low photon flux are often used in conventional applications along with widespread radiography film as X-ray detector. Further development of X-ray technology is oriented towards 3D X-ray digital imaging (Computer Tomography - CT) along with recent development of X-ray sources oriented to ”carbon nanotube-based field emission X-ray sources” [94] [95]. Radiographic inspection is mainly used to check blade production quality, while the application on in-service wind turbine is still limited.

9) Visual inspection: Only superficially visible damages such as cracks and scratches can be detected using visual inspection. The accuracy of one of the oldest applied monitoring method is not high, especially if based on ”naked-eye” principle (without aided equipment and interpreted by humans). Visual inspection is therefore not applied standalone but along with other NDT techniques as a proof of detected or supposed internal damages. Actual vision systems are installed on mobile or mobile movable platform able to control camera positions and adapt them to current needs [96] [97]. The analysis of measured results (captured images) includes different image processing techniques whereas particular pixel values are compared targeting to detect specific shape. For instance, the shape of crack or scratch is not circular but directional and based on it crack or scratch can be detected/distinguished from spatial features.

B. Structural monitoring of gearboxes and bearings - sensing techniques

Contrary to WT blades, failure modes of gearboxes are pitting, abrasion, spalling, and tooth cracking [98], whereas failure modes of bearings are roller cracking, spalling, brunelling, and fluting [98]. Taking aforementioned failure modes into consideration, structural monitoring of gearboxes and bearings has its own specifics and related adapted monitoring techniques. In these terms, vibration monitoring techniques, as well as Acoustic Emission techniques are used.

1) Vibration measurements: Vibration measurement is one of the typical structural monitoring techniques applicable to inspection of rotating parts as gearboxes and bearings. Changes in vibration characteristics of the structure like stiffness or damping are in most cases induced by damage

TABLE III
OVERVIEW OF MONITORING TECHNIQUES

	Acoustic Emission	Guided waves	Ultrasound measurements	Strain measurements	Vibration analysis	Eddy current testing	Thermography	Radiography	Visual inspection	Oil analysis	Shock pulse method
Low complexity					x	x	x	x	x		x
In-service monitoring possible	x	x	x	x					x	x	
Time consuming	x	x	x			x		x			
High costs		x	x	x						x	

occurred in a structure [99] [100] [101]. The type of sensor to be used for monitoring (laser vibrometers, velocity sensors, accelerometers, spectral emitted energy sensors, displacement sensors) depends on the frequency bandwidth of interest. As aforementioned in previous section, these structural changes are reflected in changed natural frequency and/or mode shape which in turn can be used to extract the information about the failure or damage [102]. Accordingly, damage detection and localization techniques can be classified in four groups as noted in a study of Fan et al. [102]: i) mode shape based techniques, ii) curvature shape based techniques, iii) frequency-based techniques, and iv) combined shape- and frequency-based techniques. A comprehensive studies on different damage indicators extracted from vibration measurements using time, frequency, or time-frequency analysis are present, all of them targeting to correlate size, type, and criticality of damage (damage index, strain energy, mode shape index, and others) to measured vibration signals. Additionally, Skaya et al. [103] discuss different signal signatures in terms of their sensitivity to early damage detection and propagation, as well as their robustness. The comparison herein is done between features obtained by using High-Frequency Resonance (HFR), Continuous Wavelet Transform (CWT), Hilbert-Huang Transform (HHT) analysis, as well as crest factor, kurtosis, and root mean square (RMS). Following conclusions are herein given by authors: i) crest factor is the best ranked signature with respect to robustness, but shows poor results with respect to damage size sensitivity, ii) HFR, CWT, and other time-frequency-based signatures show high sensitivity to damage size change and timely damage detection, iii) statistical signatures in general provide poor results taking in consideration sensitivity to damage change.

2) Acoustic Emission measurements: While vibration sensors are able to detect movement (velocity, acceleration) of/within structure, Acoustic Emission sensors are able to capture directly elastic waves propagating across the structure. Concerning slow rotation speed of WT, vibration monitoring technique showed unsatisfactory results in detection of failures in gearboxes/bearings in early initiation phase. For instance, Acoustic Emission measurements are used to detect failures of gearboxes/bearings such as pitting and cracking in the initiation phase [62]. As noted in [62], the variety of statistical variables based AE signals may be calculated and utilized in fault detection. Fault detection based on AE-based statistical variables is shown as a successful approach. Soua et al. [104] introduced combined vibration and AE techniques targeting to obtain both vibration and AE signatures related to unused (healthy) WT gearbox. Obtained signatures are filtered and used to identify and distinguish anomalies related to failure occurrence. Results presented in aforementioned contribution show that combined vibration/AE technique shows different results under different operating conditions, different choice of sensor types (sensitivity), as well as damage sizes. Hence, Al-Ghamd et al. [105] outline differences between vibration and Acoustic Emission measurements whereas earlier detectability of failures using AE if compared with vibration analysis is particularly pronounced. Moreover, failure criticality estimation is achievable using AE monitoring technique, which is a strong feature especially in comparison to other approaches like vibration monitoring techniques.

3) Oil analysis: One of an inceptive techniques for monitoring of bearings/gearboxes is oil analysis [104] [106]. Oil analysis can be applied online and offline involving analysis of hydraulic and/or lubrication oils. Hence, oil analysis belongs to the group of time consuming and relatively expensive techniques requiring use of spectrometers, analyzers, or Scanning Electron Microscopes (SEM). The presence of wear particles (oil contamination), particle size, and oil temperature are used as indicators for the health status of gearboxes and bearings [11]. Concerning oil analysis, it could be stated that the technique allows direct determination of health state [10].

4) Shock pulse method: Shock Pulse Method (SPM) is used for bearings condition monitoring intending to detect mechanical shock wave occurred due to the hit of the roller ball with degraded raceway area or adjacent rolling ball [10]. Signal signatures (peak value of shock pulse, maximum normalized shock value, frequency spectrum) of generated shock wave can be correlated to the bearing health state. Application of SPM is not limited exclusively to bearings condition monitoring but also can be successfully applied in other machinery consisting of metallic structures such as gearboxes. If maximum normalized shock pulse value is concerned, single values are used and correlated directly to the bearings health state thresholds without requirement on the application of additional signal analysis methods (spectrum analysis, empirical mode decomposition, etc.) [107]. As such, maximum normalized shock pulse value can be used also as an indicator of damage level/criticality. Hence, SPM enables not only the detection of incipient failures and damage criticality analysis of bearings but also their localization. Zhen et al. [107] applied SPM to real bearings signal operating under varying conditions. The authors state that the health state of bearings "may be mistakenly estimated by direct demodulation in the SPM" [107] and propose "improved redundant lifting scheme (IRLS)" [107] whereas not direct signal demodulation is applied, but preprocessing of the signal is done using wavelet transform based on lifting scheme. Moreover, Yang et al. [108] report on the application of SPM to detect WT bearing faults. According to [108], not only the detection but also localization of bearing faults in early phase using the shock pulse signal captured from the gearbox of WT system and consequent frequency spectrum analysis seems to be possible. Hence, Tandon et al. [109] compare vibration, Acoustic Emission, SPM, and stator current measurements on an example of induction motor ball bearings failure detection. As a result, the authors state that AE condition monitoring technique is the most effective technique whereas SPM follows directly after AE technique. Zhang et al. [110] discuss the impact of operating conditions (loading and rotating speed) on SPM based monitoring of WT gearboxes/bearings. As a result, the authors point out that SPM is more sensitive to the changes of rotational speed as to the loading profile change.

III. Signal-based methods for failure detection and classification

The data captured through sensing systems are typically not direct indicators of failure occurrence and failure propagation. Further processing of measured data in most of condition monitoring techniques is necessary in case of unequivocally correlation of signal signatures (extracted/selected features) to the failure modes, failure locations, and failure criticality [111]. In case of WT systems, related statements are closely related to signal signatures obtained using suitable signal processing methods discussed in previous section. In the following section, time-, frequency-, as well as time-frequency-domain signal analysis are detailed.

A. Time- and frequency-domain analysis

Time-domain signal processing methods are discussed from two different point of views: i) as quantitative/statistical methods, and ii) as modal/waveform-based approach. The main aim of statistical analysis in time domain is to extract signal signatures which can be correlated to changes occurred in the considered structure.

Discussion of time-domain signal analysis in terms of statistical methods require calculation of statistical variables capable to reveal changes in the signal/structure. The statistical variables can be mean value, root mean square, standard deviation, skewness, kurtosis, and crest factor expressed as

$$s_1 = \sum_{i=1}^{n} \frac{x_i}{n},$$

$$s_2 = \sqrt{\frac{\sum_{i=1}^{n} {x_i}^2}{n}},$$

$$s_3 = \sqrt{\frac{n \cdot \sum_{i=1}^{n} {x_i}^2 - (\sum_{i=1}^{n} x_i)^2}{n \cdot (n-1)}},$$

$$s_4 = \frac{n}{(n-1)(n-2)} \sum_{i=1}^{n} (\frac{x_i - s_1}{s_2})^3,$$

$$s_5 = \frac{n \cdot (n+1)}{(n-1)(n-2)(n-3)} \sum_{i=1}^{n} (\frac{x_i - s_1}{s_2})^4 - \frac{3 \cdot (n-1)^2}{(n-2)(n-3)},$$

$$s_6 = \frac{max(x)}{s_2},$$

$$s_7 = \frac{max|x|}{(\frac{1}{n} \sum_{i=1}^{n} |x_i|^{1/2})^2}$$ respectively.

Lists of suitably applied statistical variables are well known and given for example also in [101], [112], and [113]. Aggravating circumstance in application of statistical variables from the time domain is a selection of statistical variable to be suitable for particular change/failure. However, despite these shortcomings statistical variables are often used in analysis of vibration signals.

If time-domain signal analysis is discussed in terms of modal analysis on an example of AE signal, variables such as peak amplitude, arrival time, rise time, count, or duration ratio can be calculated and used for identification and classification purposes [114].

Conversely to time-domain signal analysis, signal analysis in frequency domain implies signal transformation in appropriate form. Concerning signal transformation in frequency domain using Fast Fourier Transform (FFT), the information about the frequency content of signal is revealed, but time scale information becomes is not relevant. Fast Fourier Transform is therefore not suitable for analysis of non-stationary signals. Statistical FFT variables are similar to aforementioned variables [115], [116], and [117].

B. Time-frequency-domain analysis

Changes occurred in a structure and/or rotating machinery are sometimes reflected in the change of frequency content of measured signals and as such can be a representative of failure occurrence and propagation. Therefore, time-frequency-domain signal analysis is seen as a capable tool for failure detection as well as classification. Time-frequency-domain signal analysis concerns transformation of signals whereas the information about frequency content as well as about the related timespan, in which referred frequency content appears, is combined. For purpose of time-frequency content analysis, traditional signal processing methods like Short Time Frequency Transform (STFT), Discrete Wavelet Transform (DWT), Continuous Wavelet Transform (CWT), Wigner-Ville Distribution (WVD), and similar are used. Whilst STFT reveals a widow-dependent time-frequency content of signal (consequently provides better frequency resolution with poor time resolution, and vice versa), DWT and CWT reveals time-frequency content of the signal using multiple scaled and shifted window function (so-called mother wavelet). Short Time Fourier Transform uses a fixed window, in which the signal can be considered as stationary, providing also limited time-frequency resolution, what is not the case with DWT and CWT. Time-frequency resolution of DWT/CWT is adjustable and better in comparison with STFT (high time resolution in high frequency bandwidth). As an example of CWT application in failure detection and classification, analysis of bearings vibration signals is discussed in a number of contributions [119] [120]. As outlined by Su et al. [119], the problem of hardly possible failure detection especially in inceptive phase of failure occurrence due to signal overwhelming by noise and additional vibrational signals is pointed out. The authors introduce herein Morlet wavelet- based filtering technique targeting to remove the noise. As noted in [119], good results regarding noise removal and detection of transient events are obtained. As outlined in [120] not only CWT coefficients can be used as signal signatures. The authors of [120] discuss wavelet-based variance analysis to compare signals and to make a statement about signals self-similarity in order to detect anomalies in the signal. Similarly, Rafiee et al. [121] consider statistical features like standard deviation, kurtosis, variance, and forth central moment of CWT coefficients in order to detect bearings and gearbox failures. Concerning possibility to detect transient events by using CWT, CWT becomes probably prevalent signal processing method in analysis of non-stationary signals [112].

The base of bilinear time-frequency distributions is the Wigner-Ville distribution. Wigner-Ville distribution in its original form does not have windows as STFT, DWT, and CWT. Wigner-Ville distribution represents distribution of signal energy in time-frequency-domain by computing FFT of the ambiguity function - auto-correlation function of signal. The aggravating circumstance in application of Wigner-Ville distribution is an application to a signal composed of two or more signal components. In such case, WVD is not equal to WVD of each particular signal component. Herein cross terms have to be taken in consideration due to the quadratic form of WVD [118]. An existence of cross terms limits the application of WVD in real applications and lead to the deployment of Pseudo-Wigner-Ville-Distribution (PWVD), Affine-Distribution (AD), Cohen-Distribution (CD), and others. Affine-Distribution belongs to shifting and scaling of WVD using kernel function transforming the signal in similar manner as CWT. Moreover, kernel function used in WVD can be adjustable to a signal to be analyzed [118]. Hence, Empirical Mode Decomposition (EMD) represents a self-adaptive technique for decomposition of non-stationary signals. As such, the signal is within EMD decomposed into empirical modes whereas each empirical mode represents oscillation mode contained in the signal. Application of EMD is useful for the signals with noise which has to be removed (for instance: vibration measurements of bearings). Empirical mode decomposition uses spline interpolation to decompose a signal in Intrinsic Mode Functions (IMFs). Intrinsic mode functions are functions with zero mean value and the same number of zero-crossings and maximum values (or differing by one). Concerning IMFs, signals can be represented as a linear superposition of IMFs. However, EMD in its original form shows poor results regarding to failure detection as an empirical modes are often overlapped [122]. To overcome the problem of overlapping modes, some improvements of EMD are introduced as bivariate EMD, orthogonal EMD, and others [123] [124]. Improvement introduced in EMD is an Ensemble Empirical Mode Decomposition (EEMD) assuming uniformly distributed white noise is superposed to the signal. Signals with superposed white noise are decomposed in IMFs providing therefore uniform distribution of signal scales. In this case, the white noise is reflected in output, but can be mitigated or even removed by ensemble mean calculation [124]. Jiang et al. [125] introduce EEMD with multiwavelet packet. Herein, two or more wavelet functions are introduced within EEMD and used for signal pre-filtering targeting to reveal weak signal signatures. Based on the reported results [125], EEMD with multiwavelet packet shows more accurate results in failure detection in comparison with EEMD. In this contribution, EEMD with multiwavelet packet is applied to the vibration signal of rotating machinery.

Empirical mode decomposition is used in Hilbert-Huang Transform (HHT) calculation [126]. Hilbert-Huang transform is an adaptive time-frequency method for analysis of non-stationary signals. The approach has better time-frequency resolution in comparison with CWT. Implementation of HHT can be roughly divided in two parts. The first part consists of signal empirical mode decomposition whereas the signal is decomposed in intrinsic mode functions. The second part consists of Hilbert transform application on each IMF revealing that way frequency and amplitude spectrum of IFMs. Fault occurrence concerning HHT is noticeable in a change of Hilbert amplitude and energy spectrum. Thus, those features are of main concern towards failure detection and quantification [127]. With respect to WT systems, HHT is useful in the analysis of vibration signals and guided wave signals.

From mentioned signal processing methods, it can be concluded that not each signal processing methods are applicable to any signal. The analysis of signals characterized by transient events, non-stationary signals, as well as signals covered with noise are basically analyzed in time-frequency-domain as transient events and non-stationary signatures are hardly revealed in time-domain. Analysis of signals covered with noise in general require the application of filtering techniques to consider the useful parts of the signal. Signal processing methods to be applied are closely related to the sensing technique. The nature of the measured signal has in turn to be taken in consideration in order to be efficient and realize accurate failure detection and diagnosis.

IV. Safety and Reliability Control Engineering Concept

Safety and Reliability Control Engineering Concept (SRCE), firstly discussed in [128], [129], introduces the idea of using knowledge about current State-of-Health and prediction of remaining lifetime integration into the control loop targeting to adapt control strategy to the current State-of-Health. The implementation leads to reliability-based (or health-state-based) system usage. In this case the reliability function of the system have to be concerned and possibly affected in terms of lifetime extension providing simultaneously optimal system usage. As opposed to well-known definition of reliability threating the reliability as probability of the system to perform predefined tasks for specified service time under specified operating conditions, in SRCE concept the reliability is defined as load-stress dependent, so as different loading profiles have different impact on system reliability. Moreover, system reliability not only depends on time but also on the character of the usage.

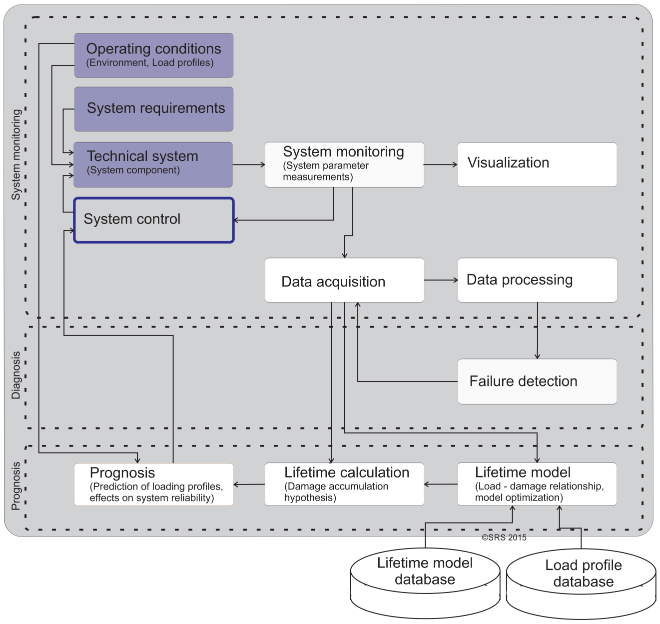

Fig. 3. Safety and Reliability Control Engineering Concept (SRCE) based on [128], [129], [130], [131]

Safety and Reliability Control Engineering Concept is herein discussed as three units/modules concept each of them taking over carefully defined tasks [130], [131]. The first level in SRCE concept implementation monitors the system with respect to relevant system parameters. After capturing and storing the measurements, the data are processed in order to detect anomalies. These anomalies, referred as faults, are concerned in the second level. Occurrence of faults and possibly the related diagnosis have a significant impact on system reliability as they are manifested in sudden loss of reliability and damage increase. Correlation of measured system parameters to the State-of-Health as well as prognosis of system lifetime is a key unit of SRCE concept. For this purpose, lifetime models are required. Based on knowledge about current and assumed or predicted operating conditions, measured system variables, and a suitably identified lifetime model, remaining lifetime can be calculated and/or estimated [130]. Failure criteria in this case have to be known in advance (exceedance of tolerable limit of damage accumulation, system parameters beyond allowable limits, signal features out of desired area, etc.). In the case of WT systems, exceedance of damage accumulation limit of one (D=1) can be threated as failure criterion stating the system not functional if this limit is exceeded. Of course this damage consideration has to be done for critical components and using the knowledge about the functional topology of the system itself. The most challenging task in SRCE concept is still the prediction of system's remaining lifetime (or used lifetime) mainly due to stochastic nature of deterioration processes. Judging by the modest existing contributions related to lifetime prediction of WT systems, linear Palmgren-Miner rule is often, when not dominantly, used along in combination with probabilistic models [17] [34] [38]. Actual improvements of the SRCE concepts are focused to lifetime model development/improvement/optimization and accurate lifetime prediction based on measured data[132].

V. Summary and Conclusion

The contribution revises recent knowledge on Structural Health Monitoring (SHM) related sensor technologies and corresponding signal processing methods. The paper does not provide a general framework but focuses to those SHM strategies applicable to WT system components. Furthermore, an examination of loading profile effects to system's lifetime is concerned. Focusing to the last three years, scientific advances in the field of fault detection and diagnosis methods in WT systems are pointed out and discussed in detail. An overview of existing reviews of SHM in WT systems is given with an emphasis on the newly developed technologies and the trends in further development. Fatigue load analysis due to its impact on system reliability and prognosis is within the special focus of this contribution. Progress in SHM is conspicuous not only in more accurate condition monitoring sensing techniques, but also in improved data processing approaches. Moreover, advanced feature extraction/classification methods and improved lifetime modeling techniques are stated. An important step ahead in SHM regarding to wind turbine systems is in the field of lifetime prognosis, adequate selection of operating conditions in relation to the current system state and predicted remaining lifetime (in comparison to the desired one). The predefined planned service lifetime of a wind turbine is achievable by an adaption of the control strategy capable of taking the current State-of-Health into account.

Still not resolved issues are identified as a lack of analysis of the task-specific appropriate sensor configurations, defined by the type, the locations, and the number of sensors, related to specific faults to be considered. As wind turbines in typically assumed applications fields are installed in wind farms, future work could be also oriented to the analysis of the overall wind farm monitoring (not only the individual wind turbine) and the simultaneous maintenance/replacement of multiple components in order to reduce operating and maintenance costs. This will include reliability- and maintenance-oriented control of the individual systems such that common repair and maintenance actions of the farm can be optimized. Alternative strategies to control the systems so that the availability of the functionality (power production) is maximized can also be realized, if the suitable knowledge with respect to diagnosis and prognosis models is available.

References

[1] W. Yang, P.J. Tavner, C.J. Krabtree, Y. Feng, Y. Qiu, *Wind turbine condition monitoring: technical and commercial challenges*, Wind Energy, Vol. 17, 2014, pp. 673-693.

[2] C.R. Farrar, K. Worden, *An introduction to structural health monitoring*, Phil. Trans. of Royal Society, Vol. 365, 2007, pp. 303-315.

[3] K. Diamanti, C. Soutis, *Structural health monitoring techniques for aircraft composite structures*, Progress in Aerospace Sciences, Vol. 46, Issue 8, 2010, pp. 342-352.

[4] R.J. Patton, P.M. Frank, R.N. Clark, *Fault Diagnosis in Dynamic Systems, Theory and Application*, Control Engineering Series, Prentice-Hall, Englewood Cliffs, NJ, 1989.

[5] R. Kothamasu, S.H. Huang, W.H. VerDuin, *System health monitoring and prognostics - A review of current paradigms and practices*, The Int. Journal of Advanced Manufacturing Technology, 2006, Vol. 28, Issue 9-10, pp. 1012-1024.

[6] Z. Hameed, Y.S. Song, Y.M. Cho, S.H. Ahn, C.K. Song, *Condition monitoring and fault detection of wind turbines and related algorithms: A review*, Renewable and Sustainable Energy Reviews, Vol. 13, Issue 1, 2009, pp. 1-39.

[7] W. Lu, F. Chu, *Condition monitoring and fault diagnosis of wind turbines*, Prognostics and Health Management Conference PHM 2010, January 2010, pp. 1-10.

[8] J. Nilsson, L. Bertling, *Maintenance Management of Wind Power Systems Using Condition Monitoring SystemsLife Cycle Cost Analysis for Two Case Studies*, Trans. on Energy Conversion, Vol. 22, Issue 1, 2007, pp. 223-229.

[9] T. Zhigang, J. Tongdan, W. Bairong, F. Ding, *Condition based maintenance optimization for wind power generation systems under continuous monitoring*, Renewable Energy, Vol. 36, 2011, pp. 1502-1509.

[10] F.P.G. Marquez, A.M. Tobias, J.M.P. Perez, M. Papelias, *Condition monitoring of wind turbines: Techniques and methods*, Renewable Energy, Vol. 46, 2012, pp. 169-178.

[11] R.W. Hyers, J.G. McGowan, K.L. Sullivan, J.F. Manwell, B.C. Syrett, *Condition monitoring and prognosis of utility scale wind turbines*, Energy Materials, Vol.1, Issue 3, 2006, pp. 187-203.

[12] K. Fischer, F. Besnard, L. Bertling, *Reliability-Centered Maintenance for Wind Turbines Based on Statistical Analysis and Practical Experience*, Trans. on Energy Conversion, Vol. 27, Issue 1, 2011, pp. 184-195.

[13] A. Kusiak, W. Li, *The prediction and diagnosis of wind turbine faults*, Renewable Energy, Vol. 36, 2011, pp. 16-23.

[14] International Renewable Energy Agency, *Renewable Energy Technologies: Cost analysis series*, Vol. 1: Power Sector, Issue 5/5, June 2012.

[15] J. Hobohm, L. Krampe, F. Peter, A. Gerken, P. Heinrich, M. Richter, *Kostensenkungspotenziale der Offshore-Windenergie in Deutschland*, Online: http://www. offshore-stiftung. com/60005/Uploaded/SOW Download— Langfassung Studie Kostensenkungspotenziale Offshore-Windenergie. pdf, 2014, access: 24.12.2015.

[16] H. Sohn, C. Farrar, F. Hemez, J. Czarnecki, *A review of structural health monitoring literature 1996-2001*, Los Alamos National Laboratory Report, LA-13976-MS, 2004.

[17] C. Farrar, N.A.J. Lieven, *Damage prognosis: the future of structural health monitoring*, Phil. Trans. of Royal Society, Vol. 365, 2007, pp. 623-632.

[18] C.C. Ciang, J.R. Lee, H.J. Bang, *Structural health monitoring for a wind turbine system: a review of damage detection methods*, Measurement Science and Technology, Vol. 19, Issue 12, 2008.

[19] B. Lu, Y. Li, X. Wu, Z. Yang, *A review of recent advances in wind turbine condition monitoring and fault diagnosis*, Proc. of Power Electronics and Machines in Wind Applications, 2009, pp. 1-7.

[20] P. Tchakoua, R. Wamkeue, T.A. Tameghe, G. Ekemb, *A review of concepts and methods for wind turbines condition monitoring*, World Congress on Computer and Information Technology (WCCIT), 2013, pp. 1-9.

[21] P. Faulkner, P. Cutter, A. Owens, *Structural health monitoring systems in difficult environments - Offshore wind turbines*, EWSHM 6th European Workshop on Structural Health Monitoring & 1st European Conference of the Prognostics and Health Management (PHM) Society, Dresden, Germany, July 3-6, 2012.

[22] H. Friedmann, C. Ebert, P. Kraemer, B. Frankenstein, *SHM of floating offshore wind turbines - challenges and first solutions*, EWSHM 6th European Workshop on Structural Health Monitoring & 1st European Conference of the Prognostics and Health Management (PHM) Society, Dresden, Germany, July 3-6, 2012.

[23] U. Smolka, D. Kaufer, P.W. Cheng, *Are sea state measurements required for fatigue load monitoring of offshore wind turbines?*, Journal of Physics: Conference Series 555, 2014.

[24] J.M. Peeringa, *Fatigue loading on a 5MW offshore wind turbine due to the combined action of waves and current*, Journal of Physics: Conference Series 524, 2014.

[25] S.A. Thorpe, *The turbulent ocean*, Cambridge University Press, NY, 2005.

[26] L. Luznik, K.A. Flack, E.E. Lust, K. Taylor, *The effect of surface waves on the performance characteristics of a model tidal turbine*, Renewable Energy, Vol. 58, October 2013, pp. 108-114.

[27] D. Matha, F. Wendt, M. Werner, P.W. Cheng, T. Lutz, *Aerodynamic inflow conditions on floating offshore wind turbine blades for airfoil design*, In: Proceedings of the Twenty-second International Offshore and Polar Engineering Conference, Rhodes, Greece, June 2012, pp. 17-22.

[28] R.J. Barthelmie, O. Rathmann, S.T. Frandsen, K. Hansen, E. Politis, J. Prospathopoulos, K. Rados, D. Cabezon, W. Schlez, J. Phillips, A. Neubert, J.G. Schepers, S.P. van der Pijl, *Modelling and measurements of wakes in large wind farms*, Journal of Physics: Conference Series 75, 2007.

[29] E.M. Bitner-Gregersen, K.C. Ewans, M.C. Johnson, *Some uncertainties associated with wind and wave description and their importance for engineering applications*, Ocean Engineering, Vol. 86, August 2014, pp. 11-25.

[30] A.N. Robertson, J.M. Jonkman, *Loads analysis of several offshore floating wind turbine concepts*, National Renewable Energy Laboratory, US Department of Energy, Office of Energy Efficiency and Renewable Energy, 2011.

[31] W. Qiu, J.S. Junior, D. Lee, H. Lie, V. Magarovskii, T. Mikami, X. Wang, *Uncertainties related to predictions of loads and responses for ocean and offshore structures*, Ocean Engineering, Vol. 86, 2014, pp. 58-67.

[32] S.E. Hirdaris, W. Bai, D. Dessi, A. Ergin, X. Gu, O.A. Hermundstad, R. Huijsmans, K. Ilijima, U.D. Nielsen, J. Parunov, N. Fonseca, A. Papanikolau, K. Argyriadis, A. Incecik, *Loads for use in the design of ships and offshore structures*, Ocean engineering, Vol. 78, 2014, pp. 131-174.

[33] J.G. Leishman, *Challenges in modelling the unsteady aerodynamics of wind turbines*, Wind energy, Vol. 5, Issue 2-3, 2002, pp. 85-132.

[34] J.F. Mandell, D.D. Samborsky, *DOE/MSU composite material fatigue database: test methods, materials, and analysis, No. SAND–97-3002*, Sandia National Labs., Albuquerque, NM (United States), 1997.

[35] N. Cosack, M. Kühn, *An approach for fatigue load monitoring without load measurement devices*, In: Scientific proceedings of the European Wind Energy Conference and Exhibition, 2009, pp. 69-73.

[36] L.V. Tudela, M. Kühn, *On the selection of input variables for a wind turbine load monitoring system*, 2nd International Conference on System-Integrated Intelligence: Challenges for Product and Production Engineering, In: Procedia Technology, Vol. 15, 2014, pp. 727-737.

[37] A. G. Palmgren, *Die Lebensdauer von Kugellagern (Life Length of Roller Bearings. In German)*, Zeitschrift des Vereines Deutscher Ingenieure (VDI Zeitschrift), Vol. 68, Issue 14, 1924, pp. 339-341.

[38] J. de Jesus Barradas-Berglind, R. Wisniewski, M. Soltani, *Fatigue damage estimation and data-based control for wind turbines*, IET Control Theory & Applications, Vol. 9, Issue 7, 2015, pp. 1042-1050.

[39] Z. Hashin, *A reinterpretation of the Palmgren-Miner rule for fatigue life prediction*, Journal of Applied Mechanics, Vol. 47, Issue: 2, 1980, pp. 324-328.

[40] R.D.B. Sevenois, W. Van Paepegem, *Fatigue Damage Modeling Techniques for Textile Composites: Review and Comparison With Unidirectional Composite Modeling Techniques*, Applied Mechanics Reviews, Vol. 67, Issue 2, 2015.

[41] W. Van Paepegem, D. Joris, *Modelling strategies for fatigue damage behaviour of fibre-reinforced polymer composites*, environment (eg moisture, toxic agents), Vol. 1, Issue. 3, 2001.

[42] C. Kong, J. Bang, Y. Sugiyama, *Structural investigation of composite wind turbine blade considering various load cases and fatigue life*, Energy, Vol. 30, Issue 11, 2205, pp. 2101-2114.

[43] E. Marino, C. Lugni, L. Manuel, H. Nguyen, C. Borri, *Simulation of Nonlinear Waves on Offshore Wind Turbines and Associated Fatigue Load Assessment*, In ASME 2014 33rd International Conference on Ocean, Offshore and Arctic Engineering, American Society of Mechanical Engineers, 2014.

[44] P. Zuluaga-Ramirez, M. Frövel, A. Arconada, T. Belenguer, F. Salazar, *Evaluation of the Fatigue Linear Damage Accumulation Rule for Aeronautical CFRP Using Artificial Neural Networks*, In Advanced Materials Research, Vol. 1016, 2014, pp. 8-13.

[45] D.An, J.H. Choi, N.H. Kim, S. Pattabhiraman, *Fatigue life prediction based on Bayesian approach to incorporate field data into probability model*, Structural engineering & mechanics, Vol. 37, Issue 4, 2011, pp. 427-442.

[46] P.J. Schubel, R.J. Crossley, E.K.G. Boateng, J.R. Hutchinson, *Review of structural health and cure monitoring techniques for large wind turbine blades*, Renewable Energy, Vol. 51, 2013, pp. 113-123.

[47] K.K. Chawla, *Composite materials: science and engineering*, Springer Science & Business Media, 2012.

[48] R. Lacal-Arntegui, *Materials use in electricity generators in wind turbinesstate-of-the-art and future specifications*, Journal of Cleaner Production, Vol. 87, 2015, pp. 275-283.

[49] L. Baldi, M. Peri, D. Vandone, *Clean energy industries and rare earth materials: Economic and financial issues*, Energy Policy, Vol. 66, 2014, pp. 53-61.

[50] A. Monfared, K. Soudki, S. Walbridge, *CFRP reinforcing to extend the fatigue lives of steel structures*, Fourth International Conference on FRP Composites in Civil Engineering (CICE2008), Zurich, Switzerland, 2008.

[51] C.W. Kensche, *Fatigue of composites for wind turbines*, The Third International Conference on Fatigue of Composites, In: International Journal of Fatigue, Vol. 28, Issue 10, October 2006, pp. 1363-1374.

[52] T. D'Antino, C. Carloni, L.H. Sneed, C. Pellegrino, *Matrixfiber bond behavior in PBO FRCM composites: A fracture mechanics approach*, Engineering Fracture Mechanics, Vol. 117, 2014, pp. 94-111.

[53] J.F. Mandell, D.D. Samborsky, H.J. Sutherland, *Effects of materials parameters and design details on the fatigue of composite materials for wind turbine blades*, EWEC-CONFERENCE, 1999, pp. 628-633.

[54] M.A. Rumsey, *An evaluation of sensing technologies in a wind turbine blade: some issues, challenges and lessons learned*, SPIE Smart Structures and Materials, Nondestructive Evaluation and Health Monitoring, International Society for Optics and Photonics, 2011.

[55] J.C. Marin, A. Barroso, F. Paris, J. Canas, *Study of fatigue damage in wind turbine blades*, Engineering Failure Analysis, Vol. 16, Issue 2, March 2009, pp. 656-668.

[56] Y. Zou, L. Tong, G.P. Steven, *Vibration-based model-dependent damage (delamination) identification and health monitoring for composite structures - A review*, Journal of Sound and Vibration, Vol. 230, Issue 2, 2000, pp. 357-378.

[57] M. Malena, G. de Felice, *Debonding of composites on a curved masonry substrate: Experimental results and analytical formulation*, Composite Structures, Vol. 112, 2014, pp. 194-206.

[58] T. D'Antino, C. Pellegrino, *Bond between FRP composites and concrete: assessment of design procedures and analytical models*, Composites Part B: Engineering, Vol. 60, 2014, pp. 440-456.

[59] D.A. Vajari, F.B. Srensen, B.N. Legarth, *Effect of fiber positioning on mixed-mode fracture of interfacial debonding in composites*, International Journal of Solids and Structures, Vol. 53, 2015, pp. 58-69.

[60] T.F. Drouillard, F.J. Laner, *Acoustic Emission. A Bibliography with Abstracts*, IFI/Plenum, 1978.

[61] *Standard Terminology for Nondestructive Examinations*, E 1316-90, 1990.

[62] A. Purarjomandlangrudi, G. Nourbakhsh, *Acoustic emission condition monitoring: An application for wind turbine fault detection*, Int.Journal of Research in Engineering and Technology, Vol. 2, Issue 5, 2013, pp. 907-918.

[63] E.Y. Kim, A.C. Tan, J. Mathew, B.S. Yang, *Development of an online condition monitoring system for slow speed machinery*, In Engineering Asset Lifecycle Management, Springer London, 2010, pp. 743-749.

[64] C.U. Grosse, O. Masayasu, *Acoustic emission testing*, Springer Science & Business Media, 2008.

[65] D. Baccar, D. Söffker, *Wear Detection by Means of Wavelet-based Acoustic Emission Analysis*, Mechanical Systems and Signal Processing, Vol. 60-61, August, 2015, pp. 198-207.

[66] B. Yeter, Y. Garbatov, C.G. Soares, *Spectral fatigue assessment of an offshore wind turbine structure under wave and wind loading*, Developments in Maritime Transportation and Exploitation of Sea Resources: IMAM 2013, 2013, pp. 425-433.

[67] K.S.C. Kuang, S.T. Quek, C.G. Koh, W.J. Cantwell, P.J. Scully, *Plastic optical fibre sensors for structural health monitoring: A review of recent progress*, Journal of Sensors, Vol. 20, 2009.

[68] S. Käseberg, M.B. Schaller, K. Holschemacher, *CFRP systems with embedded FBG for structural monitoring and retrofitting*, EWSHM 6th European Workshop on Structural Health Monitoring & 1st European Conference of the Prognostics and Health Management (PHM) Society, Dresden, Germany, July 3-6, 2012.

[69] P. Ferdinand, *The evolution of optical fiber sensors technologies during the 35 last years and their applications in structural health monitoring*, 7th European Workshop on Structural Health Monitoring, July 8-11, 2014, In: Proc. Le Cam, Vincent and Mevel, Laurent and Schoefs, Franck, pp. 914-929.

[70] S. Hurlebaus, L. Gaul, *Smart layer for damage diagnostics*, Journal of intelligent material systems and structures, Vol. 15, Issue 10, 2004, pp. 729-736.

[71] A.G. Anisimov, B. Müller, J. Sinke, R.M. Groves, *Strain characterization of embedded aerospace smart materials using shearography*, In SPIE Smart Structures and Materials, Nondestructive Evaluation and Health Monitoring, International Society for Optics and Photonics, 2015.

[72] G. Ye, B. Neal, A. Boot, V. Kappatos, C. Selcuk, T.H. Gan, *Development of an Ultrasonic NDT System for Automated In-Situ Inspection of Wind Turbine Blades*, In EWSHM-7th European Workshop on Structural Health Monitoring, 2014.

[73] H. Sohn, D. Dutta, J.Y. Yang, M. DeSimio, S. Olson, E. Swenson, *Automated detection of delamination and disbond from wavefield images obtained using a scanning laser vibrometer*, Smart Materials and Structures, Vol. 20, Issue 4, 2011.

[74] B. Park, Y.K. An, H. Sohn, *Visualization of hidden delamination and debonding in composites through noncontact laser ultrasonic scanning*, Composites Science and Technology, Volume 100, 2014, pp. 10-18.

[75] J.G. Chen, R.W. Haupt, O. Buyukozturk, *Operational and Defect Parameters Concerning the Acoustic-Laser Vibrometry Method for FRP-reinforced Concrete*, NDT & E International, 2014.

[76] J.G. Chen, R.W. Haupt, O. Buyukozturk, *Acoustic-laser vibrometry technique for the noncontact detection of discontinuities in fiber reinforced polymer-retrofitted concrete*, Materials evaluation, Vol. 72, Issue 10, 2014, pp. 1305-1313.

[77] M. Scheerer, T. Cardone, A. Rapisarda, S. Ottaviano, D. Francesconi, *Online damage detection on metal and composite space structures by active and passive acoustic methods*, EWSHM 6th European Workshop on Structural Health Monitoring & 1st European Conference of the Prognostics and Health Management (PHM) Society, Dresden, Germany, July 3-6, 2012.

[78] C. Heinze, M. Sinapius, P. Wierach, *Lamb Wave Propagation in Complex Geometries - A Minimal Model Approach*, In: Proceedings of the 5th International Workshop on Aircraft System Technologies (AST 2015), pp. 383-390. Shaker Verlag, 2015.

[79] R. Raisutis, E. Jasiuniene, R. Sliteris, A. Vladisauskas, *The review of non-destructive testing techniques suitable for inspection of the wind turbine blades*, Ultrasound, Vol. 63, Issue 1, 2008, pp. 26-30.

[80] L. Gaul, P. Pinto, S. Hurlebaus, L.J. Jacobs, *Localization and Sizing of discontinuities Using Lamb Waves*, Proceedings of the 4th International Workshop on Structural Health Monitoring, DEStech Publications, Lancaster, PA, 2003, pp. 379-386.

[81] V. Papantoni, M. Rose, H.P. Monner, M. Sinapius, *Active structural acoustic control with a loudness optimized actuator placement*, International Workshop on Aircraft System Technologies, Hamburg, Germany, 2015.

[82] W.H. Leong, W.J. Staszewski, B.C. Lee, F. Scarpa, *Structural health monitoring using scanning laser vibrometry: III. Lamb waves for fatigue crack detection*, Smart Materials and Structures, Vol. 14, Issue 6, 2005, pp. 1387-1395.

[83] U. Berger, *Onboard - SHM for Life Time Prediction and Damage Detection on Aircraft Structures Using Fibre Optical Sensor and LAMB Wave Technology*, EWSHM 6th European Workshop on Structural Health Monitoring & 1st European Conference of the Prognostics and Health Management (PHM) Society, Dresden, Germany, July 3-6, 2012.

[84] I. Antoniadou, N. Dervilis, E. Papatheou, A.E. Maguire, K. Worden, *Aspects of structural health and condition monitoring of offshore wind turbines*, Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences, Vol. 373, 2015.

[85] R.F. Gibson, *Modal vibration response measurements for characterization of composite materials and structures*, Composites science and technology, Vol. 60, Issue 15, 2000, pp. 2769-2780.

[86] K. Koyama, H. Hoshikawa, G. Kojima, *Eddy current nondestructive testing for carbon fiber-reinforced composites*, Journal of Pressure Vessel Technology, Vol. 135, Issue 4, 2013.

[87] Y. He, G. Tian, M- Pan, D. Chen, *Non-destructive testing of low-energy impact in CFRP laminates and interior defects in honeycomb sandwich using scanning pulsed eddy current*, Composites Part B: Engineering, Vol. 59, 2014, pp. 196-203.

[88] H. Heuer, M.H. Schulze, *Eddy current testing of carbon fiber materials by high resolution directional sensors*, In Smart Material Structures, NDT in Aerospace Conference, 2011.

[89] B. Gao, L. Bai, W.L. Woo, G.Y. Tian, Y. Cheng, *Automatic defect identification of eddy current pulsed thermography using single channel blind source separation*, Instrumentation and Measurement, IEEE Transactions on, Vol. 63, Issue 4, 2014, pp. 913-922.

[90] M. Perterer, F. Höchtl, A. Kiefmann, H. Baier, V. Senner, *Ultrasonic And Thermographic Monitoring of Impact induced damage of CFRP Structures*, In SAMPE 2010 Spring Conference, 2010.

[91] B. Yang, D. Sun, *Testing, inspecting and monitoring technologies for wind turbine blades: A survey*, Renewable and Sustainable Energy Reviews, 2013, Vol. 22, pp. 515-526.

[92] L. Cheng, G.Y. Tian, *Comparison of nondestructive testing methods on detection of delaminations in composites*, Journal of sensors, 2012.

[93] R. Hanke, T. Fuchs, N. Uhlmann, *X-ray based methods for non-destructive testing and material characterization*, Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, Vol. 591, Issue 1, 2008, pp. 14-18.

[94] R.J. Parmee, C.M. Collins, W.I. Milne, M.T. Cole, *X-ray generation using carbon nanotubes*, Nano Convergence, Vol. 2, Issue 1, 2015. pp. 1-27.

[95] A. Panna, A.A. Gomella, K.J. Harmon, P. Chen, H. Miao, E.E. Bennett, H. Wen, *Performance of low-cost X-ray area detectors with consumer digital cameras*, Journal of Instrumentation, Vol. 10, Issue 5, 2015.

[96] D.Y. Kim, W.S. Jung, S. Lim, J.H. Hwang, C.W. Pack, *Visual testing system for the damaged area detection of wind power plant blade*, Robotics (ISR), 2013 44th International Symposium on. IEEE, 2013.

[97] K.R. Till. U.S. Patent Application 13/180, 942, 2011.

[98] M.A. Aziz, H. Noura, A. Fardoun, *General review of fault diagnostic in wind turbines*, 18th Mediterranean Conference on Control and Automation MED, 2010, pp. 1302-1307.

[99] D. Montalvao, N.M.M. Maia, A.M.R Ribeiro, *A review of vibration-based structural health monitoring with special emphasis on composite materials*, The Shock and Vibration Digest, Vol. 38, Issue 4, 2006, pp. 295-324.

[100] L. Wenxiu, F. Chu, *Condition monitoring and fault diagnostics of wind turbines*, Prognostics and Health Management Conference, 2010. PHM'10. IEEE, 2010.

[101] M.S. Safizadeh, S.K. Latifi, *Using multi-sensor data fusion for vibration fault diagnosis of rolling element bearings by accelerometer and load cell*, Information Fusion, 18, 2014, pp. 1-8.

[102] W. Fan, P. Qiao, *Vibration-based damage identification methods: A review and comparative study*, Structural Health Monitoring, Vol. 10, Issue 1, 2011, pp. 83-111.

[103] P. Shakya, A.K. Darpe, M.S. Kulkarni, *Vibration-based fault diagnosis in rolling element bearings: ranking of various time, frequency and time-frequency domain data-based damage identification parameters*, International journal of condition monitoring, Vol. 3, Issue 2, 2013, pp. 53-62.

[104] S. Soua, P. Van Lieshout, A. Perera, T.H. Gan, B. Bridge, *Determination of the combined vibrational and acoustic emission signature of a wind turbine gearbox and generator shaft in service as a prerequisite for effective condition monitoring*, Renewable Energy, Vol. 51, 2013, pp. 175-181.

[105] A.M. Al-Ghamd, D. Mba, *A comparative experimental study on the use of acoustic emission and vibration analysis for bearing defect identification and estimation of defect size*, Mechanical systems and signal processing, Vol. 20, Issue 7, 2006, pp. 1537-1571.

[106] A.H. Tsang, *Condition-based maintenance: tools and decision making*, Journal of Quality in Maintenance Engineering, Vol. 1, Issue 3, 1995, pp. 3-17.

[107] L. Zhen, H. Zhengjia, Z. Yanyang, C. Xuefeng, *Bearing condition monitoring based on shock pulse method and improved redundant lifting scheme*, Mathematics and computers in simulation, Vol. 79, Issue 3, 2008, pp. 318-338.

[108] R. Yang, J. Kang, X. Zhang, H. Teng, H. Li, *Application of SPM to Detect the Wind Turbine Bearing Fault*, TELKOMNIKA Indonesian Journal of Electrical Engineering, Vol. 12, Issue 3, 2014, pp. 1875-1880.

[109] N. Tandon, G.S. Yadava, K.M. Ramakrishna, *A comparison of some condition monitoring techniques for the detection of defect in induction motor ball bearings*, Mechanical systems and signal processing, Vol. 21, Issue 1, 2007, pp. 244-256.

[110] R. Zhang, J. Kang, L. Hao, X. Zhang, H. Teng, H. Li, *Research on Operating Condition Effect on the Shock Pulse Method*, TELKOMNIKA Indonesian Journal of Electrical Engineering, Vol. 12, Issue 7, 2014, pp. 5392-5398.

[111] S.B. Kotsiantis, D. Kanellopoulos, and P.E. Pintelas, *Data Preprocessing for Supervised Leaning*, International Scholarly and Scientific Research & Innovation 1(12), 2007, pp. 856-861.

[112] Z. Xu, J. Xuan, T. Shi, B. Wu, Y. Hu, *Application of a modified fuzzy ARTMAP with feature-weight learning for the fault diagnosis of bearing*, Expert Systems with Applications, Vol. 36, Issue 6, 2009, pp. 9961-9968.

[113] Y. Lei, Z. He, Y. Zi, *Application of an intelligent classification method to mechanical fault diagnosis*, Expert Systems with Applications, Vol. 36, Issue 6, 2009, pp. 9941-9948.

[114] R. Gutkin, C.J. Green, S. Vangrattanachai, S.T. Pinho, P. Robinson, P.T. Curtis, *On acoustic emission for failure investigation in CFRP: Pattern recognition and peak frequency analyses*, Mechanical Systems and Signal Processing, Vol. 25, Issue 4, 2011, pp. 1393-1407.

[115] Y. Lei, Z. He, Y. Zi, *A new approach to intelligent fault diagnosis of rotating machinery*, Expert Systems with Applications, Vol. 35, Issue 4, 2008, pp. 1593-1600.

[116] Y. Lei, Z. He, Y. Zi, Q. Hu, *Fault diagnosis of rotating machinery based on multiple ANFIS combination with GAs*, Mechanical Systems and Signal Processing, Vol. 21, Issue 5, 2007, pp. 2280-2294.

[117] H. Aljoumaa, D. Söffker, *Multi-Class Approach based on Fuzzy-Filtering for Condition Monitoring*, IAENG International Journal of Computer Science, Vol. 38, Issue 1, 2011, pp. 66-73.

[118] W.H. Prosser, M.D Seale, B.T. Smith, *Time-frequency analysis of the dispersion of Lamb modes*, The Journal of the Acoustical Society of America, Vol. 105, Issue 5, 1999, pp. 2669-2676.

[119] W. Su, F. Wang, H. Zhu, Z. Zhang, Z. Guo, *Rolling element bearing faults diagnosis based on optimal Morlet wavelet filter and autocorrelation enhancement*, Mechanical systems and signal processing, Vol. 24, Issue 5, 2010, pp. 1458-1472.

[120] A. Ziaja, I. Antoniadou, T. Barszcz, W.J. Staszewski, K. Worden, *Fault detection in rolling element bearings using wavelet-based variance analysis and novelty detection*, Journal of Vibration and Control, 2014.

[121] J. Rafiee, M.A. Rafiee, P.W. Tse, *Application of mother wavelet functions for automatic gear and bearing fault diagnosis*, Expert Systems with Applications, Vol. 37, Issue 6, 2010, pp. 4568-4579.

[122] J. Dybaa, R. Zimroz, *Rolling bearing diagnosing method based on Empirical Mode Decomposition of machine vibration signal*, Applied Acoustics, Vol. 77, 2014, pp. 195-203.

[123] Y. Lei, J. Lin, Z. He, M.J. Zuo, *A review on empirical mode decomposition in fault diagnosis of rotating machinery*, Mechanical Systems and Signal Processing, Vol. 35, Issue 1, 2013, pp. 108-126.

[124] Y. Lei, Z. He, Y. Zi, *Application of the EEMD method to rotor fault diagnosis of rotating machinery*, Mechanical Systems and Signal Processing, Vol. 23, Issue 4, 2009, pp. 1327-1338.

[125] H. Jiang, C. Li, H. Li, *An improved EEMD with multiwavelet packet for rotating machinery multi-fault diagnosis*, Mechanical Systems and Signal Processing, Vol. 36, Issue 2, 2013, pp. 225-239.

[126] S.T. Quek, P. S. Tua, Q. Wang, *Detecting anomalies in beams and plate based on the HilbertHuang transform of real signals*, Smart materials and structures, Vol. 12, Issue 3, 2003, pp. 447-460.

[127] R.A. Esmaeel, J. Briand, F. Taheri, *Computational simulation and experimental verification of a new vibration-based structural health monitoring approach using piezoelectric sensors*, Structural Health Monitoring, Vol. 11, Issue 2, 2012, pp. 237-250.

[128] D. Söffker and U.K. Rakowsky, *Perspectives of monitoring and control of vibrating structures by combining new methods of fault detection with new approaches of reliability engineering.*, Proc. 12th ASME Conf. on Reliability, Stress Analysis, and Failure Prevention, Virginia Beach, April 1997, in: Pusey, H.C. (ed.): A Critical Link: Diagnosis to prognosis. A publication of the Society for Machinery Failure Prevention Technology, 1997, pp. 671-682.

[129] D. Söffker, U.K. Rakowsky, P.C. Müller and O.H. Peters, *Perspektiven regelungstheoretischer Methoden zur Überwachung dynamischer Systeme aus sicherheitstechnischer Sicht*, at-Automatisierungstechnik, Vol. 46, 1998, pp. 295-301.

[130] K. Wolters, D. Söffker, *The potential of the Safety and Reliability Control Engineering Concept as framework for reliability-based utilization strategies*, Structural Health Monitoring 2005 (Chang, F.K. (Editor)), Proc. of the 5th Int. Workshop on Structural Health Monitoring, Stanford University, Stanford, CA, Sept. 2005, pp. 1353-1360.

[131] K. Wolters, *Formalismen, Simulation und Potenziale eines nutzungsdaueroptimierenden Zuverlässigkeitskonzepts*, Dr.-Ing. thesis, University of Duisburg-Essen, 2008.

[132] N. Beganovic, D. Söffker, *Wear Process Lifetime Prediction Based on Parametric Model Applied to Experimental Data*, Proc. IEEE Conference on Prognostics and Health Management PHM 2015, Austin, TX, USA, 2015, pp. 1-6.

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