Condition monitoring of wind turbines: Techniques and methods

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Abstract
Wind Turbines (WT) are one of the fastest growing sources of power production in the world today and there is a constant need to reduce the costs of operating and maintaining them. Condition monitoring (CM) is a tool commonly employed for the early detection of faults/failures so as to minimise downtime and maximize productivity. This paper provides a review of the state-of-the-art in the CM of wind turbines, describing the different maintenance strategies, CM techniques and methods, and highlighting in a table the various combinations of these that have been reported in the literature. Future research opportunities in fault diagnostics are identified using a qualitative fault tree analysis.

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1. Introduction

Only time will tell whether the forecasts by WWEA [1] for continuing growth in global wind power capacity [2] will be realised as shown in Fig. 1. But to make wind power competitive with other sources of energy, availability, reliability and the life of turbines will all need to be improved. As the wind energy sector grows, business economics will demand increasingly careful management of costs. For a 20-year life, the operations and maintenance (O&M) costs of 750 kW turbines might account for about 25%–30% of the overall energy generation cost [3] or 75%–90% of the investment costs [4].

Furthermore, one projection in 2002 was that the O&M costs for 2 MW turbines (which together with 2.5 and 3 MW turbines have since become the workhorses of the wind power industry) “might be 12% less than an equivalent project of 750 kW machines” [5]. But new wind farms typically have higher capacity and comprise more machines. The turbine data in Fig. 2 [6] suggest that larger turbines fail more frequently and thus require more maintenance. Reducing inspection and maintenance costs has thus become increasingly important as wind turbine size and numbers have continued to rise.

Of course, some WT components fail earlier than expected and, because unscheduled downtime can be so costly [7], condition monitoring systems (CMS) are employed to “improve WT availability and reduce the O&M costs” [8]. However there is a degree of uncertainty about the appropriateness of applying specific maintenance policies to WT components. This paper discusses the applicability of various maintenance strategies to WT condition monitoring, reviews the available techniques and methods in the literature, and presents a fault tree analysis (FTA) summarising the ways in which WTs can fail. The discussion focuses on the three blade up-wind variable speed turbine with double feed asynchronous generator which is the dominant type of WT currently in use worldwide [9].

2. Wind turbines

Most WT machines are three-blade units comprising the major components illustrated in Fig. 3 [10]. Driven by the wind, the blades and rotor transmit energy via the main shaft through the gearbox to the generator, the main shaft being supported by the bearings, and the gearbox being such that the generator speed is as near as possible to optimal for the generation of electricity. Alignment with the direction of the wind is controlled by a yaw system and the housing (or “nacelle”) is mounted at the top of a tower.

Some defects such as leaking and corrosion can be detected by visual inspection; discolouration of component surfaces may indicate slight temperature variations or deteriorating condition, and the sound coming from the bearings can also indicate physical condition [11,12]. However, many of the most typical failures like cracking and roughness on the surfaces of the blades, electric short circuits in the generator, and overheating of the gearbox all demand a more sophisticated approach to maintenance.

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3. Maintenance theory

Maintenance is required to make sure that the components continue to perform the functions for which they were designed. The basic objectives of the maintenance activity are to deploy the minimum resources required to ensure that components perform their intended functions properly, to ensure system reliability and to recover from breakdowns [13].

3.1. Corrective, scheduled and condition based maintenance

Classical theory sees maintenance as either corrective or preventive. The former (also known as unscheduled or failure based maintenance) is carried out when turbines break down and when faults are detected or failures occur in any of the components. Immediate refurbishment or replacement of parts may be necessary [14] and unscheduled downtime will result. Corrective maintenance is therefore the most expensive of strategies and wind farm operators will hope to resort to it as little as possible. The various stages are shown in Fig. 4.

By contrast, the objective behind preventive maintenance (PM) is to either repair or replace components before they fail as shown in Fig. 5 [14]. This has most straightforwardly been achieved by scheduled maintenance, also known as time based (or planned) maintenance and involving repair or replacement at regular time intervals as recommended by the supplier and regardless of condition. Scheduled maintenance activities in WT include the changing of oil and filters, and the tightening and torqueing of bolts.

But reducing failures in this way comes at the cost of completing maintenance tasks more frequently than absolutely necessary and not exhausting the full life of the various components already in service. An alternative is to mitigate against major component failure and system breakdown with condition based maintenance (CBM) in which continuous monitoring and inspection techniques are employed to detect incipient faults early, and to determine any necessary maintenance tasks ahead of failure [15]. This involves acquisition, processing, analysis and interpretation of data and selection of optimal maintenance actions [16] and is achieved using condition monitoring systems [17–19]. CBM has been shown to minimise the costs of maintenance, improve operational safety, and reduce the quantity and severity of in-service system failures. Byon and Ding [20] have demonstrated its applicability to WTs, and McMillan and Ault [21] have used Monte Carlo simulation to evaluate its cost effectiveness when applied to WTs. CBM is now the most widely employed strategy in the WT industry.

3.2. Reliability centred maintenance

The state-of-the-art way of deciding upon maintenance strategy in the WT industry is reliability centred maintenance (RCM), which has been formally defined as “a process used to determine what must be done to ensure that any physical asset continues to do whatever its users want it to do in its present operating context” [22]. It involves maintaining system functions, identifying failure modes, prioritizing functions, identifying PM requirements and selecting the most appropriate maintenance tasks [23] with the objective of managing system failure risk efficiently [24]; operational and maintenance policies are optimised such that the overall maintenance task is reduced [14]. RCM has been recognized and accepted in many industrial fields, such as steel plants [25], railway networks [26] and [27], ship maintenance and other industries [28]. RCM in the wind turbine industry is addressed by Andrawus et al. [29].
4. Condition monitoring of wind turbines

On the basis that a “significant change is indicative of a developing failure” [30], condition monitoring systems (CMS) [13] comprise combinations of sensors and signal processing equipment that provide continuous indications of component (and hence wind turbine) condition based on techniques including vibration analysis, acoustics, oil analysis, strain measurement and thermography. On WTs they are used to monitor the status of critical operating major components such as the blades, gearbox, generator, main bearings and tower. Monitoring may be on-line (and hence provide instantaneous feedback of condition) or off-line (data being collected at regular time intervals using measurement systems that are not integrated with the equipment) [31].

With good data acquisition and appropriate signal processing, faults can thus be detected while components are operational and appropriate actions can be planned in time to prevent damage or failure of components. Maintenance tasks can be planned and scheduled more efficiently, resulting in increased reliability, availability, maintainability and safety (RAMS) whilst downtime, maintenance and operational costs are reduced [8]. CM techniques are thus used throughout the industry [32,33] and benefits are “especially shown for offshore wind farm(s)” [34] because of not only the high costs of O&M at sea but also the typically larger turbines. Several techniques are available.

4.1. Vibration analysis

Vibration analysis continues to be “the most popular technology employed in WT, especially for rotating equipment” [35]. Different sensors are required for different frequencies: “position transducers are used for the low-frequency range, velocity sensors in the middle frequency area, accelerometers in the high frequency range and spectral emitted energy sensors for very high frequencies” [36].

As for applications, it is appropriate for monitoring the gearbox [37–43], the bearings [11,12,44–46] and other selected WT elements as listed in Table 1; the sensor configuration in a nacelle is illustrated in [37]. Furthermore “Tandon and Nakra [47] presented a detailed review of the different vibration and acoustic methods, such as vibration measurements in the time and frequency domains, sound measurements, the shock pulse method and the acoustic emission technique, for CM of rolling bearings” [48].

4.2. Acoustic emission

Rapid release of strain energy takes place and elastic waves are generated when the structure of a metal is altered, and this can be analysed by acoustic emissions (AE). The primary sources of AE in WTs are the generation and propagation of cracks, and the technique has been found [49–51] to detect some faults earlier than others such as vibration analysis [52]. The measurement and interpretation of AE parameters for fault detection in radially loaded ball bearings has been demonstrated at different speed ranges in [53]. In addition, the application of AE for the detection of bearing failures has been presented in [54]. Acoustic monitoring has some similarities with vibration monitoring but whereas “vibration sensors are mounted on the component involved” [36] so as to detect movement, acoustic sensors are attached with flexible glue with low attenuation and record sound directly. AE sensors have been used successfully not only in the monitoring of bearings and gearboxes but also for damage detection in blades of a WT as discussed in [55]. Its application is also possible to an in-service WT for a real-time rotating blade [56,57]. Non-destructive testing techniques using acoustic waves to improve the safety of wind turbine blades are presented in [58], and to enable the assessment of the damage criticality for blades of small WT based on AE data in [59,60]. The use of AE is gradually growing for both CM of rotating WT components as well as blades.

4.3. Ultrasonic testing techniques

Ultrasonic testing (UT) techniques are used extensively by the wind energy industry for the structural evaluation of wind turbine towers and blades. UT is generally employed for the detection and qualitative assessment of surface and subsurface structural defects [13,25,61]. Ultrasonic wave propagation characteristics allow estimation of the location and type of defect detected, thus providing a reliable method of determining the material properties of the principal turbine components. Signal-processing algorithms including time-frequency techniques and wavelet transforms can be used to extract more information [62–65]. An ultrasound technique to visualize the inner structure of wind turbine blades is presented in [66], the deployment of UT techniques for inspection of the whole multi-layered structure of the WT blade and to find defects like delaminations, lack of glue, etc. is illustrated in [67]; and the ultrasonic air-coupled technique has been used to research internal defects in wind turbine blades [68]. Ultrasonically-obtained images make it possible to recognise the geometry of defects and to estimate their approximate dimensions. Jasiuniene et al. [69] adapted air-coupled ultrasonic technique for better identification of the shape and size of defects in a WT blade. A review of other methods can be found in [70].

4.4. Oil analysis

Whether for the ultimate purpose of guaranteeing oil quality or the condition of the various moving parts, “oil analysis is mostly executed off-line by taking samples” [35] despite on-line sensors having (for years) been “available at an acceptable price level” [35,36] for monitoring oil temperature, contamination and moisture [71]. Little or no vibration may be evident while faults are developing, but analysis of the oil can provide early warnings; a case study of a WT gearbox is described in [72]. In the “case of excessive filter pollution, oil contamination or change in component properties, characterization of the particulates can give an indication of excessive wear” [36]. Such approaches are particularly effective and cost-efficient in avoiding catastrophic failures [73,74]. On-line oil analysis is gradually becoming more important with several on-going pilot projects.

4.5. Strain measurement

Strain measurement using strain gauges can be very useful for lifetime forecasting and protecting against high stress levels, especially in the blades. An assessment of strain gauge signal interpretation from strain gauge sensors installed on the blade has been performed in order to adjust calibration practices and sensor selection [75]. Optical fibre sensors are still very expensive [35] but cost-effective systems based on fibre optics are being developed. References [56,76,77] illustrate how load monitoring can be performed using strain sensors in the rotor blades. Strain measurement can be expected to grow in importance as an input to CM.
4.6. Electrical effects

CM of electrical equipment such as motors, generators and accumulators is typically performed using voltage and current analysis. Discharge measurements are used for medium and high voltage grids. A spectral analysis of the stator current [78] in the generator can be used for detecting isolation faults in the cabling without influencing WT operation.

Electrical resistance can also be used for the structural evaluation of certain WT components. Electrical resistance varies with stiffness and abrupt changes can be used to detect cracks, delaminations, and fatigue. Hence, the technique can be applied to in-service WTs. References [79–81] demonstrate how the resistance principle is useful for detecting fatigue damage in particular. These techniques are at the moment confined to research-related activities but there is significant potential for applying them successfully in the field.

4.7. Shock pulse method (SPM)

The SPM has been used as a quantitative method for condition monitoring of bearings, and works by detecting the mechanical shocks that are generated when a ball or roller in a bearing comes in contact with a damaged area of raceway or with debris [82]. Signals are picked up by transducers, and analysis—e.g. using a normalized shock value [83]—gives an indication of system condition [84]. Low frequency signals of vibration collected in the nacelle and caused by other sources can easily be filtered electronically. A case study of SPM with a piezoelectric transducer is described in [85]. The method is occasionally used by the industry to support vibration measurements.

4.8. Process parameters

Maintenance based on process parameters and the detection of signals exceeding predefined control limits is common practice in WTs, control systems becoming increasingly sophisticated and diagnostic capabilities ever better. Transient and oscillatory stability were analysed with different wind scenarios for electricity generation process in [86]. For explanation of the use of signals and trending for fault detection based on parameter estimation, see [87].

4.9. Performance monitoring

The relationship between parameters such as power, wind speed, blade angle and rotor speed can also be used for an assessment of WT condition and for the early detection of faults [88]. Previous work includes power and voltage flicker analysis with variable wind speed and turbulence [86]. “Similar to estimation of process parameter(s), more sophisticated methods, including trending, are not often used” [36]. The torque and power generated with wind time series taken in the field from an anemometer is considered in [89].

4.10. Radiographic inspection

Radiographic imaging of critical structural turbine components using X-rays is only rarely used although it does provide useful information regarding the structural condition of the component being inspected. Radiographic imaging depends “on the different level of absorption of X-ray photons as they pass through a material” [70]. So as “to detect tight delaminations or cracks, having gaps less than 50 μm, the backscatter X-ray imaging technique” [70] is employed. X-Ray imaging is useful to locate the internal defects of the WT, and the main advantage of X-ray inspection is the accuracy of this technique [90]. A transportable radiographic system for WT blades has been recently demonstrated as “a solution to detect defects and reduce the cost of inspection” [91].

4.11. Thermography

Thermography is often used for monitoring electronic and electric components and identifying failure [92]. The technique is only applied off-line, and often involves visual interpretation of hot spots that arise due to bad contact or a system fault. At present the technique is not particularly well-established for on-line CM, but cameras and diagnostic software that are suitable for on-line process monitoring are starting to become available. Infrared cameras have been used to visualize variations in blade surface temperature [93–95] and can “effectively indicate cracks as well as places threatened by damage” [96]. In the longer term, this might be applicable to WT generators and power electronics too.

Pulsed thermography can be employed for the structural evaluation of blades but due to the bulky equipment involved this is not a standard methodology amongst wind turbine operators. Early investigations of carrying out thermographic measurements of in-service blades using helicopters to deploy the IR cameras has not yet been proven satisfactorily and faces serious difficulties of implementation.

Table 1 Condition monitoring techniques in WT, where: a: Statistical methods; b: Time domain analysis; c: Cepstrum analysis; d: Fast Fourier transformation(FFT); e: Amplitude demodulation; f: Wavelet transformation; g: Hidden Markov models; h: Novel techniques.

| Table 1 | Condition monitoring techniques in WT, where: a: Statistical methods; b: Time domain analysis; c: Cepstrum analysis; d: Fast Fourier transformation(FFT); e: Amplitude demodulation; f: Wavelet transformation; g: Hidden Markov models; h: Novel techniques. | Bladess | Rotor | Gearbox | Generator | Bearings | Tower |
| --- | --- | --- | --- | --- | --- | --- |
| Vibration | [56], [a 134], [f135] | [37], [c 108], [a 113] | [d10], [d 32], [a 37], [c 38], [b 39], [f 40], [b 41], [e 42] | [f 43], [e 104], [c 107], [f 119], [f 125], [f 126, 136], [c 106], [c 137] | [d10], [a 37], [c 38], [a 44], [d 11], [f 40], [b 41], [e 42] | [f 43], [e 104], [c 107], [f 120], [f 123], [g 130], [f 135], [f 138], [f 139] |
| Acoustic emission | [56], [a 59, 88, 140], [a 141], [f 143] | [a 95], [f 125] | [a 53], [de 84], [b 105, 144], [a 145] | [a 53], [de 84], [a 82], [f 19, 83] |
| Ultrasonic techniques | [56], [a 59, 88, 140], [a 141], [f 143] | [a 95], [f 125] | [a 53], [de 84], [a 82], [f 19, 83] |
| Oil analysis | [56], [a 59, 88, 140], [a 141], [f 143] | [a 95], [f 125] | [a 53], [de 84], [a 82], [f 19, 83] |
| Strain | [79, 81] | [a 94] | [a 94] |
| Shock Pulse methods | [79, 81] | [a 94] | [a 94] |
| Process parameters | [a 87] | [a 86] | [a 86], [b 89], [cd 149] |
| Performance monitoring | [88] | [c 149] | [a 86], [b 89], [cd 149] |
| Radiographic inspections | [69, 91] | [h 87] | [h 87] |
| Thermography | [93–95] | [h 87] | [h 87], [11, 12, 151] |
5. Sensory signals and signal processing methods

Regardless of the technique, the capability of a CMS relies upon two basic elements: the number and type of sensors, and the associated signal processing and simplification methods utilized to extract important information from the various signals. An electronic measurement system will acquire the data, and then process and distribute them to an observer or other technical control system.

Data acquisition will involve measuring the required variables (e.g., current, voltage, temperature, speed) and turning them into electronic signals. To do so effectively will involve judicious choice and placement of the right type and number of sensors; conditioning (performing basic operations including amplification, filtering, linearization, and finally modulation/demodulation) may be necessary to reduce the susceptibility of the signals to interference. Optimization techniques may then be employed [97] in the processing of the signals by a digital signal processor (DSP), involving not only the processing itself but also sorting and manipulation as necessary. Subsequent distribution will be to either a screen, computer, storage device or other system. There are several options, including e.g. Ethernet networks with TCP/IP protocol together with WLAN for a WT for communicating with either a Farm Server or a supervisory command and data acquisition (SCADA) system. The latter is a particular computer-based system that allows local and remote control of the functions of a WT, gathering data from the wind farm and analysing them in order to report operational performance, and hence ensure efficient operation. SCADA uses various signal processing methods, the most relevant to WT being those covered below and in Table 1.

5.1. Statistical methods

One common application of statistical algorithms for the purposes of CM is to analyse the data signals from the various sensors in WTs. Common statistical measures such as root mean square (RMS) and peak amplitude are widely used for the diagnosis of failures but more advanced features are also being developed [37,74,82,86,98,99]. Other important statistical parameters are the maximum value, minimum value, mean, peak to peak, standard deviation, shape factor, crest factor, impulse factor, definite integral, energy ratio and kurtosis.

5.2. Trend analysis

When applied to WT, trend analysis refers to the concept of collecting data from the various sensors and looking for trends. It requires particular algorithms [37,100,101], and applications include the monitoring of pitch mechanisms although most common is its use on power output patterns from WT generators. Note that trend estimation is a different technique specifically for forecasting.

5.3. Filtering methods

Sometimes there are redundant data that contain information that is not useful and must be eliminated so as to avoid compromising the computations. For example, the vibrations from a nacelle will have to be filtered whilst measuring the vibration of the gearbox inside [84]. A method using least median squares that filters in parallel with estimating the power curve is presented in [102], and filtering with and without a classical statistical method (based on standard deviation) is described and compared in [103]. The drawback of filtering whilst monitoring trends is that the parameters have to be adjusted to take account of varying operating conditions.

5.4. Time-domain analysis

Analysis in the time domain is a way of monitoring WT faults like resistive and inductive imbalances between the rotor and the stator phases, and turn-to-turn faults in the rotor windings of the generator. Variations in current signals and trends are typically used for vibration analysis [39,41,104], oil analysis [72] and AE [105].

5.5. Cepstrum analysis

The power cepstrum is a time based approach defined as “the inverse Fourier transform of the logarithmic power spectrum” [106]. The cepstrum is well suited for applications to equipment diagnostics in a WT. Gear vibration spectra commonly show sidebands of meshing frequency and its harmonics arising from the modulation of tooth meshing waveform [38,107]. For gearboxes in good condition, the sideband level generally remains constant with time. Therefore, changes in the number and amplitude of the sidebands normally indicate deterioration. The presence of several families of sidebands and other components can complicate the distinction and evaluation of the sideband spacing [108].

5.6. Time synchronous averaging (TSA)

TSA, also called time domain averaging, is a signal processing technique that serves as the basis for many gear fault detection algorithms. The method is for identifying a rotating bearing defect by measuring the vibration of a rotating bearing and obtaining a waveform signal. It may also help in identifying the source of vibration in WT gearboxes [109]. For instance, a cracked gear tooth in a WT gearbox that meshes once per revolution produces a highly periodic vibration signature which can be very weak. TSA can be used to highlight the vibration signal features taking place over a given period, and can work with non-periodic signal components, filtering the noise of the time-domain signal. Once the average time signal is achieved, it is possible to compute the FFT (as below). A review of other TSA algorithms is presented in [110].

5.7. Fast-Fourier transform (FFT)

The FFT [111] algorithm is used for the conversion of a digital signal from the time domain into one in the frequency domain. Particular frequency ranges correspond to particular states (e.g. fault-free, defective bearing), the ranges reflecting the rotational speed of the main shaft and the shape and size of the element concerned. All bearing elements generate vibration at specific frequencies (referred to as fault frequencies) and hence FFT finds most usage in gearbox monitoring [10,32]. FFT is also used for bearings [10,11] wherein, if damage starts to develop, the shape of the vibration distribution deviates from the nominal Gauss-shaped curve [11,12]. “The advantage of frequency domain analysis over time domain analysis is its ability to identify and isolate certain frequency components of interest” [112].

5.8. Amplitude demodulation

This approach can extract very low-amplitude and low-frequency periodic signals that might be masked by other higher energy vibrations as in WT gearboxes [43,104]. While the raw spectrum can be useful for monitoring gear mesh frequencies, the envelope spectrum provides superior sensitivity to bearing defect frequencies in WT applications [84]. With its high sensitivity, demodulation has
been proven to be good for evaluating defects that produce impacting, e.g. rolling contacts in bearings and tooth-to-tooth contacts in the gear meshes [42]. It also helps to reduce the complexity of the analysis, the main advantage being that it provides excellent visibility of bearing defects frequencies without the interference of gear mesh frequencies in the same spectrum. Despite the advantages for WT gearboxes, some barriers to implementation remain. The selection of transducer location is crucial to guarantee the results and, if the demodulation process is based on low-pass filtering, the original amplitude of the original defect signals is not preserved.

5.9. Order analysis

FFT is useful for studying oscillations in constant speed wind energy converters (WEC) when applied to time series signals. However, this algorithm is not suitable for variable speed WEC where a different algorithm based on rotational angles is required, i.e. so-called order analysis, particularly well-suited for rotor imbalances and aerodynamic asymmetries [38]. Torsional oscillation of the nacelle generates a signal which is out of phase with any transverse oscillations, so they can be separated and analysed individually [113]. Interpolation and production of the order spectrum then leads to the computation of the FFT. Such analysis may be used for monitoring the overall rotor condition including surface roughness, mass imbalance and aerodynamic asymmetry.

5.10. Wavelet transforms

Wavelet transformation is a time-frequency technique similar to short time Fourier transform (STFT) but more appropriate for non-stationary signals. It provides a time-frequency 3D map of the signal being analysed in [114,115] and involves decomposing it into a set of sub-signals or levels with different frequencies [116,117]. It is applied to WTs in order to monitor the vibration level caused by misalignment, bearing and other problems, and can be used as a general sign or indication of a faulty WT. Wavelet transforms have been applied to waveform data analysis in fault detection and diagnostics of various WT parts including gears [118,119], bearings [120,121], and other mechanical systems [122,123]. Assessment of the effectiveness and reliability of wavelet transforms and comparison with other vibration analysis techniques has been completed by Dalpiaz and Rivola [124]. Baydar and Ball [125] successfully applied wavelet transforms to vibration signals and acoustic signals [40,43,126]. FFT (and indeed RMS) have also been used to estimate the maximum amplitude of the wavelet coefficients which helps in discriminating between normal and damaged components [127].

5.11. Hidden Markov models

Hidden Markov models (HMM) have successfully been applied to the classification of patterns in trend analysis [128] and CM [126]. Atlas et al. developed a method to predict wear accurately [129], when applying a method for monitoring of milling processes with HMM. “Ocak and Loparo [130] presented the application of HMM in bearing fault detection” [126], and the dynamic statistical characteristics that exist in the current observations of vibration signals in the machine have been modelled using HMM utilizing a Markov chain.

Fig. 6. Fault tree for WT.
5.12. Novel techniques

Fault detection and diagnosis (FDD) is a sophisticated adaptation of CMS that incorporates ‘intelligent’ algorithms suitable for early detection of incipient faults providing an insight into the corresponding level of criticality [19]. FDD methods can be model-based or non-model based depending upon the way process knowledge is incorporated within the signal processing unit; a more specific classification is shown in [38].

Artificial intelligence (AI) is essentially employed to reproduce human reasoning as accurately as possible, the reasoning process being based on the behaviour of the system, and written down in terms of rules. The dynamic nature of the environments in which WT systems operate has led to the emergence of predictive maintenance plans that take qualitative account of the environment as well as its actual effect on the condition of the components.

Expert systems or so-called rule-based diagnostic systems “detect and identify incipient faults in accordance with the rules representing the relation of each possible fault with the actual monitored equipment condition” [131]. They have to fulfil two capabilities so as to be effective: the acquisition and integration of new knowledge, and also the explanation of their reasoning [132].

6. Fault tree analysis (FTA)

For detailed CM study, identification of potentially hazardous events and an assessment of their consequences and frequency of occurrence are necessary. One of the most popular approaches for this purpose is FTA [133], a so-called “fault tree” (FT) being a diagrammatic way of describing the complete set of possible causes that can lead to failure. FTA thus allows identifying and then quantifying the initiating failure causes that will help set the stage for developing a PM program fit to maintain system reliability at the required level with particular attention given to aggressive environmental factors. The process involves two stages: selection of the various components that are to be considered for analysis, and then assessment of how the component states affect the condition variables that will be measured by the CM system. Both are critical and have a significant impact on the accuracy of the model.

Here, the FT reproduced in Fig. 6 was constructed starting with the top event: wind turbine failure. For each of the same components as highlighted in Fig. 3 in turn, this was then successively broken down via the various possible intermediate failures using AND or OR logic gates so as finally to yield the basic failure events at the lowest levels e.g. corrosion of pins, pitting, deformation of the outer bearing race and other rolling elements, or indeed abrasive wear [35].

7. Conclusions

The primary focus of this review of CM and the various mathematical methods for signal processing is upon WT gearboxes and bearings, rotors and blades, generators and power electronics, rather than system-wide turbine diagnosis. An inventory of the available CM techniques along with signal processing algorithms has been provided and selection of a set of techniques which is feasible and better suited for WTs has been made possible. The review is summarised in Table 1, which may be read from the viewpoint of either techniques (row-wise) or components (column-wise). The references of the different methods used by the researchers in the components of WT and techniques for CM are collected in the next table. The methods reported in the literature are indicated by the letters.

For each element of the WT there are different techniques that can be employed, and for all of these techniques there are mathematical methods available and referenced in the literature. The main obstacles facing the designers of condition monitoring systems for WT wind turbines clearly continue to be:

i. selection of the number and type of sensors;
ii. selection of effective signal processing methods associated with the selected sensors; and
iii. design of an effective fusion model (i.e., the combination of sensors and signal processing methods which give an improved performance);

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Acronyms

AE    acoustic emission
AI    artificial intelligence
CBM   condition based maintenance
CM    condition monitoring
CMS   condition monitoring system
FDD   fault detection and diagnosis
FFT   fast Fourier transform
FT    fault tree
FTA   fault tree analysis
HMM   hidden Markov model
O&M   operation and maintenance
PM    preventive maintenance
RMS   root mean square
RCM   reliability centred maintenance
SCADA supervisory command and data acquisition
SPM   shock pulse method
TSA   time synchronous averaging
UT    ultrasonic testing
WEC   wind energy converter
WT    wind turbine

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