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Review

Gearbox condition monitoring in wind turbines: A review ☆

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ABSTRACT

Wind turbine technology is experiencing rapid growth with respect to size, market share, and technological design. Operational and maintenance cost directly determine whether the system is efficient in terms of energy production in comparison with other types of power plants. Condition monitoring of wind turbines is the major field of studies in recent years aiming to increase lifetime expectancy of components while reducing operation and maintenance cost. Operators and researchers are focusing on improving fault detection techniques in order to render wind turbines more reliable. Gearbox in wind turbines has the greatest share of downtime among all other components affecting directly the cost of operation and maintenance. This paper gathers a review on different methods and techniques for gearbox condition monitoring in wind turbines. Furthermore, various methods and techniques in the literature will be presented in order to get an insight onto the most used methods in wind turbine gearbox condition monitoring. Challenges and future aims are also discussed to determine the focus of condition monitoring systems.

Contents

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1. Introduction

Wind power gained remarkable attention in the past decade since worldwide policies are fighting climate change through the support and investment into renewable energy sources. Recent investments into renewable energy-based power plants increased to a level of 3–1 compared with fossil fuel and nuclear power plants. Compared to a 50 GW mark in 2014 [1], 2015 witnessed the highest annual installation with 63 GW (22% increase) [2]. Statistics shown in Fig. 1 prove that wind power installation is soaring towards leading the path to electrical power production. With such a big role rise important challenges regarding reliability, cost-effectiveness and energy security. In order to tackle the challenges facing wind turbine energy, researchers shifted their attention towards condition monitoring and preventive maintenance in order to reduce operation cost and downtime of wind turbines. Failures of wind turbines during the last decade have gradually decreased while remaining an important issue to tackle considering the aim of cutting down operation and maintenance cost.

Wind turbines withstand randomly changing weather conditions, temperature, wind shear, wind speed, and load. Wind turbines are a combination of several complex systems connected altogether (hub, drive shaft, gearbox, generator, yaw system, electric drive, etc.). With the numerous and various parts in wind turbine systems, failures could occur to any of the components causing either end of operation or damage to other components. Reported failure rates of different system components are shown in Fig. 2a [4]. All components are prone to failure. Nonetheless, the focus of manufacturers is shifted towards which of the components will cause the longest downtime for maintenance and impose the highest repair costs. Fig. 2b shows the downtime caused by every component failure occurrence. Gearboxes come second in the downtime per failure due to their size and robust link to other components making it harder to access, repair, or even replace [5].

Gearboxes operate under harsh environmental conditions. They are responsible of stepping up the speed transmitted by the low speed shaft (LSS), towards meeting the requirement of that of the high speed shaft (HSS) that drives the generator. Thus, they endure all the vibrations caused by the turbine-side components and wind, along with all fluctuations imposed by the load through the generator. Faults in gearboxes may occur to several components among which: tooth crack, internal shaft, HSS bearing, LSS bearing, ring gear, helical gear, poor lubrication, housing, etc.

This paper will go through, and discuss different approaches, techniques, and methods for gearbox condition monitoring in wind turbines and will be structured as follows: Section 2 goes through the condition monitoring basics, process, and approaches. Section 3 mentions different lubrication analysis techniques for wind turbine gearbox fault detection. Followed by acoustic emission analysis in Section 4. Section 5 discusses different vibration analysis techniques applied to wind turbine gearbox fault detection. While Section 6 goes through several machine current–based techniques for fault detection. Section 7 discusses the application of SCADA for gearbox fault detection. Section 8 will interpret and conclude on the material mentioned throughout the article.

2. Condition monitoring process and approaches

Reliability remains the major manufacturers' concern and it is achieved by consistently dealing with faults through strategies and techniques capable of preventing or at least minimizing the effect of these faults. Faults are usually

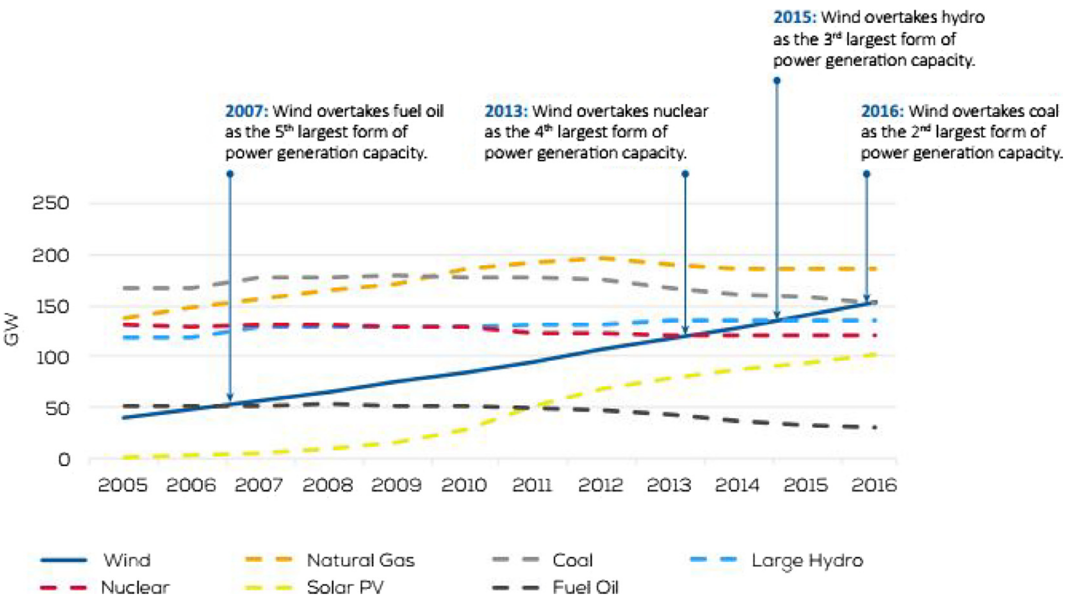

Fig. 1. Evolution of the cumulative power capacity in the European Union of different power sources [3].

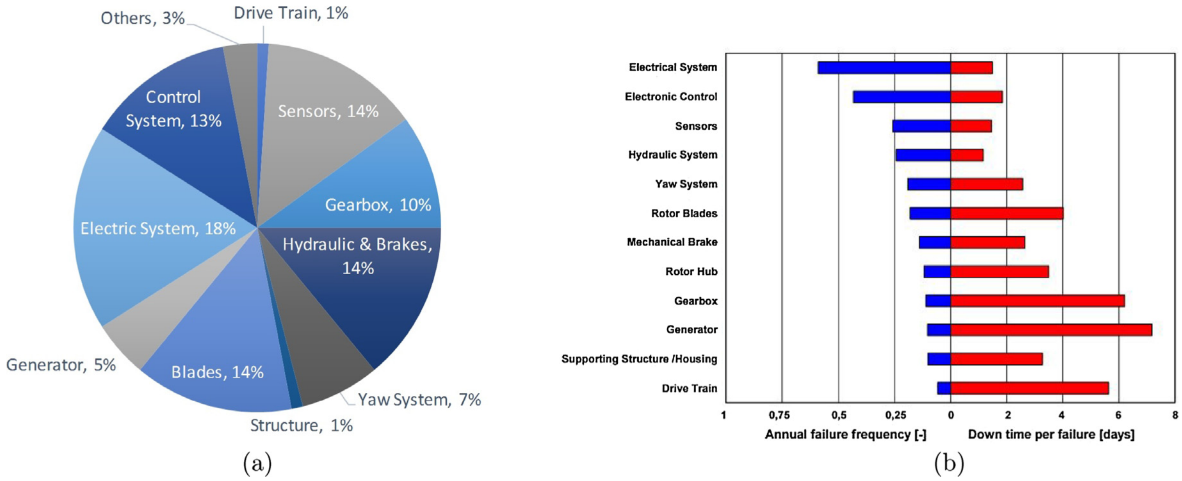

Fig. 2. (a) Failure occurrence rates of the main components of wind turbines. (b) Failure frequency versus downtime per failure [4].

categorized to be: electrical faults (winding insulation failure, ground deficiency, wrong connection, etc.), mechanical faults (rotor bars degradation, demagnetization, shaft bending, bearing failure, gearbox malfunction, etc.), machine drive system failures (inverter failure, supply line shortage, transients in the voltage and current sources, etc.). Moreover, environmental factors and specially wind transients have a major effect on rotating mechanical components. The preceding faults and factors push the system to show irregular symptoms during operation (vibration and noise, rise of temperature, output power fluctuation, acoustic noise, voltage and current variations, drastic speed change, etc.) [6,7]. This is achieved through efficient condition monitoring systems. Condition monitoring comes hand in hand with all installed wind turbines in order to establish maintenance and repair strategies. Maintenance strategies can be summed up in three criteria: run to break, preventive maintenance and condition-based maintenance, see [7,8], where the latter has the upper hand over the traditional not used run to break approach and the unpractical preventive maintenance [9]. Condition monitoring strategies rely on autonomous online algorithms responsible for early mechanical and electrical defect detection. The condition monitoring plan starts through a time-domain and/or frequency-domain data analysis, then a decision is reached on the type of fault and its severity. In the end, a feedback command is sent either to human interface or a pre-programmed routine, to limit or halt the system operation for maintenance. As aforementioned replacing the components of wind turbines and specially gearboxes and generators is a tedious and costly task and requires complete shut down. This proves the importance of implementation of condition monitoring guaranteeing:

1. Premature breakdown prevention with early maintenance and component protection.
2. Intact parts replacement avoidance.
3. Remote supervision and diagnosis.
4. Maintenance planning actions during low wind seasons and increasing the overall capacity factor of wind turbines.

Condition monitoring techniques used nowadays are capable of instantly detecting defects prior to failures. They can even predict which gearbox component is defective. Gearboxes are mechanical systems where some components operate in a lubricated environment, lubrication analysis, acoustic emission analysis and vibration analysis can be applied to detect faults. Nevertheless, the challenge resides in applying the electrical analysis to a mechanical system. Condition monitoring of gearboxes can be done through the following approaches:

1. Lubrication analysis intends to preserve oil quality and guarantee the best possible operation environment for the components involved. Lubrication analysis is usually done offline through the examination and testing of samples. Recent technologies and techniques are introducing online monitoring through the installation of sensors for particle counting and moisture level supervision. In addition, oil filters may as well be a good indicator of any fault when they become excessively polluted due to component wear.
2. Acoustic emission analysis is applied through sensors responsible of capturing the sound emitted by the gearbox operation through sound level meters. Devices with anti-aliasing and high sampling rate are used for measurement, converting pressure levels and vibration into voltage signals. Acoustic emission analysis and vibration analysis target the same type of collected data. Nonetheless, the first approach 'listens' to vibrations, while the latter measures them.
3. Vibration analysis is the most known and applied technique for condition monitoring. All rotating machinery have a vibration signature [10]. Any alteration or fault occurring to any of the mechanical components will alter that vibration profile. Monitoring the vibration frequency would give insight onto whether a component is defective or not. In wind turbines, vibration analysis can be applied on all mechanical components such as blades, bearings, gearbox, generator, shaft, and drive train.

4. Electrical analysis rose in recent years as a replacement for vibration analysis but is still in the early stages and needs more research to serve its purpose. Electrical analysis aims to eliminate data collection error through the reduction of sensor installation, and reduce wind turbine operation cost by reducing the number of sensors and therefore reducing the need for maintenance and repair. The basics of this analysis is complete dependency on the three-phase current and voltage signals produced by the wind turbine to monitor its operation and detect any fault in its components. It is known that faults occurring inside wind turbine mechanical components cause fluctuations in both current and voltage signals. Therefore, through time–frequency analysis of those signals one can detect added frequency components resulting from faults. Its advantage is the accuracy of the data collected for there is no need to filter sensor measurements [11].

In the following, an insight is presented on the recent advances and methods used in condition monitoring of gearbox faults through the aforementioned approaches.

3. Lubrication analysis

Oil and lubrication analysis is one among many important condition monitoring approaches. Oil cleanness, viscosity and temperature give insight onto how the gearbox of any wind turbine is performing. Oil cleanness has a large effect on life expectancy of gearboxes with an estimation of up to 50% of increase/reduction in overall run-time. Many methods are used to test and analyze lubricant samples, among which are on-line (particle count, temperature and viscosity monitoring, etc.), and off-line (oil filter analysis for flow and cleanness characteristics) [21]. Preserving a clean environment of operation for mechanical components inside the gearbox is vital in order to detect mechanical faults as well as extend their lifetime expectancy. Oil condition monitoring rely on the use of multiple purpose sensors. [22] detailed the multiple types of sensors as shown in Table 1. Some references in Table 1 introduce sensors used in generators. Nevertheless, gearboxes operate in same lubricated environment as generators (see Table 2).

In [23] an optical fiber refractometer was fabricated and characterized based on LMR for gearbox synthetic lubricant degradation at working temperature in wind turbines. Results concluded that thinner coating results in higher sensitivity.

Zhu et al. (2013) used online sensors to study lubrication condition monitoring and degradation [24,25]. Wind turbine gearbox Remaining Useful Life (RUL) is studied using viscosity and Dielectric Constant sensors while applying particle filtering technique for interpretation. Results concluded good lubricant deterioration monitoring and RUL prediction. Particle population improved prediction accuracy with a reservation considering processing time when it is increased.

Oil debris monitoring is an effective method in detecting faults in wind turbines. Dupuis et al. [26] applied oil debris monitoring for gearbox health monitoring in wind turbines. The technique relies on counting debris particles while measuring their size through sensors in order to assess the severity of the fault in the gearbox. More data are needed to introduce complex gearbox damage models in order to improve oil debris monitoring techniques.

Recent studies are trying to recreate the environment in which the gearbox of a wind turbine operate. Coronado et al. [27] put together a Highly Accelerated Life Test (HALT)/Highly Accelerated Stress Screening (HASS) test chamber in which oil sensors properties can be assessed. The study is done under changing operating temperature and vibration levels. The results showed some deviation in the sensor measurement specially with extreme temperature conditions. Under other normal conditions the results were accurate to a certain extent. Despite the deviation in the measurements, the future development on the test bench and chamber may well reach a certain level of accuracy allowing researchers the testing of various scenarios including oil characteristics as well as mechanical characteristics of the gearbox.

4. Acoustic Emission (AE) condition monitoring

Acoustic Emission (AE) condition monitoring studies the sound emitted by vibrations of mechanical systems such as generators and gearboxes. High frequencies are the subject of study and analysis (100 kHz to 1 MHz) [8,28,29]. Since all mechanical rotating systems have a vibration signature [10], acoustic signatures are also available and any alteration in these signatures indicate the deterioration of a component. The main and major drawback of AE condition monitoring is the noisy background which introduces other components' noise and reduce the accuracy in fault detection of the monitored component. Many AE applications for rotating mechanical systems fault detection can be found in the literature for other systems than wind turbine [30–32]. In the following, AE methods for gearbox fault detection in wind turbines (Table 3).

Table 1
Types of sensors used in oil condition monitoring.

Reference	Sensor type	Measured parameter
[12]	Humidity sensor	Percentage of water in the lubricant
[13,14]	Particle concentration sensor	Particle size distribution
[15–17]	Conductivity sensor	Electrical conductivity level used to monitor oil oxidation rate
[14,18]	Dielectric constant sensor	Dielectric constant
[19]	Viscosity sensor	Kinematic viscosity
[20]	Quality & properties sensor	Electrochemical impedance spectroscopy (EIS)

Table 2
Summary of methods for lubrication analysis in wind turbine gearbox.

Reference	Method
[23]	Lossy Mode Resonance (LMR) based optical fiber refractometer
[24,25]	Online lubrication oil condition monitoring and RUL prediction using viscosity and DC sensors along with a particle filtering technique
[26]	Oil debris count and size detection through sensors
[27]	Chamber for HALT/HASS for oil sensor properties assessment

Table 3
Summary of methods for Acoustic Emission condition monitoring of wind turbine gearboxes.

Reference	Method
[33]	LabView-based online gearbox monitoring system
[34]	Heterodyne technique with Time Synchronous Averaging (TSA) and Kurtosis
[35]	DRFF and DBMs for 11 different gearbox operating conditions
[36,37]	Comparative study between AE and vibration analysis for wind turbine gearbox fault detection
[38]	Time Of Arrival (TOA) with Continuous Wavelet Transform (CWT) on Morlet waves to localize faults

Wei et al. [33] designed a LabView-based online monitoring system for gearbox operation monitoring and fault detection. Authors concluded efficacious fault type locating and detecting, while claiming its superiority over vibration analysis techniques.

Heterodyne techniques used in communication were introduced to preprocess AE signals for wind turbine gearbox fault detection in [34]. Time Synchronous Averaging (TSA) and spectral Kurtosis were later proposed for feature extraction and gear fault detection. Using the Heterodyne technique reduced the sampling rate from the order of MHz to kHz. The results showed effective gear tooth fault detection.

An advanced application to gearbox fault detection was introduced by Li et al. [35] with the use of Deep Random Forest Fusion (DRFF). AE sensor and an accelerometer are used to extract data for monitoring. The wavelet packet transform is then used to extract statistical parameters. Deep representations of these parameters are developed using two Deep Boltzmann Machines (DBMs). A random forest is proposed to fuse the outputs' DBMs as the integrated DRFF model. 11 different gearbox operating conditions were tested where the method scored 97.68% of classification rate. The results show a superiority to other AE methods for gearbox fault detection and condition monitoring.

Partial tooth cut faults in gearbox were investigated in [36], and bearing defect of wind turbine gearbox in [37] where a comparative study was conducted between AE and vibration analysis. Results showed that AE is more stable in fault detection performance, while it was capable to isolate damage levels. Vibration analysis failed to do so since it is affected by mechanical resonance.

A recent study used the AE to detect and localize gear faults [38]. The study relies on obtaining the time of arrival of AE signals, which with the continuous wavelet transform on Morlet wavelets extracts compressive waves to represent the AE signals. The linear correlation between the time of arrival and the propagation distance will localize the fault inside the gearbox. The method is proved superior in localizing the faults.

5. Vibration analysis

Most signal processing techniques rely on Fourier Transform (FT) to represent signals in frequency or time–frequency domains. Frequency methods give information regarding frequency, amplitude and phase of signals. In addition to all these characteristics, time–frequency methods give insight onto how the aforementioned characteristics shift with time. Table 4 shows the conventional signal processing methods along with the advantages and disadvantages of each one [39].

Table 4
Conventional fault detection methods in vibration analysis.

Technique	Pros	Cons
Fourier Transform (FT) [40]	Fast and easy application	Only frequency analysis
Short Time Fourier Transform (STFT)[41]	Gives either good time or good frequency resolution Window function dependent	Gives either good time or good frequency resolution Window function dependent
Wigner-Ville Distribution (WVD) [42]	Good time frequency resolution	Critical cross interference terms
Wavelet Transform (WT) [43]	Good time resolution for high frequencies Good frequency resolution for low frequencies	Basic function choice
Empirical mode [44] Decomposition (EMD)	Nonlinear & non-stationary signal processing	End effect mode mixing
Support Vector Machine (SVM) [45]	Accurate representation of I/O relationship	No control over data points number

Signal processing applications for vibration analysis of gearbox started early on in the 1980s. McFadden et al. used phase modulation for early detection of defects in gearboxes, and amplitude and phase modulation for gear fatigue detection [46–49]. The HT was extensively used in the literature for gearbox vibration analysis [50,51] where Feldman [52] put together a full tutorial on the application of the HT for diagnosis in vibration analysis of mechanical systems. Staszewski et al. [53] applied the WVD through two pattern recognition procedures in order to detect tooth faults in gearboxes. Smith [54] put together the basics for gear vibration analysis along with methods, strategies and applications aiming to better analysis of noise in gearboxes. In addition, a tech report by Zakrajsek [55] summed up some of the research done in the 1980s in vibration analysis of gearboxes. Moreover, the EMD was also used for early on for nonlinear and nonstationary signal processing [44], and later on for gear fault detection [56–59]. Support Vector Machine (SVM) was first introduced by Cortes and Vapnik [45], who applied it as an artificial intelligence methodology for classification and regression data. Furthermore, SVM gained interest for its capability in generating accurate representation of the relationship between the input and output even with a small amount of training information. It was used for condition monitoring and fault detection through vibration analysis in many systems [60–62]. The main drawback was in the incapability of controlling the number of data points by the algorithm leading to heavy computational load in the case of large number of training data.

Despite the breakthroughs traditional methods offered in the field of diagnosis and condition monitoring, drawbacks mentioned in Table 4 needed to be solved in order to get accurate results in a very complex system such as wind turbines. Modern signal processing requirements in speed and accuracy conclude that neither of these methods alone can do the job of tracking and analyzing nonlinear and non-stationary signals such as those measured in wind turbines. In the aim of tackling these challenges, researchers turned their attention towards supporting methods, which combined with conventional ones, give better results in the analysis of systems. In the following, advanced combined methods were used to detect gearbox faults in wind turbines are discussed.

Spectral kurtosis for tooth crack detection in planetary gearbox of wind turbines was studied in [63]. Authors obtained the results without time synchronous averaging. They observed that tooth crack had a very short duration and rarely occurred. This led to insufficiency of information to retain high frequency pulses. Fast wind variations were also studied in order to observe the effect in the meshing patterns. Authors concluded that more advanced algorithms are to be deployed in order to render the method more efficient and fast in detecting tooth crack faults. Moreover, a detailed load change can very much contribute in understanding their effect on the vibration analysis.

An upgraded Hilbert Transform (HT) was applied in [64] in order to detect gear defects. The EMD was used to decompose the measured signal into Intrinsic Mode Functions (IMF). The modified HT showed a better resolution in comparison with the traditional transform and that of the WT.

In [65] the Ensemble EMD (EEMD) is used to decompose the gearbox vibration signals into mono components that will be used in the energy separation algorithm to estimate the amplitude envelope and instantaneous frequency of the modulated signals. The proposed method was simulated and implemented on a test rig where wear and chipping faults of a planetary gearbox of a wind turbine were detected and located.

In a more advanced EMD application, Dybala et al. [66] introduced the health index used to give insight regarding the state of health of the gearbox. The advantage of the proposed method is that the health index gives an alert signal prior to fatal failure of the gearbox allowing preventive maintenance and repair.

Feng et al. [67] applied the adaptive optimal Kernel method for planetary gear faults detection and diagnosis. The method has fine resolution and is deprived from cross-term interference. Making it suitable to extract time-varying planetary gearbox frequencies under non-stationary conditions. It is used to detect time-varying frequency components during variable speed operation while diagnosing the planetary gear fault through the characteristic frequencies. Both simulation and experimental results were concurrent regarding the detection of faults under non-stationary conditions.

The Teager-Kaiser Energy Operator (TKEO) used alongside the Desa–1 energy separation algorithm in [68] is a good alternative for the HT. It gives clean and smooth signals when analyzing mono-components. It was shown in the study that varying loads causes difficulties in condition monitoring and fault detection. The Empirical Mode Decomposition is used in that case to separate a major part of the time-varying load influences from the vibration signals. Allowing the damage-related signal components available for further analysis using either HT or TKEO. Damage features were extracted using the TKEO through instantaneous amplitude computation which indicates the frequency region of the harmonics caused by a fault.

Urbanek et al. in [69] studied the effects on the vibration based feature value by the generator output power and rotational speed. Three dimensional charts of the feature value under consideration were drawn. The charts results indicate the occurrence of faults during operation and which of both generator output and rotational speed has the greatest effect on each feature. The study shows that studying the vibration of different wind turbine components without taking into account the transient in power and rotational speed may result in inaccurate results regarding the severity of the fault. However, the drawback of the study resides in the fact of localizing the fault. It is capable of detecting the occurrence of a fault without giving any insight onto which component is faulty.

A novel method was proposed by Kidar et al. [70] based on the Estimation of Signal Parameters via Rotational Invariant Technique (ESPRIT) by using a sliding window. The study proposes a comparison between the HT and ESPRIT for the detection of gearbox cracked tooth. The results showed that the ESPRIT with the sliding window is capable of monitoring the variation of the instantaneous phase when both amplitude and frequency modulations are present. However, the Hilbert transform performed only in the case of frequency modulation.

Feng et al. [71] used the iterative generalized demodulation to improve the synchrosqueezing method. While the synchrosqueezing method deals only with mono-component, constant frequency signals it is not usable for multi-component signals. Using the iterative generalized demodulation allows the estimation of the instantaneous frequency of each mono-component using the synchrosqueezing. This method regenerates the original signal by the superposition of the time–frequency representation and the restored instantaneous frequency. It is characterized by a fine resolution and an effective planetary gearbox detection.

Diehl and Tang [72] used a Dynamic Gearbox Model (DGM) and a Harmonic WT (HWT) in order to detect a fault in the pinion of a two-stage gearbox. Accelerometers were used to extract the data which was analyzed by the HWT. The results show good results in mimicking the nonstationary behavior of the gearbox under changing speed. An advantage in the method used is highlighted by the advanced DGM used that reflects the gearbox dynamcis at higher level.

Ha et al. [73] proposed an Autocorrelation-based Time Synchronous Averaging (ATSA) method to deal with the physical interaction between the ring, sun and gears in the gearbox. It is used to determine the optimal shape and range of the window function of the TSA using actual kinetic responses. The ATSA has two main characteristics regarding data-efficiency for TSA processing, and signal distortion prevention during TSA process. The method showed improved results in comparison with the conventional TSA process in the case of limited stationary data.

Sharma et al. [74] also proposed a TSA-based method to detect gear tooth crack. The Modified TSA (MTSA) proposed filters out noise using speed based resampling and cubic spline interpolation. In addition, a comparative study was done regarding condition indicators (Root Mean Square (RMS), kurtosis, crest factor, FM0, FM4, M6A, NB4, energy ratio, NA4,energy operator, and two proposed condition indicators PS-I, PS-II). The proposed MTSA showed improvements regarding Signal to Noise Ratio (SNR) and reduction in processing time while using the cubic spline. The comparative study for condition indicators concluded more better crack evolution sensing while using the proposed PS-I and PS-II. The study was done in variable speed conditions under constant load, a future application would technically consider the investigation of a variable load effects on the results and the accuracy of the proposed MTSA and condition indicators.

In [75], the time–frequency method used is based on the Vold-Kalman filter applied to planetary gearbox under non-stationary conditions. A higher order energy separation algorithm is used to detect time-varying frequency components. The Vold-Kalman filter separates arbitrary complex signals into mono-components. In addition, higher order energy separation is capable of instantaneous frequency estimation of signals. The time-varying frequency components of planetary gearbox vibration signals during transient speed operation are revealed. The distributed and localized sun gear faults have been successfully diagnosed. This method performs well under non-stationary conditions.

In [76] an iterative generalized time–frequency reassignment method is used to detect planetary gearbox faults under non-stationary conditions. The method guarantees the decomposition of multi-component signals into mono-component signals of constant frequency while improving time–frequency readability. While no outer or inner interference exist, the proposed method shows good time–frequency resolution in detecting fault frequency components of both localized and distributed gear faults.

A new Supervised Order Tracking Bounded Component Analysis (SOTBCA) is proposed in [77] that improves the noise resistance ability of the Bounded Component Analysis (BCA) method with the assistance of the order tracking technique. The use of an AutoRegressive (AR) filter gives the SOTBCA a supervision characteristic making it suitable for gear fault detection. Based on the BCA framework, SOTBCA is able to identify dependent/correlated components in the vibration analysis. The series of experiments and results proved that the proposed SOTBCA is capable of:

1. Effective recovery of closely correlated sources contaminated with heavy noise
2. Correct reconstruction of the vibration source signal excited by the gear crack
3. Detection of cracks with various depths and at different driving speeds in the wind turbine gearbox while the vibration intensity of the reconstructed gear cracked source in the Cyclic Spectral Density (CSD) spectra increases with the increase of crack level.

A pattern recognition approach based on WT and FFT for fault detection and diagnosis was used in [78] to monitor the mechanical parts. It is intended to detect fault in inaccessible parts of the wind turbine, or when installing several sensors would be very costly considering projected maintenance. The sound energy is captured using strategically placed sensors. Then the first and second harmonics are studied using WT and FFT. Based on a fuzzy clustering using the RMS is done to emphasize the relation between the sound energy and vibration peaks then by a classification one could find the unusual pattern that indicates the presence of a defect.

Fractal theory was also used for wind turbine gearbox fault detection. Ziaja et al. [79] used fractal theory along with the orthogonal wavelet transform to decompose and compare vibration signals of both healthy and faulty gearbox data. In addition, Li et al. [80] applied the fractal theory along with the EEMD which decomposed the vibration signal into frequency bands. The fractal dimension reflects the gearbox operating conditions. Both methods were capable of detection gearbox faults.

Co-integration focuses on signal periodicity features to detect fault occurrence when co-integration relationship is broken. A recent research conducted by Dao et al. applied the co-integration technique in order to detect faults in wind turbines [81]. The approach was applied to SCADA data and showed effectiveness in detecting faults for nonlinear operation. Zhao et al. [82] applied the co-integration method to compare normal gearbox vibration signals and faulty ones. Vectors relationship with both sets of vibration signals data showed good detection of the faulty gearbox data.

A novel tacho-less fault signature detection is proposed in [83]. The fault signature enhancement algorithm wraps the measured vibration signals in order to project the original timescale to a new transformed timescale where the time-varying speed of the shaft is squeezed towards a constant reference speed. Hence, the frequencies proportional to the time-varying speed of the shaft are squeezed into respective individual peaks. The proposed method showed good results in detecting fault harmonics in non-stationary modes without the requirement of rotational speed measurement, while relying solely on the vibration signals.

Conventional condition monitoring methods adopt Blind Source Separation (BSS) in mechanical systems [84,85]. However, the approaches applying BSS consider the case where the number of signal sources is the same as the number of sensors. Which is not the case in [86], where an Undetermined BSS (UBSS) is applied as a novel method for bearing fault detection in gearboxes. A Sparse Component Analysis (SCA) solution is used to estimate the number of sources before source signal recovery stage is done. The method uses the STFT to move into the time–frequency domain. The estimation of the source number is done using EMD and Singular Value Decomposition (SVD). Fuzzy C-Means (FCM) clustering is then used to estimate the mixing matrix before applying the I_1 norm decomposition to recover the source signals. The results proved that the joint EMD-SVD method for source number estimation is capable of performing under noisy conditions. In addition, the recovered signals through FCM and I_1 have independent frequency bands reducing the complexity of fault detection.

6. Machine Current Signature Analysis (MCSA)

Vibration analysis may have been the most used and applied approach for fault detection in rotating machinery and specifically in wind turbines. However, applying vibration analysis requires vibration sensors and their respective supporting circuits to transform the signal and measured data into usable ones. This increased the cost of installation with an added value for expensive sensory systems and their maintenance and repair, not mentioning the rather noisy data collected by those sensory systems that needs additional filtering. All those reasons pushed operators and research to look into other methods that would be cheaper to install. Electrical analysis appeared as a unique and effective approach, considering that both current and voltage signals are easy to monitor and several early and recent studies as the one done by Schoen et al. [87] and Marzebali et al. [11] proved that vibrations inside the mechanical components (shaft, gearbox, bearing, etc.) appear in the electrical signatures of the wind turbine generator. However, some insignificant incipient faults may not be detected as long as the noise amplitude remains greater. Lin et al. [88] applied the EMD for current signal analysis while the K-nearest algorithm was used to gearbox oil leakage fault detection. The method showed successful results in the detection of the fault (Table 5).

Mohanty et al. [89] applied the MCSA for a multi-stage gearbox condition monitoring while one tooth or two teeth were removed, using a Discrete Wavelet Transform (DWT). FFT analysis showed that the vibration signatures' low frequencies have sidebands across the spectrum. Whereas, the high frequencies were undetectable. Applying the DWT to decompose the current signal followed by the FFT on some of the results was able to trace the sidebands of the high frequencies of vibration.

Ardakani et al. [90] used a novel dual level TSA method, in order to enhance the motor current signature content while emphasizing the components of the mechanical faults inside the gearbox. The method was capable of diagnosing pitting and eccentricity faults during transient speeds. This method was applied in a no-load scenario, future work will take into account the transients in load profiles as well as speed transients.

A recent observer developed by Masmoudi et al. [91] is capable of amplifying mechanical fault signatures enabling operators the detection of less significant wear or faults. The previous facts put the electrical analysis approach in the lead in condition monitoring of wind turbines. Other methods were also developed for better detection of gearbox faults will be discussed in the following.

Lu et al. [92] designed a current based method for variable speed wind turbine gear faults detection. The method uses the stator current signal analysis to identify the characteristic frequencies of gear faults. An adaptive signal re-sampling algorithm with fault feature extraction and fault detectors were added to the method to deal with time varying frequencies. The simulated and experimental results matched concerning fault detecting and isolation. The research proposes the Vold-Kalman [75] filter based multiscale method as an effective way to locate the faulty component.

Table 5
Summary for MCSA applications for wind turbine gearbox fault detection.

Reference	Method
[89]	MCSA with DWT and FFT for tooth crack fault detection
[90]	MCSA with novel TSA method emphasizing mechanical fault signature
[91]	Mechanical fault signature amplification based on current and voltage signals
[92]	Adaptive signal re-sampling algorithm with fault feature extraction and fault detectors for time varying frequency analysis
[93]	MCSA with DWT and dual level TSA

Motor current signature during variable speed is used in [93] to monitor wind turbine gearbox health status. Discrete wavelet and dual level time synchronous averaging were used for gearbox condition monitoring. The data were extracted during a ramp up under no load with gears in the following conditions: gear with no defect, gear with aging pitting fault, and a gear with intentionally made eccentricity. Both methods showed good results in detecting and characterizing the health of the gearbox, with a slight advantage for the dual level time synchronous averaging method regarding the discrimination of healthy and pitting gears.

In addition, electrical analysis is mainly used in generator fault detection. Methods in the category of Machine current Signature Analysis (MCSA) use stator or rotor currents' signals in order to monitor generator faults after applying spectral analysis. It is interesting to investigate the ability of the techniques and algorithms used for generator fault detection in monitoring other mechanical components -primarily gearboxes- faults. In the following, a brief insight onto the recent techniques applied to generator condition monitoring that might improve electrical analysis techniques for gearbox fault detection (Table 6).

In [94] a diagnosis technique is proposed based on current frequency sliding pre-processing, and discrete wavelet transform. The computation of wavelet signals mean power, at different resolution levels, is used as a dynamic fault indicator for quantifying fault severity. The proposed method is effective for both stator and rotor faults under speed transients and varying fault conditions. The application used a Doubly Fed Induction machine and proved its validity in stator and rotor fault detection.

Djurovic et al. [95] analyzed the stator current and total power spectra to detect electrical asymmetries in the rotor of wound rotor and Doubly Fed induction generators. Real time fault frequency tracking was implemented using concise analytical expressions to describe fault frequency variation under varying speed. The study was carried out using variable speed scenarios for current and power frequency components for both healthy and faulty conditions for comparison. The method applied along with the algorithm developed show that both stator current and total power spectra are valid for fault detection. The tests carried out can be applied to large operating wind turbines.

Pirez et al. [96] introduced the Machine Square Current Signature Analysis (MSCSA) that starts by measuring the induction machine current, then the square of the current is computed, and in the last part a frequency analysis of the square current is performed. This method increases the information extracted of the current signal. The method is applied to identify broken bars and rotor eccentricity. A comparison between vibration analysis and MCSA was carried out in [98], where MCSA was more efficient in detecting rotor bar fault in an induction machine.

A wider comparison between vibration analysis and MCSA was presented in [97]. The method uses Multiclass Support Vector Machine (MSVM) algorithms to predict induction machine faults. An experimental test rig was used to extract varying speed signals and external torques used for vibration analysis. Ten different often encountered faults were considered (electrical and mechanical faults, individually and collectively). Then fault prediction was done using either vibration analysis or MCSA in a first stage, then a combination of both techniques in a second stage. The results conclude that MSVM is very effective in detecting mechanical faults in vibration and electrical-vibration analysis. However, an SVM approach is sufficient in the case of electrical analysis for electrical fault detection. In addition, it is worth checking [99,100] where a wider range of applications for Machine Current Signal Analysis (MCSA) is used to detect generator faults.

7. Supervisory Control And Data Acquisition (SCADA)

Nowadays SCADA systems are deployed for all wind farms. They are responsible for monitoring several parameters related to wind turbine components (temperature of gearbox, bearings, and lubricant, vibration levels, tower acceleration, drive train acceleration, etc.). In addition, they monitor different factors as input to wind turbines (wind speed, wind deviations), or outputs (rotor speed, blade angle, output active and reactive power). Process models are not usually available for SCADA analysis [62], that relies on collecting data making data-based analysis techniques preferable. SCADA data analysis allows early detection of faults to support maintenance decision based on healthy early operation data, and those faulty updated ones. These data tend to accumulate fast and in large amounts making it a tedious job to analyze and deduce the health status of turbine's components. Condition monitoring research applications of wind turbines require decisions regarding the component under study, the parameter(s) or signal(s) from which the component's status is to be deduced, and the method(s) or technique(s) used for data processing and analysis [101] (Table 7).

SCADA application for wind turbine gearbox fault detection are numerous and various in the literature among which are the following:

Table 6
Summary for MCSA applications for wind turbine generator fault detection that could be used for gearbox fault detection.

Reference	Method
[94]	Current frequency sliding pre-processing and DWT
[95]	Real time fault frequency tracking with analytical expressions for varying speeds
[96]	MSCSA for frequency analysis based on the square of the current
[97]	MSVM with vibration analysis and/or MSCA

Table 7
Summary for SCADA applications for wind turbine gearbox fault detection.

Reference	Method
[102,103]	Multi-agent system based on a multi-layer neural network system of normal wind turbine behavior based on SIMAP tool for diagnosis
[104]	SCADA monitoring of oil temperature for gearbox fault detection
[105]	ANN model–based wind turbine with SCADA analysis for gearbox bearing fault detection
[106,107]	Instantaneous torque determination based on SCADA data
[108]	Instantaneous torque determination based on rotor speed and power output during 10 min of SCADA data

Zaher et al. [102,103] developed a multi-agent system capable of managing the useful data fed to monitor a component's behavior. A multi-layer Neural Network system of normal wind turbine behavior was developed in order to compare its parameters with the ones extracted by the SCADA. The study employed the SIMAP detailed tool for diagnosis and maintenance of processes applied to wind turbine gearbox health monitoring in [109].

Feng et al. [104] used SCADA oil temperature to monitor and detect faults in the gearbox. Zhang et al. [105] used Artificial Neural Networks (ANN) to put together a SCADA data analysis system based for gearbox bearing fault detection based on its temperature data.

Alvarez et al. [108] used 10 min of SCADA recorded data of power output and rotor speed in order to reconstruct the distribution of instantaneous torque. It resulted in a drastic amelioration in the remaining useful life prediction of wind turbine gearbox, compared to an older method that disregards torque fluctuations in the 10 min range applied in [106,107].

8. Discussion and conclusion

Condition monitoring of wind turbines is an evolving field. Operators, researchers, and nations are highly focusing on improving wind turbine efficiency as a reliable replacement for the old polluting fossil fuel based electricity plants or dangerous nuclear plants. In order to reach an efficient system, it is vital to increase the lifetime expectancy of each component. Gearboxes cause a great share of the downtime of wind turbines when a fault occurs. Condition monitoring of gearboxes can be done through numerous and various approaches and techniques. Lubrication analysis is still the hardest to be applied since it relies on oil sample analysis or sensory systems. Oil sample analysis is done offline and might detect faults when it is too late. Moreover, sensory systems for debris detection are costly and require maintenance. On the other hand, several lubricant parameters can be indicators either for lubricant degradation (viscosity, humidity, etc.), or component failure (debris). The challenge in lubrication analysis come down to well chosen monitored parameters and the set of sensors to be installed responsible to monitor these parameters.

Acoustic Emission analysis has been employed in all mechanical rotating systems. It is capable of detecting faults and lately localizing them. Since AE analysis deals with signals of high frequency, it is seen that signal processing techniques are used to extract signal features for gearbox fault detection in wind turbines. The main important and tedious challenge when using AE resides in the isolation of noises. Background internal and external noises interference may well render signal analysis useless for fault feature detection.

Vibration analysis is still the most used approach. It appeared with the rise of the industrial era while sensory systems were developed in parallel to meet the requirements. Applying these sensory systems to wind turbines was not that hard until encountering very vital issues. Wind turbines are expected to last around 20 years (as system-wise or component-wise). Expectations were not met, while sensory systems failed alone on many occasions to detect faults. Many techniques, processing methods and algorithms were added to increase fault detection ability. One can mention that the Teager-Kaiser Energy operator (TKEO), Estimation of Signal Parameters via Rotational Invariant Technique (ESPRIT) and the Time Synchronous Averaging (TSA) based methods stand out as very promising methods in fault detection in gearboxes. It is vital that the work is carried on in order to increase the accuracy of these methods.

Electrical analysis is a recent, modern, non-intrusive method for fault detection. It is being used for fault detection of different mechanical components (bearings, shafts and gearboxes) and for generator fault detection. However, its drawback resides in the incapability of locating faults, yet. Recent research in the gearbox field show a lot of promise for fault detection. Major work is needed to push electrical analysis to the next level of locating faults, since its application will render the sensory systems useless and reduce design, installation, operation and maintenance costs. MCSA is a very promising approach for condition monitoring. However, it is majorly being applied for generator fault detection, and the techniques developed have become very efficient in recent years in detecting generator faults. It has become vital to project the techniques and methods used in generator fault detection based on current analysis, to monitor different mechanical component behavior and specially gearbox. It is clear that researchers are mainly focusing on non stationary environment studies. The stationary scenario has already been extensively studied using the traditional frequency analysis techniques. Nevertheless, imitating the real operating environment of wind turbines can only be done through non stationary scenarios where the transients in wind profiles are accurately fed to the whole system.

SCADA systems are gaining growing interest since they rely on data–based analysis and neural networks. Recent applications show advanced results while the superior feature of SCADA is its capability of collecting large amount of data of various parameters (wind speed, wind direction, component temperature, lubricant temperature, output speed and power, etc.).

However, this feature is its weakness since this large amount of data require powerful and effective processing techniques. Application of SCADA is dividing the monitoring period into 10 min interval of data analysis in order to reduce quantity of analyzed data.

Condition monitoring of gearboxes in wind turbines faces several challenges. They start by choosing the most convenient condition monitoring approach. All approaches need accompanying techniques for processing and analysis. With this vast number of techniques none is capable of determining the most accurate and effective one. Recent advanced techniques have a very promising future in condition monitoring processes as aforementioned. However, the more advanced the technique, the more complex it becomes [110]. Which raises the question of user–friendliness and processing speed since operators are dealing with large amounts of data. Systems like SCADA are facing this challenge and false fault alarms and misdiagnosis are being encountered.

In addition, condition monitoring procedures are carried out from distant central stations where collected data is acquired wirelessly. Therefore, faults have to be predicted early by a reasonable time, since planning system inspection and maintenance require a fair amount of time. Thus, condition monitoring systems should be capable in the future to predict faults, plan maintenance period in what makes wind turbine downtime as lower as possible, and keep system monitoring at the same time. In order to do so, condition monitoring systems have to have available historical data for several weeks, or even months to be able to set the right alarms for preventive maintenance.

In the end, condition monitoring systems are facing the issue of cost/pay–back rate. The more complex the condition monitoring system the more it costs operators, and with large wind farms installation several systems have to be used. Cost impact and financial benefits of condition monitoring systems have to be further investigated in order to evaluate whether or not installing these systems has its intended impact met. A real life case study was carried out in Germany regarding the life cycle of condition monitoring and the findings after 7 years of operation indicated an annual rate of return of 1% [111].

Since wind turbines have several components on which the same approaches can be applied for fault detection and analysis (bearings, gearbox, drive shaft, generator, etc.), future research has to take into consideration the application of other advanced methods applied for other components. Other condition monitoring methods and techniques have been found in [112–117] including fault detection of bearings, drive shaft, generator, etc.

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