Chapter

Optimal Design and Operational Monitoring of Wind Turbine Blades

Francis Xavier Ochieng, Craig Matthew Hancock, Gethin Wyn Roberts and Julien Le Kernec

Abstract

The wind turbine blade is a critical component of any wind energy system. Its design, testing, and performance monitoring play a key role in power generation. With the increased use of composites and longer blades, a need to review existing monitoring sensors and use emergent novel ones is urgent among industry practitioners. In addition, an overview relating blade testing to Campbell diagrams and non-contact sensors have not been addressed as part of blade optimization. Based on design loads under IEC 61400-23 standards, the chapter explores various contact and non-contact sensors for design validation as well as their exploratory use in a three-tier structural health monitoring (SHM) framework for blade's operational performance monitoring. The chapter also includes a case study in the non-contact use of ground-based radar (GBR) in the optimal design of blades and real-time in-field monitoring using condition parameters. Lastly, the chapter addresses the lack of practical guidelines in the complementary use of GBR within a 3-tier SHM framework. Such use has the intent of building a cohesive understanding of GBR use for blade optimization and operational monitoring.

Keywords: wind turbine, blade structural monitoring, ground-based radar, sensors, Campbell diagram

1. Introduction

In-operation and design of load-carrying wind turbine (WT) blades, structural prediction of its vibratory characteristics are required in order to avoid resonance. Such characterization normally utilizes contact sensor-based forced-response and eigenvalue analysis. In detecting structural damage or obtaining validating condition parameters (CP) during design, the main practice is using either differential guided wave-based signal analysis or vibration-based damage detection (VBDD) [1]. Of the latter singular value decomposition (SVD) for structural damage detection has become widespread [1–3].

SVD works by comparing current sensor data to measurements taken from the healthy structure under varying environmental and operational conditions (EoC). Thus, the measurement from one sensor can be compared to prior acceptable or operating ranges (tolerance) of the static and unbalanced dynamic parameters of the structure.

In the case of WT, unbalanced parameters (also called condition parameters [CP]) are used. These are those parameters describing the resonant vibration due to unbalance of a vibrating or rotating object (i.e. divergence between the centre of geometry and centre of mass) [4]. Of the unbalanced parameters, [5–7] note that natural frequencies may comparatively be less prone to error than others unbalanced parameters like mode shapes and modal damping. They thus provide a ready application in using it for structural health monitoring (SHM) of the WT blades [8] both during design and operation.

To help in the acquisition of natural frequencies, the most widespread sensors used are gyroscopes and accelerometers [9–11]. These sensors, however, suffer from 3 key challenges: impractical to use on rotating WT blades, require laborious installation procedure, its results are vulnerable to EoC especially temperature, and lastly, the sensors are not easily portable. Other contact sensors like Fibre Bragg sensors are also widely used. Subsequently, there is a need to consider non-contact sensors like Laser or radar-based has become urgent.

2. Challenges in WT blades design optimization and operational monitoring

The singular goal of an optimization process or methodology is the exploration of the best possible solutions to a given problem. Implicit in this exploration is a continuum of solutions being considered against a set criterion. In WT modeling this would refer to maximizing or minimizing some function relative to some set options. Wherein the set would comprise of a range of choices existing at a time.

WT blades, unlike commercial aircraft blades, are comparatively more fatigue critical structures (see **Figure 1**). This means that their design is dictated not only by fatigue and ultimate strength but as also by aeroelastic considerations. For aircraft blades, their design is mainly dictated by fatigue and ultimate strength. The import of this being, as pointed out later, is that aircraft blades need only a few

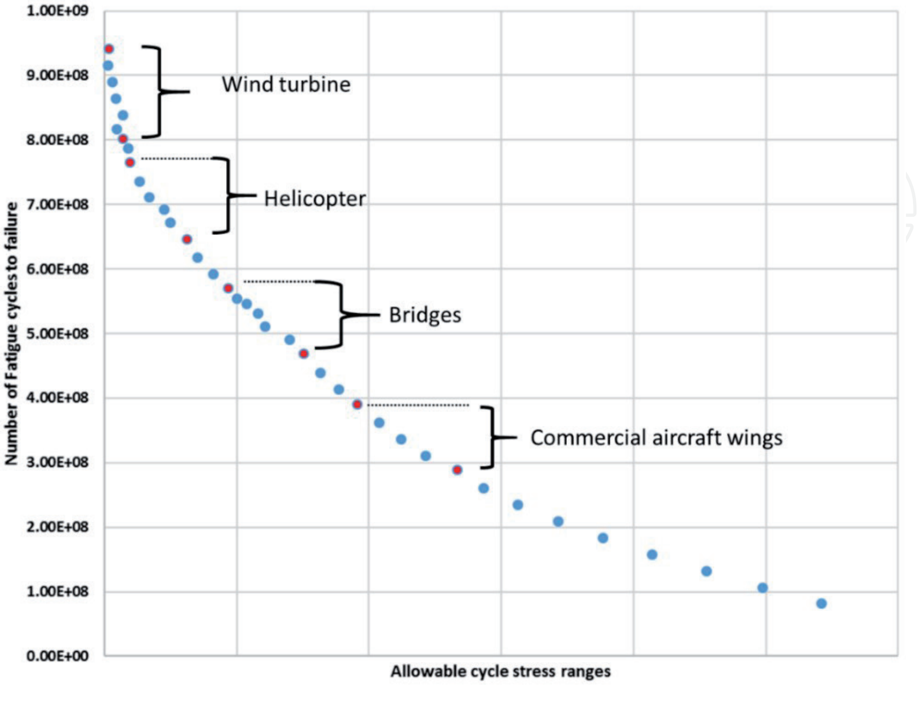

Figure 1.
S-N curves for various structures.

physical fatigue tests, unlike WT blades. This makes wind-turbine blade design, testing and certification expensive.

Usually, the approach for the WT type or component certification is physical testing using contact sensors to obtain metrics edge- and flap-wise deflection, mode shapes and modal frequencies for load cycles between 3×10^6 to 3×10^7, and to extrapolate the load cycles up to 109 for the lifetime of the wind turbine of 20–25 years using numerical simulations [12]. Generally, for a full-scale test, the allowable scatter between the actual tests and simulations is by a factor of 10 [12]. Two or more tests are thus needed to obtain a reliable conclusion.

The simulation is achieved by first undertaking a 10-min load simulation for a range of wind speeds. The results of each 10-min load analysis for each wind bin are then multiplied by 20 years, and the results for each load bin summed up to obtain a complete load distribution. Extreme loads are approached in a similar manner, but use made of a 50-year extreme 10-min average wind speeds with turbulence.

The challenges posed by these approaches are three-fold:

i. Rare events are not accounted for by the modeling framework [13]. This is bound to happen, since as the turbulence simulation is run, longer runs result in the tails of the stochastic inflow distribution of each average wind bin being filled with turbulence. Thus, a discrete averaged run multiplied by the 20 years lifetime may not capture this cumulative turbulence effect.

ii. Arising from the deficiency to capture the rare events, the statistics may not effectively estimate the peak load, which will occur during the wind turbine operating lifetime [13]. Currently, reliable estimates of such peak loads are not feasible due to lack of sufficient data. This is mainly due to the aerodynamic cyclic loading arising from wind shear and gravity making application of statistical modeling difficult.

iii. The IEC 61400-1 and IEC 61400-23 [14, 15] do provide specific design parameters that wind turbines designers can utilize. However, the standards do not specify

  a. The number of turbulence simulations is needed to establish the set probability and confidence levels for load predictions [13, 16].

  b. The load prediction processes, and material properties are decided based upon codified minimum safety factors that account for uncertainty. For homogenous materials, this would normally work. However, the use of composites presents a challenge due to its heterogeneous and visco-elasticity nature [16, 17].

  c. In addition to the design challenges, the EoCs of wind turbines are transient (non-periodic), consequently, the potential deflections during design and in real-life operating conditions are based on simulations in the time-domain [14–16]. This provides the minimum and maximum limits for the deflections that various sensors within the mast, and nacelle monitor. However, exact values are not easily determined for proper real-time system health monitoring.

Subsequently in **Figure 2**, the utilization of a non-contact sensor within a 3-tier SHM framework is demonstrated to significantly help in the design process, by providing real-time data on wind turbines in different operating environments. This it

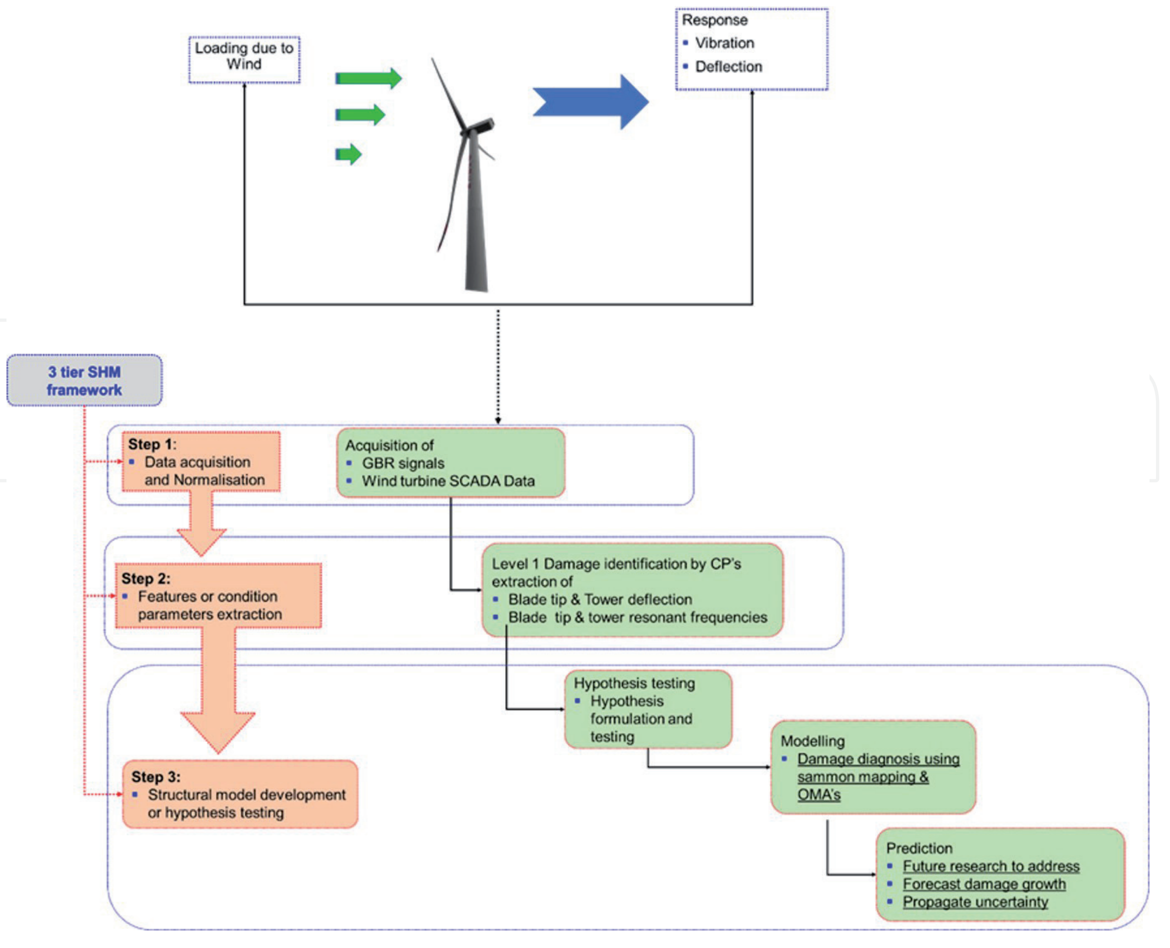

Figure 2.
GBR role in 3-tiered SHM of wind turbines.

achieves by enabling level 1 damage identification and prediction of future damage. A need thus exists to integrate such a non-contact sensor in not only the design process (**Figure 2**) but more importantly to help in the structural health monitoring (SHM) of WT using existing 3 or 4-tier SHM framework.

3. Tiered SHM framework for WT blades design optimisation and operational monitoring

Damage to WT structures can be identified much earlier with structural health monitoring (SHM) approaches. A recent study by [11], delineates two forms of SHM framework —a 3 or a 4-tier SHM framework.

The 4-tier SHM framework is based on 4 tiers/components [11], where:

- tier 1 is the determination if the damage is present,
- tier 2 locates the damage,
- tier 3 quantifies the severity of the damage, and
- tier 4 predicts the remaining service life of the system

Another SHM framework employs 3 sequential methodological steps viz.: (1) data normalization; (2) feature extraction using CP, and (3) health classification normally by way of hypothesis testing (HT) [11, 12].

In either SHM framework cases, data normalization provides a critical first step in health classifications since it compares the features of the structure in an unknown state (damaged or undamaged) to healthy features under the same environmental and operational conditions (EoCs).

Application of the 3-tier SHM framework has been done before [18] for a 3 kW small laboratory size WT. In that study [18] testing of the modularity of the 3-tier framework in SHM was undertaken. Data was collected from contact sensors placed in different parts of the WT. This data was then binned, analyzed and validated with receiver operating curves (RoC) to determine the damage classification capabilities of the framework. Residual-based CP's were utilized during feature extraction due to their sensitivity to both damage and EoC's.

Significant results from this study were that each tier can be considered as an independent (modular) and provide sufficient information for decision making on the structure's health. Secondly, that damage detection improved significantly if data clustering and binning were done before tier 2. However, the study was limited to the use of contact sensors for validation the 3 SHM framework and it used a comparatively smaller WT (3 kW).

A newer study [37] implemented the use of a non-contact Ground-Based-Radar (GBR) sensor within a 3-tier SHM framework. The study enabled the acquisition of frequencies and deflection condition parameters (unbalanced parameters as applied to SHM) with error margins of less than 10%. The application of the 3-tier SHM as applied in the study, for purposes of WT blades design and optimisation was as shown in **Figure 2**.

The role of SHM in dealing with the fatigue and emergent emphasis of aero-elasticity phenomenon like flutter is critical in integrating environmental and operational conditions (EoC) into SHM framework. The environmental conditions include: temperature, humidity, wind speeds, rainfall and irradiance whilst the operating conditions would include: cut-in and cut-out windspeeds, stall and pitch conditions, grid interconnection and whirling movements.

A review of various SHM approaches by [19] suggested that vibration-based damage detection (VBDD) methods provide the best SHM practices for beam-like structures. Other studies [20], however, suggest residual or differential imaged based signal analysis as being superior. For both approaches, damage occurrence (level 1 damage detection) [1] can be achieved. However [20], indicates that damage localization (level 2 damage detection) can be achieved only with the residual approach for real-life operating conditions. Such conditions were similar to those experienced by bridges or WT under operation.

4. Contact and non-contact sensors for WT

4.1 Contact sensors

The most common approach adopted to obtain the natural frequencies of structures is to place accelerometers at various locations on it and record the vibration responses from which the frequencies can be extracted. Accelerometers are commonly used due to their low cost and small mass which will not significantly affect the total mass of structures, hence vibration properties. However, the limitation of this approach is that the sensors need to be placed on the structures which may in some cases like those of rotating WT blades are neither accessible nor desirable.

In [37] a review of contact sensors is done within the context of wind turbine blade monitoring. This is summarized in **Figure 3**. Where the contact

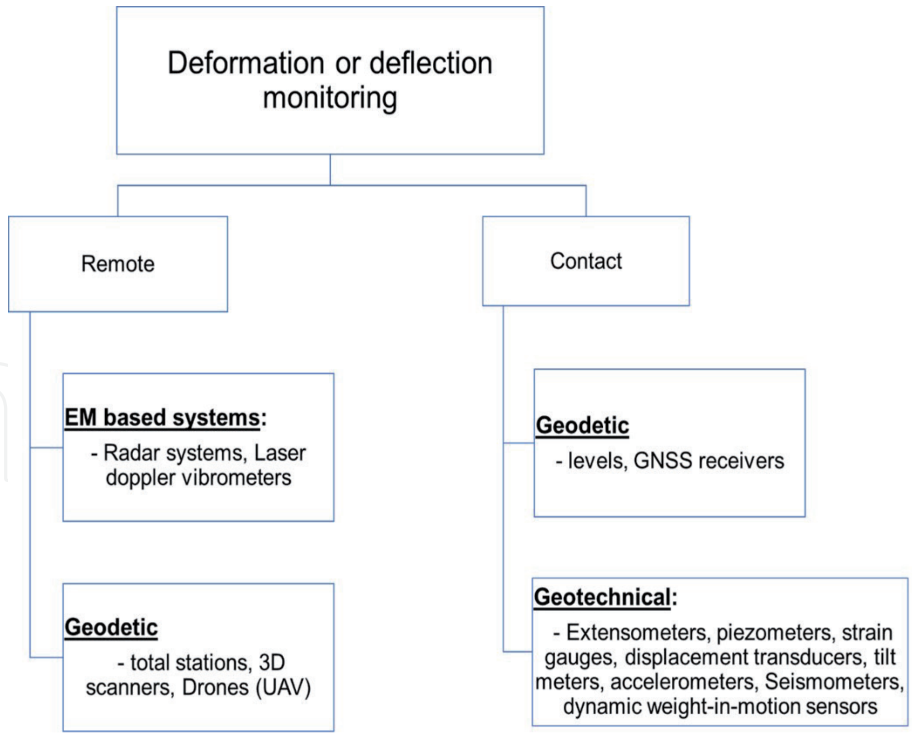

Figure 3.
Typology of sensors applicable to wind turbine blades.

and non-contact (remote) sensors are clustered in 3 main groups; Geodetic, Electromagnetic (EM) based and Geotechnical.

4.2 Non-contact sensors

While contact sensors like strain gauge sensors and accelerometers have been used in the monitoring of modal frequencies, the use of non-contact methods for beam testing has not been so widespread. **Table 1** depicts some of these non-contact sensors.

A number of non-contact methods like infrared thermography and photogrammetry have been demonstrated by [29, 33–35], for damage location under a 3-tier SHM. Other approaches like laser doppler vibrometer [26, 36] as a standalone or in conjunction with photogrammetry [6] have been employed in laboratory situations or for parked/non-rotating WT.

These methods do however face limitations particularly in the determination of modal frequencies, distributed strain, and deflection when the blades are in dynamic motion [37]. The main reasons for limitations are due to working principle employed, fast resolution of the EM, sound or light wave and environmental influences, which exacerbate the variations and errors in results.

4.3 Novel GBR for WT blades design optimisation and operational monitoring

Another novel approach has been the use of a quasi-monostatic ground-based real aperture radar (GBR). For this, a number of studies utilizing GBR for SHM have been done in the recent decade for beam-like structures (bridges and buildings) [38–40], towers [41–44] and for WT blades [11, 45, 46]. Specifically, the GBR provides a non-contact approach for design optimisation and operational monitoring of an operating WT [37].

As opposed to a monostatic radar using the same antenna alternately for transmission and reception, a quasi-monostatic radar has two antennas, one for

Sensor	Working principle	Limitations
Infrared thermography [21–25]	Utilizes infrared images to capture temperature occurring on damaged locations. Based on temperature increases of malfunctioning working components.	• Thermal images maybe unstable due to defocusing. • Can't acquire unbalanced parameters • useful for progressed or faults that have advanced.
Laser based systems [26-28]	Employs coherent radio waves to acquire modal parameters based on frequency shifts depicted in their interferograms.	• Input signal distortion and nonlinearity of the deflection mirror drive system • Cannot measure out-of-plane WT blade deflection due to speckle dropout errors (an optical phenomenon). • Cannot measure WT blades when in full rotation (>50m/s rotation). They limited to sensing up to 24.5m/s.
Photogrammetry systems [20, 29-32])	Employs either Digital Image correlation (DIC), target-less approaches, or 3 dimensional point tracking (3DPT)	• Requires optical reflectors or surface patterning mounted on WT blades. • Limited to low-frequency measurements. • High aeroelastic damping and dominant rotational harmonics influence results.

Table 1.
Non-contact sensors for WT blades monitoring.

transmitting and one for receiving. They are collocated that is the separation distance d_s is much less than the distance R between the radar antennas and the target ($d_s \ll R$) when compared to a bistatic radar [47]. Consequently, the equation to determine the maximum range (R) for monostatic radar is employed for quasi-monostatic radar.

When viewed from the GBR, the WT would consist of moving blades, almost stationary nacelle and a slightly moving tower. The nacelle is considered almost stationary since it rotates to enable to face the blades to the oncoming wind in addition to being stationary in situations of wind coming from a dominant direction. Generally, WT has large RCS in the order of 60 dBsqm (10^6 m^2) in the X-Band [48] and slightly less for the Ku band (~54 dBsqm), dependent on frequencies and blade aspect angle [49].

Even in the event of the blade rotation being low, the blade tip velocity will range between 50 and 150 m/s which is generally within the speed range of an aircraft. Hence providing a challenge to discern large WT from aircraft. This demerit, however, provides an advantage since it allows using Doppler frequency shift in the GBR backscattered signal, to distinguish between the tower, nacelle and blades.

It also allows the determination of the radial velocity (deflection velocity, v) of a target [50]. This is achieved by analysis of micro-doppler signatures, similar to the analysis of micro-doppler signatures of rotating helicopter blades [48]. Two important considerations are necessary in assessing such WT micro-doppler signatures:

- The radar cross-section (RCS) of a WT is much higher than that of a helicopter blade due to strong stationary reflections from the tower, nacelle and other ground clutter.
- The micro-doppler signatures may have doppler components of multiple bounces due to radar bouncing from blade to turbine tower to blades again before returning to the GBR.

The multi-bounce and stationary reflections may be best assessed using the design or expected operational parameters such as operational modal analysis (OMA's), in this case using Campbell diagrams.

The GBR acquires and processes the unbalanced/conditional parameters data in 5 key steps as shown in **Figure 4**. The data is acquired by radar, transformed into range profile using Fourier transform with possible windowing, thereafter deflection and modal frequencies CP's are obtained by phase extraction and power spectral density (PSD) respectively.

The maximum range R_{max} for the quasi-monostatic radar [47, 51] occurs when the received signal is equal to the minimum detectable signal S_{r_min}, and is found by Eq. (1).

$$R_{max} = \sqrt[4]{\left(\frac{P_t G_t G_r \lambda^2 \sigma}{(4\pi)^3 S_{r\_min}}\right)} \tag{1}$$

S_{r_min} is the minimum detectable signal by the receiver antenna that would allow target detection and is expressed by $S_{r\_min} = k\,T_0 B F_n (SNR_1)$.

Where $k\,T_0 B$ is referred to as thermal noise from the ideal ohmic conductor, k is Boltzmann constant, T_0 standard temperature at 290 K, B receiver bandwidth, $F_n = (\textit{noise out of practical reciever}) / (k\,T_0 B)$. For a signal to be detectable it has to be larger than the F_n by a factor called Signal to noise ratio (SNR_1). In addition, P_t is the transmitted power in Watts at the transmitter antenna, G_r and G_t are the antenna gains for the receiver and the transmitter respectively, while λ is the radar signal wavelength in m, and σ the radar cross-section area (RCS) in square metres.

The different time stamps of the return waves P_r, distinguishes them from each other allowing particular sections of the blade or mast to be identified in the

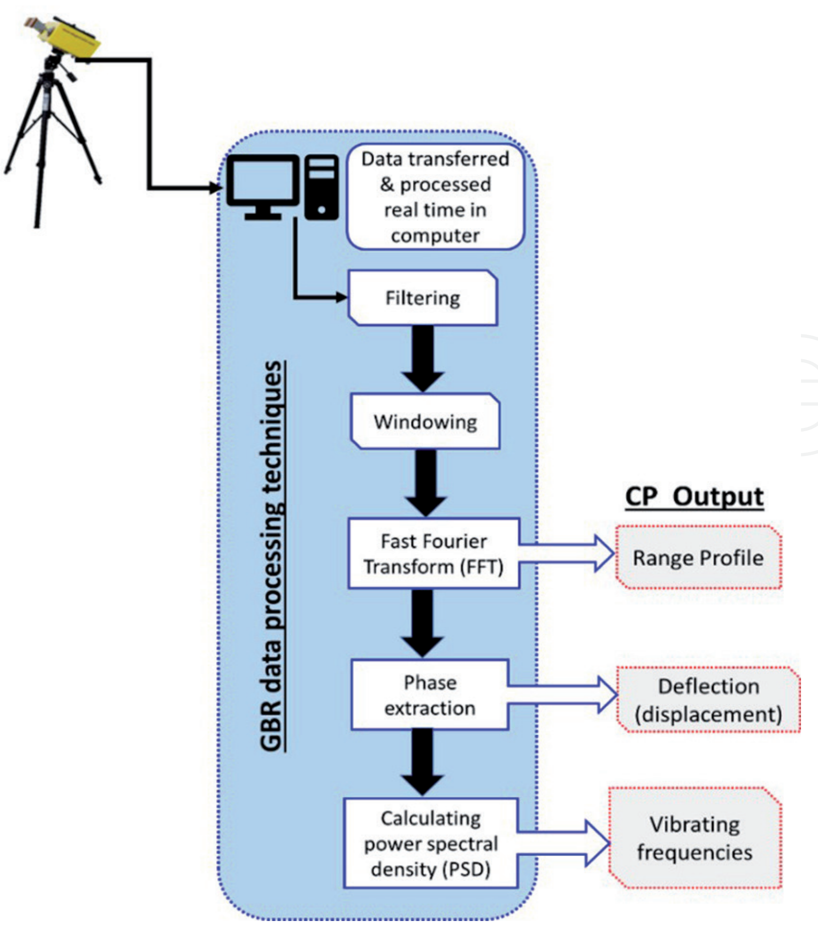

Figure 4.
GBR processing techniques.

corresponding time domain signal analysis. **Figure 5** demonstrates the setup for such signal acquisition; with pulse width τ in seconds and the inter-pulse period T_0 measured in seconds.

The product $P_t G_t$ is known as the effective radiated power (ERP), while $\sigma/4\pi R^2$ is the fraction of the ERP intercepted and backscattered by the target.

A worst-case scenario is normally considered in order to know the maximum detection range R_{max}, which will occur when P_r is at its minimum [51] Eq. (2). P_r is inversely proportional to the fourth power of the range Eq. (2) [51].

$$\mathrm{P}_{rmin} \propto \frac{1}{R_{max}^4} \tag{2}$$

To determine the unambiguous range, Eq. (2) uses the inter-pulse period T_0 [51].

$$T_0 = \frac{2R_{amb}}{c} \equiv R_{amb} = \frac{cT_0}{2} \tag{3}$$

Where c is the speed of light (3×10^8 m/s) is the velocity of light and τ is the time taken by the radar to hit the target and return.

To acquire the modal frequency, which is twice the total Doppler frequency, Eq. (4) is used. Herein the total Doppler frequency (f_D) is the frequency shift obtained by the difference between the carrier frequency (f_O) and reflected signal (f'_O) [52, 53], in a blade tip movement away and back towards the radar.

$$f_D = f'_O - f_O \approx \frac{2v}{c} f_O = \frac{2v}{\lambda} \tag{4}$$

where λ is the wavelength corresponding to the frequency of the transmitted wave. Note that v (the radial velocity of the target along the LoS of the radar). Velocity is defined as positive when the object is moving away from the radar. v can be obtained from f_D and vice versa because they are proportional. The Doppler information can only be extracted by recovering the phase history of the signal over time and therefore requires the GBR receiver to have the phase information of its waves be constant (be coherent) [54].

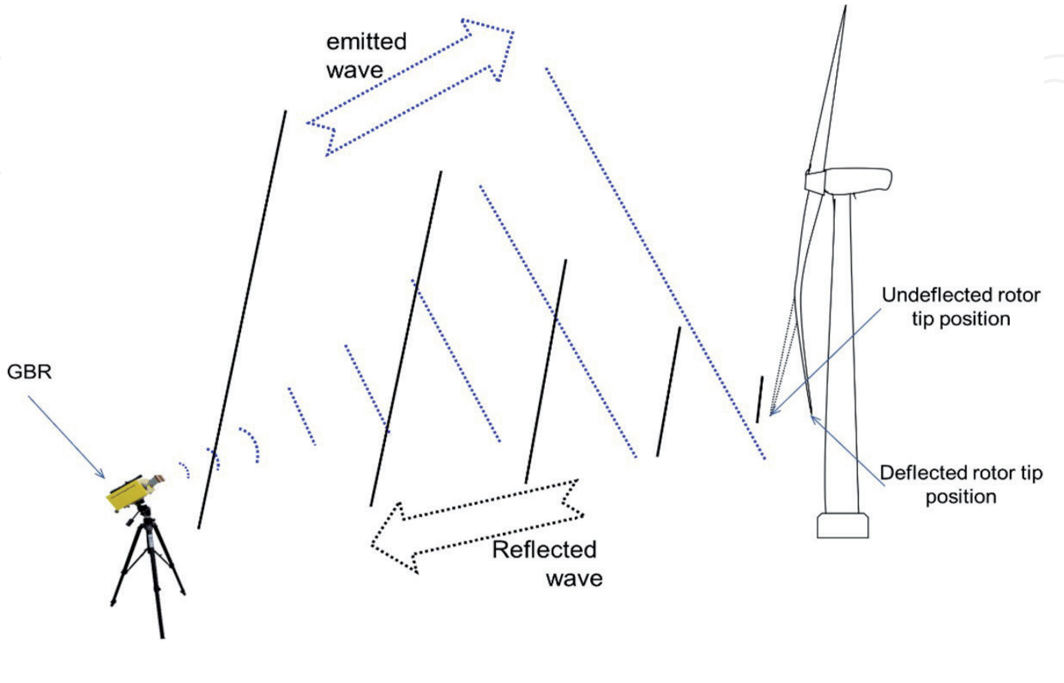

Figure 5.
GBR acquisition of unbalanced parameters using micro-doppler effects.

A 3-step process is utilized in radar target recognition that can be exploited for non-contact sensors application in a 3-tier SHM framework. The process entails

1. Acquire the Echo signal and analyze it using both SNR and RCS (tier 1 of the 3-tier SHM framework).

2. Feature extraction of target features from RCS sequences with known target category, then give a recognition criteria based on the relation between the target and its feature [55, 56] (tier 2 of the 3-tier SHM framework).

    - Feature extraction as a process aims to choose a subset of the original echo signal by the elimination of redundant information, yet extracting as much information as possible using as few features as possible [57]. Two approaches to features extraction are achieved by either

    - Extracting physical features from the time domain, such as extracting the cyclical nature of the RCS sequence [55] or

    - Extracting features from the transform domain (such as Fourier transform, wavelet transform, Merlin transform) [58].

3. Finally, recognize the damage or structure state by the recognition criteria (tier 3 of the 3-tier SHM framework).

The purpose of recognition criteria is to enable the identification of CP's and for this use can be made of principal component analysis or multidimensional scaling (MDS). MDS is a mostly a two-dimensional mapping or projection of data through the preservation of inter-point distances. It can either be a metric MDS like Sammon mapping or non-metric (neural networks, fuzzy networks, evidential and Bayesian approaches) [59, 60].

Of the four non-metric MDS methods—neural networks, fuzzy, evidential and Bayesian, the latter two provide the most relevance in terms of signal decomposition for damage recognition using recognition criteria. Evidential reasoning does not require prior knowledge of the probability distribution function. It is a method of fusing the different probability distribution functions given by different pieces of evidence. Thus give a recognition criterion based on the new probability distribution after fusing [57].

On the other hand, the Bayesian method requires the knowledge of the prior distribution. Then the minimum error rate or the minimum risk criteria can be given, and the target can be recognized by the criteria [57]. The Bayesian method in conjunction with non-contact sensors provides superior results in situations where no prior distribution existed either in the form of validated ground truth from contact sensors or in form of operational modal analysis techniques (OMA's).

The Campbell diagram is a form of OMA that is provided by the WT manufacturer for each wind turbine manufactured based on its design and potential operational parameters. Thus, it provides the apriori distribution of similar features required by the SHM framework.

5. Future trends and conclusions

While contact sensors have been widely employed in the design optimisation and monitoring of wind turbine blades, the use of non-contact sensors has not been fully highlighted. Specifically in the design optimisation and monitoring of blades, use of a 3-tier SHM framework and employing GBR are novel approaches. They offer new features and benefits in design and monitoring of WT blades.

With the advent of the fourth industrial revolution comprising of big data and internet of things, the GBR offers an opportunity to blend non-contact monitoring with improved design optimisation and monitoring of WT blades. One such technology is the use of GBR. However, future works in the deployment of GBR will need to focus on whirling movements of the WT nacelle and subsequent acquisition of condition parameters.

In conclusion this chapter has summarized the features and benefits as well as suggesting approaches and recommendations for future work, trends, and research. This is embedded in a conceptual framework that addresses the potential needs of WT blades trends in the future. It has further extended the complementary role and understanding of GBR in this role as a non-contact sensor, while proposing the integration of GBR as a non-contact sensor within the 3-tier SHM framework, to enable practitioners to undertake frequency based damage detection of WT blades. The main reasons for use of non-contact sensors is to address current challenges of installing contact sensors on operating/rotating WT, need for reduced SHM costs and lastly inappropriateness in use of contact sensors have had limited field and laboratory tests were undertaken on them.

Further, it has introduced the IEC 61400-23 standard for full structural monitoring of blades and relate it to sensors and Campbell diagram as an approach to optimization and operational monitoring of blades.

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