Title: A survey on data acquisition methods in conditional monitoring of wind turbines

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Abstract

The generation of electrical power through wind turbines has significantly increased nowadays. However, these systems are prone to faults that can disrupt the network and incur substantial costs for the generation units. Therefore, effective maintenance scheduling becomes crucial. A major challenge faced by wind turbines is their maintenance requirements, as any interruption in their operation and power generation can result in significant economic losses. Consequently, meticulous planning is indispensable to minimize such consequences. This paper that is the first part of the study conducts a survey of data acquisition methods in condition monitoring of wind turbines. In the second part, signal processing techniques for condition monitoring of wind turbines are presented. Furthermore, the paper examines a range of studies that have implemented practical condition monitoring methods in wind turbines, delving into the associated challenges and proposing potential solutions. Various methods such as vibration analysis, acoustic analysis, electrical parameter analysis, AI-based techniques, and fault-tolerant control have been employed for wind turbine maintenance. However, limitations exist in terms of data availability and computational burden. Future challenges include developing algorithms that require less data, reducing computational requirements, updating models with new conditions, enabling early detection and proactive maintenance, and reducing maintenance costs.

Keywords: wind turbine, conditional monitoring, fault prediction, fault tolerance, artificial intelligence

I. Introduction

As the worldwide growth of wind power generation continues, wind turbines are playing an increasingly important role in the present and future of renewable energy and wind turbines (WTs) with permanent magnet synchronous generators (PMSG) are mostly integrated with power systems as popular energy conversion systems [1][2]. However, there are two major challenges facing the current wind generation landscape that threaten this global role. Firstly, a significant number of existing wind turbines have reached their estimated lifespan of 20 years and require additional maintenance services. Secondly, new wind turbine technology is moving towards larger turbines in remote offshore locations, which creates new challenges for inspection and maintenance. As a result, the operation and maintenance (O&M) costs of wind turbines, both onshore and offshore, have recently received more attention. Wind turbines are complex aero-electro-mechanical systems that are often installed in remote locations and constantly exposed to harsh weather conditions, as well as different aerodynamic, gravitational, centrifugal, and gyroscopic loads. These factors collectively contribute to a high frequency of faults and failures in wind turbines, unlike conventional power plants. [3] [4] [5]

Maintenance access is problematic and costly due to the large size of turbines and safety regulations, which limit maintenance services to certain weather conditions and daylight hours relatively low air humidity, temperatures above 10 degrees Celsius, and decreased wind speeds (8-12 m/s) [6]. Offshore wind farms face additional challenges due to the harsh marine environment, causing higher failure rates and maintenance complications, such as difficult access, higher logistics costs, and the need for specialized manpower [7] [8]. The low reliability of wind turbine equipment and the resulting unplanned outages and stoppages have led to increased O&M costs, which now constitute a significant portion of the total cost of wind power generation [9] [10] [11]. O&M costs currently makeup about 10-30% of the total energy production cost of an onshore wind farm once it becomes operational. [12]. Furthermore, while offshore wind farms can generate more wind energy, their O&M costs can increase by up to 25-50% of the total energy production cost, representing a significant rise [13]. To combat these costs, it is necessary to improve wind turbine reliability and availability through appropriate condition monitoring solutions.

Section (II) presents the necessity and types of maintenance schedules. Section (III) covers the types of data and methods for data acquisition for condition monitoring. In section (IV), a survey of research focused on wind turbine fault detection, isolation, tolerance, and data challenges is presented. Finally, in section (V), the conclusion is proposed.

II. Maintenance scheduling

A. Reliability Centered Maintenance

RCM is a maintenance planning concept aimed at ensuring that systems continue to meet the needs of their users in their current operating context. The effective adoption of RCM results in improved cost-effectiveness, enhanced reliability, increased machine uptime, and a better comprehension of the level of risk that the organization is managing. Wind turbines are expensive equipment, and a catastrophic failure, such as a tower collapse, can result in irreparable economic and technical losses. Thus, proper maintenance is essential. Conventional maintenance planning is applied in three ways:

- Corrective maintenance,
- Preventive maintenance,
- Predictive maintenance.

In corrective maintenance, equipment is allowed to run until it fails, which is a significant drawback of this method. In preventive maintenance, despite the periodic inspections, failures may still occur in the mid-term of the inspection period, making this method also flawed. Predictive maintenance requires a large amount of historical information to predict future events, so a lack of data can hinder this method. As mentioned, each maintenance method has its own advantages and disadvantages, which are compared in Table I [14].

Reference [15] proposes a combined approach for wind turbine generator maintenance by integrating time-based maintenance (TBM) and condition-based maintenance (CBM) strategies. A stochastic state model based on stochastic differential equations (SDE) accurately represents generator degradation. The model considers component failure using a proportional hazards model and incorporates random fluctuations with Brownian motion. The analysis highlights the benefits of combining TBM and CBM and proposes a joint maintenance strategy. The model's practical application validates its effectiveness. Researchers In [16] introduce an optimized maintenance plan for a 2MW wind turbine to minimize costs. The study utilizes a two-layer optimization framework and Monte Carlo simulation to estimate component failure times. The results offer insights into the optimal number of preventive maintenance actions and timing, enhancing overall maintenance efficiency. The approach can be applied to wind farms and similar engineering systems. Authors In [17] introduce a preventive maintenance system for wind turbines that utilizes deep computational learning techniques. The system aims to detect surface damage on turbine blades, reducing downtime and manual inspection risks. It consists of an Android application, convolutional neural networks for image processing, a portable telescope, and a motorized mount. The system autonomously scans blade surfaces, presents defect findings to the user, and has been successfully validated in a real wind farm setting. In reference [18], authors focus on the predictive maintenance of wind turbines using a deep learning model and a supervisory control and data acquisition (SCADA) system. By preprocessing the data and addressing imbalanced classes, the proposed method achieves early detection of abnormal conditions. Compared to traditional statistical analysis and data mining approaches, the deep learning model demonstrates higher precision rates and can identify potential faults up to 72 hours in advance. The study highlights the importance of comprehensive data preprocessing and the effectiveness of the proposed deep-learning approach in wind turbine maintenance.

B. Fault-Tolerant Control Systems

Maintenance can be performed without interrupting the operation of the system during a fault occurrence. The term used to describe this concept is fault tolerance, which refers to a system's capacity to maintain its operation even when faced with faults or errors. Fault-Tolerant Control Systems (FTCS) have been developed and classified into two main categories: Active FTCS (AFTCS) and Passive FTCS (PFTCS) [19].

a) AFTCS

The Active Fault-Tolerant Control System (AFTCS) comprises three subsystems: a Fault Detection and Isolation (FDI) module, a reconfiguration mechanism, and a reconfigurable controller. The FDI module constantly provides real-time fault information to the controller, which then utilizes this data to reconfigure itself through the AFTCS. The FDI plays a critical role in identifying and isolating defective components, allowing the controller to adapt to the new conditions by being reconfigured.

b) PFTCS

The architecture of the Passive Fault-Tolerant Control System (PFTCS) is comparatively straightforward in contrast to AFTCS. It lacks an FDI unit and a controller reconfiguration mechanism. In this method, the normal and abnormal conditions are recognized by a controller with parameters defined at the design stage.

A brief comparison of AFTCS and PFTCS is presented in Table II [20].

III. Conditional monitoring: Data Acquisition methods

Conditional monitoring (CM) refers to the practice of observing a machinery's condition parameter, such as temperature or vibration, to detect substantial fluctuations that may suggest the emergence of a fault [21]. Most practical CM methods are as follows that’s scheme is shown in Figure 1 :

A. Electrical Base Method

This method involves utilizing the voltage and current signals of electrical equipment to identify faults or potential problems. By analyzing the voltage and current signals, the accuracy of the equipment's performance can be determined. One such approach is the assessment of harmonic patterns in the voltage and current signals [22]. Because the control and protection systems of electrical equipment use electrical signals, there is no need for additional sensors, which reduces implementation costs and improves reliability. The use of electrical signals in analysis improves the reliability of the CM method compared to other methods, as it is simple to implement, highly reliable, and low-cost [23]. This method is commonly used in electrical equipment, such as in detecting generator faults (such as internal short circuits and bearing faults, etc.) [24].

B. Vibration signals

Today, vibration signals are widely used in rotary machines for fault detection and prediction [25], such as generators and wind turbines [26]. In this method, the movement or vibration of the equipment is expressed in the form of time signals or frequency diagrams. Since the characteristics of each piece of equipment are fixed and unique, healthy equipment will not change over time. However, when a fault occurs, these characteristics will change. By using different methods, equipment defects can be determined [27].

Vibration signals are broadly classified into two categories: stationary and non-stationary. Stationary signals have static characteristics over time, such as periodic vibrations caused by a worn-out bearing. In other words, these signals have a fixed frequency [28]. On the other hand, non-stationary signals have a frequency that changes over time, such as vibration signals in a generator's rotor due to a growing crack inside a work piece [29].

To analyze stationary signals, methods based on the Fourier transform are usually used, while non-stationary signals are typically analyzed using the Hilbert Transform (HT) [30], wavelet transform (WT) [31], or short-time Fourier transform (STFT) [32].

C. Acoustic Emission (AE)

As is known, the sound waves of equipment in a healthy operating mode are unique, and if a fault occurs, the sound waves emitted from the equipment will change. This change in sound may be due to deformations, corrosion, or cracking that occur prior to equipment failure [33]. For example, Electric machines can produce acoustic emission (AE) due to various sources such as cyclic fatigue, impacts, turbulence, friction, cavitation, material loss, and leakage, among others [34].To acquire data, sensors are positioned on the surface of the material, and the data collected by each sensor is tracked. If there are any imperfections present in specific areas, then the signal characteristics from the closest sensor to the disruption would exhibit distinct variations. By analyzing the discontinuity, it is possible to determine the defect position and suspect area of the structure.

Broadly, there are two methods of data analysis. The first method involves analyzing fundamental signal parameters such as energy and amplitudes. However, sometimes it can be challenging to detect faults using this approach [35].Another approach involves using the entire waveform instead of just the parameters. This approach enables the utilization of signal processing techniques such as wavelet-based acoustic emission characterization, which has demonstrated superior performance compared to the previous approach [36].

D. Lubrication Oil Analysis

Lubrication oil plays a crucial role in minimizing friction between moving surfaces in electrical and mechanical machines. Lubrication oil analysis (LOA) involves assessing fluid properties such as fluid viscosity, additive levels, oxidation properties, and specific gravity, along with fluid contamination including moisture, metallic particles, coolant, air, and wear debris [37]. The quality of the oil is evaluated using various methods such as particle filtration, spectrographic oil analysis, analytical ferrography, and radioactive tracer methods. A sample of the oil must be taken from the machine and examined in a laboratory to study its chemical composition [38], [39].

E. Infrared thermography

The health of equipment and components can be assessed by measuring their temperature, which is a widely used indicator. This technique is based on two laws - Planck's law and Stefan-Boltzmann's law - which state that all objects with a temperature above 0 K (-273°C) emit electromagnetic radiation in the infrared region of the electromagnetic spectrum [14]. Infrared thermography (IRT) involves capturing the infrared radiation emitted by an object using thermal imagers to identify any abnormal heat patterns or thermal anomalies. Such anomalies can be indicative of potential faults, defects, or inefficiencies in a system or machine [40].

Condition monitoring of electrical machines using IRT relies heavily on the temperature measurement of the equipment being tested [41]. Infrared thermography is typically divided into two categories: quantitative and qualitative thermography. The quantitative approach measures the precise temperature values of objects, using ambient temperature as a reference point. The qualitative approach measures the relative temperature values of hotspots compared to other parts of the equipment under similar conditions and identifies the locations of hotspots [42].

F. Ultrasound Base Methods

Ultrasound is widely used in the condition monitoring of equipment, and structures as it provides a non-destructive method of testing for faults, defects, and other issues. It is particularly useful for detecting issues in rotating equipment such as bearings and gears, as well as for detecting leaks in boilers, condensers, and other pressure vessels [43]. In active ultrasonic testing, a guided beam of ultrasound is transmitted into the equipment, and the characteristics of the emitted and received signals are analyzed to determine the presence and location of any subsurface discontinuities. In passive ultrasonic testing, the ultrasound is detected through physical processes without the need for a transmitted signal. This method is commonly used for contact monitoring techniques such as bearing faults and gear damage. Overall, ultrasound provides a quick and effective means of condition monitoring, allowing maintenance teams to quickly identify and address potential issues before they escalate into major problems [44].

G. SCADA

The operation of this system is such that the information of each equipment parameter, including 1) voltage, current, and electric power, 2) temperature, 3) rotor speed, 4) wind speed, and other parameters, is saved and sent to the control center with a recording rate ranging from a few seconds to several minutes [45]. The SCADA system, by using suitable algorithms, provides rich information on wind turbine performance which can be used for condition monitoring, fault prediction, and lifetime estimation of wind turbines [46]. However, as is known, this system is not designed for conditional monitoring due to its low sampling rate. For that reason, a significant amount of information regarding the characteristics of wind turbine faults is lost, making it challenging to detect most of the information related to wind turbine faults through analysis in the time-frequency and frequency domain [47].

H. General Parameters

Correct, temperature, torque, and strain are indeed considered general parameters used in wind turbine condition monitoring [48]. Together with other parameters such as wind speed, rotor speed, voltage, current, and electric power, they offer a comprehensive assessment of the wind turbine's health and performance. The information gathered from these parameters helps to identify any potential faults or issues with the wind turbine and also aids in fault prediction and lifetime estimation [49].

a. Temperature

Temperature is one of the most crucial parameters in the maintenance and condition monitoring of equipment [50], especially when it comes to wind turbines. During normal operation, it is essential that the temperature of the equipment does not exceed its limit. The abnormal temperature in a wind turbine is usually a result of defects in the gearbox, short circuits in the generator's windings, or excessive rotor speed [51]. This temperature parameter provides valuable information about the performance of the equipment and is used for fault prediction in the generator, gearbox, bearings, and wind turbine power drive. It is an economical and reliable method of monitoring equipment conditions. However, its main disadvantage is that it cannot detect the fault location on its own [52]. To effectively use this parameter, standards for equipment condition monitoring must be defined.

- IEEE-Standards 1310-2012 [53]
- IEEE-Standards 1718-2012 [54]
- ISO-Standard 17359-2006 [55]

b. Torque

This parameter, used in rotating equipment such as generators, is measured by torque sensors or through the electrical parameters of the machine [56]. The utilization of torque sensors in wind turbine condition monitoring demands a significant number of sensors, leading to the complication of the process and an increase in investment costs. This method is not used commercially due to these limitations [57].

c. Strain

Strain sensors are commonly used on a large scale for wind turbine blade condition monitoring [58]. These sensors are usually applied in large numbers on the surface of the blades or in different layers to detect structural defects or damage [59], such as blade icing, mass imbalance, or lightning strikes by using the information they provide. Compared to methods based on sound and vibration, this method has several advantages, including not requiring a high sampling rate, enabling faster diagnosis of structural faults, and not needing a power supply for sensors. However, the disadvantages of this method include its lack of sufficient accuracy compared to other methods, increasing complexity, and investment cost [58].

The comparison of the different types of signals used in condition monitoring is shown in Table III [60]. The table provides an overview of various monitoring techniques employed in condition monitoring systems (CMS) for different components in a system. These techniques include vibration analysis, acoustic emission (AE), strain measurement, torque monitoring, temperature sensing, oil parameter analysis, electrical signal monitoring, SCADA signal analysis, infrared thermography, and ultrasound inspection. Each technique has its own set of characteristics, such as intrusiveness, complexity, online or offline capability, incipient fault detection, fault detection, fault location, fault identification, signal-to-noise ratio (SNR)/sampling frequency, cost, standardization, and usage in a Commercial system.

These monitoring techniques play a crucial role in detecting and diagnosing potential faults or anomalies in various components such as bearings, blades, gearboxes, generators, shafts, towers, and more. By continuously monitoring these components, maintenance teams can identify early signs of faults, enabling them to take timely corrective actions and avoid unplanned downtime or costly repairs.

It's important to note that while some techniques, like vibration analysis and AE, SCADA and Electrical signals are widely used and standardized in CMs applications, others may have limitations or are not commonly employed like in CMs. Factors such as cost, complexity, and the specific requirements of the monitored components influence the selection and implementation of these techniques.

By leveraging a combination of these monitoring techniques, organizations can be understanding the health and performance of their systems. This enables proactive maintenance strategies, optimizing operational efficiency, and ensuring the reliability and longevity of critical assets.

IV. Conditional monitoring: a literature review (wind turbine)

Researchers in [61] introduce a new online vibration-based diagnosis method for monitoring high-speed bearings in wind turbines. The method utilizes the adaptive resonance theory 2 (ART2) for the unsupervised classification of extracted features and incorporates the Randall model adapted to the bearing's geometry. The time domain, frequency domain, and time-frequency domain are explored for improved fault characterization.

In [62] researchers use condition monitoring techniques such as vibration analysis and acoustic signal analysis to detect tooth chip breakage and tooth root crack failures in a wind turbine gearbox. Wavelet analysis and statistical features are employed, and the results indicate accurate early detection using vibration signals at stationary loads and acoustic signals at non-stationary loads.

Reference [63] proposes a multiview fault diagnosis framework for wind turbine gearboxes, combining current and vibration signals. Using unsupervised multiview learning based on canonical correlation analysis (CCA), the method extracts enhanced fault-related features and achieves superior diagnosis performance, particularly for compound faults, compared to unimodal signal-based methods.

Reference [64] investigates the correlation between dimensional parameters and electrical asymmetry indicators in laboratory-based systems compared to actual wind generators. The study compares small-scale off-the-shelf wound rotor induction machines (WRIMs) and micromachines. The findings show that micromachines accurately reflect fault-related harmonics and transient operating conditions, making them suitable for developing condition monitoring strategies for real wind turbine systems.

Reference [65] introduces a new approach for current-based gearbox fault diagnosis in wind turbines. It uses a multiview sparse filtering method to extract informative features from raw current signals, improving fault diagnosis performance. Reference [66] proposes an electrical signature analysis (ESA)-based method for detecting external bearing defects in electromechanical drivetrains. The method utilizes electrical measurements from the terminal machine, offering advantages over vibration-based methods. A new signal model based on torsional resonances is developed and validated experimentally. The ESA-based method demonstrates effective fault detection even at low speeds, with benefits in terms of cost, complexity, and reliability. Reference [67] presents a noninvasive fault diagnosis method for bearing failures in DFIG-based wind turbines using the modulation signal bispectrum (MSB) detector. The MSB method analyzes the stator current signals to detect torque oscillations and identifies spectral components related to bearing faults. The proposed current-based MSB method offers a cost-effective solution without requiring additional sensors and has potential applications in various industries

In [68] authors focus on identifying major fault types in large-scale permanent magnet wind turbines. Theoretical analysis is conducted on rotor eccentricity, stator winding short circuit, and permanent magnet demagnetization. The wavelet analysis algorithm is used to analyze the abnormal electromagnetic signal waveform and extract characteristic frequencies.

Reference [69] proposes an integrated acoustic emission (AE) monitoring scheme for detecting and localizing incipient faults in the main bearing (MB) of wind turbines. The scheme includes a high-frequency envelope autocorrelation (HFEA) method for accurate rotating speed estimation, an adapted spectral coherence (ASC) technique for identifying faulty sources, and a damage localization model for improved maintenance efficiency. This scheme offers a promising tool for wind turbine health management and inspection efficiency improvement. In reference [70], authors explore the use of acoustic emission (AE) monitoring to detect and analyze gear surface wear in a planetary gearbox. AE provides valuable information about surface friction, surpassing the limitations of traditional monitoring methods. The study identifies AE event width as an effective indicator for monitoring gear active surfaces. A data reduction algorithm-based condition indicator is proposed for AE-based gear monitoring, taking into account system-specific factors.

Reference [71] presents a fault diagnosis method for pitch bearings in wind turbines using acoustic emission technology. The method involves selecting acoustic emission signals with cracking characteristics based on kurtosis value and extracting fault features using wavelet spectrum theory. An online monitoring system based on acoustic emission is developed and successfully identifies crack faults in pitch bearings using wavelet packet transform and time-frequency spectrum analysis.

In reference [72] A method for analyzing stator current characteristics is proposed to detect blade imbalance in double-fed induction generators (DFIGs). The method utilizes coordinate transformation and simulation models to analyze fault characteristics under different conditions. It effectively determines the severity of the fault by monitoring changes in the characteristic frequency's amplitude.

Reference [73] proposes an ensemble approach for anomaly detection and fault diagnosis in wind turbines using SCADA data. Historical SCADA data from healthy turbines are used to create a reference space, and anomalies are detected by comparing predicted behavior with this reference. Fault diagnosis is performed by analyzing the distributions and correlations of SCADA data. The approach is validated using data from field wind turbines, demonstrating its ability to detect anomalies and diagnose faults before maintenance shutdowns are required. In reference [74], authors propose a novel spatio-temporal multiscale neural network (STMNN) for fault diagnosis of wind turbines using SCADA data. The STMNN captures complex temporal and spatial correlations in the data through its multiscale deep echo state network and multiscale residual network modules. To address the data imbalance issue and improve diagnosis performance, researchers use focal loss as the loss function. In reference [75], researchers propose a novel fault diagnosis method called adaptive multivariate time-series convolutional network (AdaMTCN) for wind turbines using SCADA data. It employs resampling and multivariate time series convolutional networks (MTCN) to extract enriched features. Multiple MTCN models are combined using an adaptive decision fusion method. Experimental results show AdaMTCN's excellent diagnostic performance with complex SCADA data. Reference [76] proposes a data-driven approach for wind turbine fault diagnosis and early warning using SCADA data. Our method improves anomaly data processing and feature measurement accuracy. The proposed wind turbine condition monitoring scheme provides advance warnings for generator, gearbox, and hydraulic system failures. The warning lead times are 3.67 hours, 5.17 hours, and 2.33 hours, respectively.

Reference [77] proposes a semi-supervised anomaly detection model for wind turbines using SCADA data. The model captures inter-variable correlation and temporal dependence, achieving superior performance compared to existing methods. The F1-score outperforms baselines by 3.86% in the unsupervised model and reaches 98.60% with the auxiliary discriminator.

In reference [78], AFTC system was presented using partial adaptation based on the Terminal Back-stepping Sliding Mode (TBSM) control strategy for adjusting the pitch angle of variable-speed wind turbines in the presence of faults in the actuators and sensors. Additionally, in this research, an estimation method based on time delay was employed as an online fault estimation algorithm for identifying and isolating faults. In reference [79], a safe load reduction plan is presented under the title of "Fault-Tolerant Control of the pitch System" individually, aiming to adjust the blade angle in the presence of blade activation fault.

In reference [80], authors investigate control methodology for variable-speed variable-pitch wind turbines considering uncertain nonlinear dynamics, system faults, and external disturbances. The goal is to maximize power extraction by designing optimal desired states. A model-based nonlinear controller is developed, and radial basis function neural networks are used to estimate unknown nonlinearities. An adaptive neural fault tolerant control approach is proposed to handle uncertainties and unknown actuator faults. Simulation studies confirm the effectiveness of the method. In reference [81], researchers present a cooperative control scheme for wind farms, aiming to improve reliability and availability. By using a fuzzy model reference adaptive control approach, the scheme addresses power generation issues caused by blade erosion and debris buildup.

In reference [82], an adaptive control system was designed for wind turbines with the objectives of reducing faults in the pitch system, maintaining the generator power at the nominal value, and minimizing mechanical stresses.

Reference [83] presents an experimental comparison between a fault-tolerant control strategy and a classical proportional-integral controller for a symmetrical six-phase induction generator. The proposed variable structure control approach effectively handles unbalanced currents and enables power generation even with a loss of stator phases. The controller demonstrates robustness and good regulation performance in both healthy and faulty modes. Reference [84] proposes a robust, fault-tolerant control system for wind energy applications. It introduces an observer-based approach to handle sensor failures and irregular conditions, specifically focusing on the generator speed sensor. The system does not require controller reconfiguration and utilizes anticipated speed information.

Studies proposed in this section are summarized in Table IV, including: monitored components, data types, and methods.

V. Conclusion

Incorporating an array of monitoring techniques is imperative for the thorough evaluation of wind turbine conditions. Among these techniques are vibration analysis, acoustic emission, electrical signal assessments, and the comprehensive analysis of SCADA data. Their combined implementation significantly enhances the rapid and accurate detection of faults that may arise within critical turbine components. By promptly pinpointing these issues, the need for unscheduled maintenance disruptions and the associated high-cost repairs is effectively diminished. The scholarly resources referred to in this article introduce pioneering methodologies that intricately improve the process of diagnosing faults and their subsequent management. This approach not only serves to optimize the overall performance of wind turbines but also accentuates the mounting significance of avant-garde research in heightening operational reliability and efficiency. This paper is the first section of two-part paper. In the second part that is published in a separate paper, widely used signal processing techniques for condition monitoring of wind turbines are presented.

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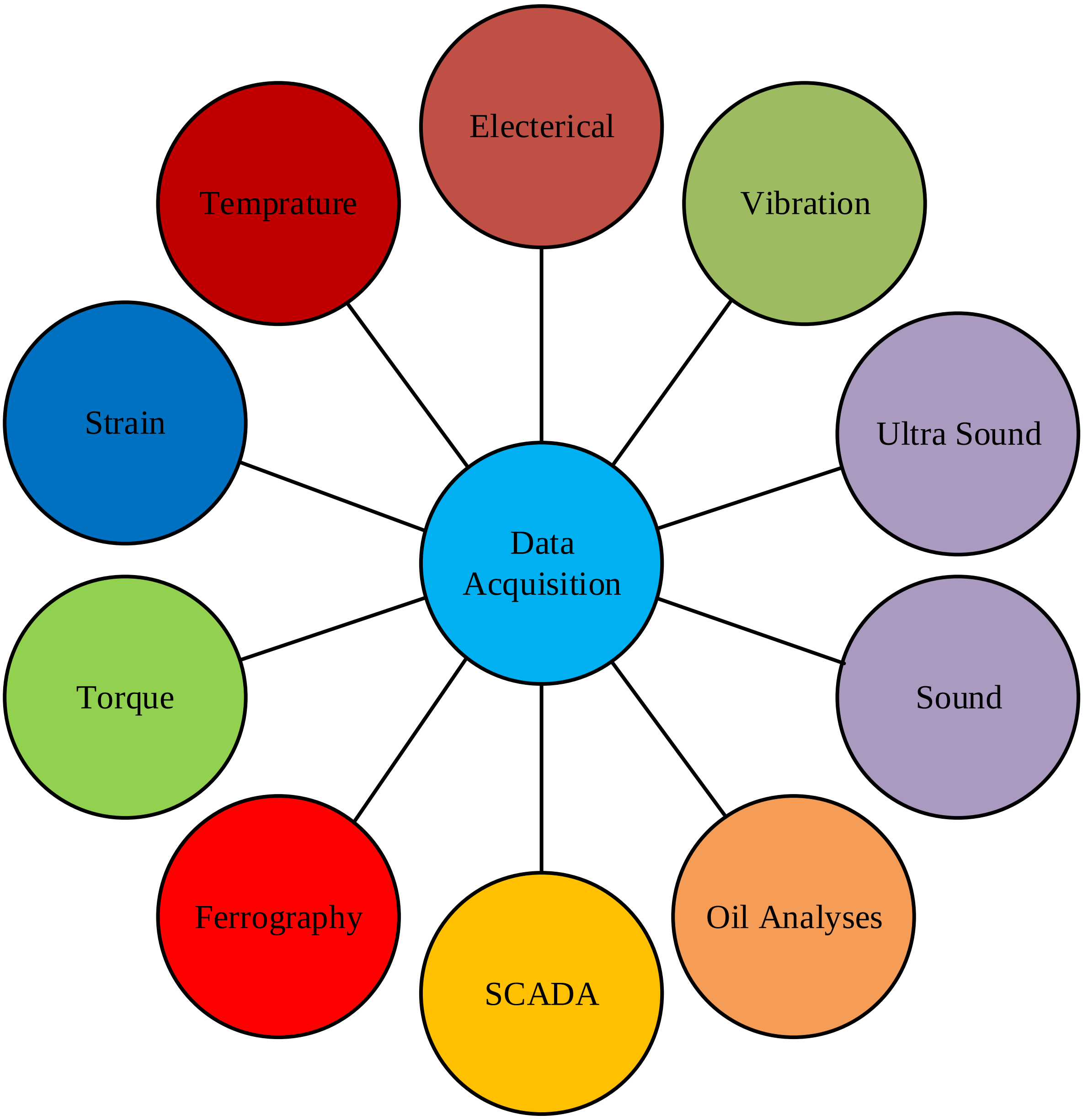

Figure 1:Most practical CM methods

Table I: Comparison of Conventional Maintenance Methods [14]

Method	Advantages	Drawbacks
Corrective maintenance	Maintenance expenses during operation are kept at a minimum Components are utilized for their maximum lifespan	High risk in consequential damages resulting in extensive downtimes No maintenance scheduling is possible Spare parts logistics are complicated Long delivery periods for parts are likely
Preventive scheduled maintenance	Low downtime Scheduled maintenance Easy spare part logistics	Higher maintenance costs Components will not be used for maximum lifetime
Predictive condition-based maintenance	Full lifetime use of components Low expected downtime Scheduled maintenance Easy spare part logistics	Reliable information about the remaining lifetime of the components is required High effort for condition monitoring hardware and software is required Cost of another layer in the system Identification of appropriate condition threshold values is difficult

Table II:Comparison between AFTCS and PFTCS [20]

System's Property	AFTCS	PFTCS
Architecture	Complex	Simple
Time Response	Slow	Fast
Fault Detection	Online / Real Time	Offline
Computations	Large	Relatively Small
Fault Detection and Isolation (FDI)	Essential	Not Required
Controller Reconfiguration	Required	Not Required
Noise Effect	can corrupt the system and result in erroneous decision-making	Robust to Noise
Time delay	Possible due to noise	No Time Delay
Faults nature	Various	Fixed predefined faults are accommodated
Control Structure	Variable	Fixed

Table III: Comparison of different signals for WT CMFD [60]

Signal	Monitored components	Intrusive	Complexity		Capability					SNR/ Sampling frequency	Cost	Std	Used in Com CMs
			Install	Signal process	Online/Offline	Incipient fault detection	Fault detection	Fault location	Fault identify				
Vibration	Bearing, blade, gearbox, generator, shaft, tower	Yes	High	Medium	Online	Yes	Yes	Yes	Yes	High/Medium	High	Yes	Yes
AE	Bearing, Blade, gearbox	Yes	High	High	Online	Yes	Yes	Yes	Yes	High/High	High	Yes	Yes
Strain	Blade	Yes	High	Medium	Online	Yes	Yes	Yes	Yes	High/low	High	No	Yes
Torque	Blade, gearbox, generator, shaft	Yes	High	Medium	Online	Yes	Yes	Yes	Yes	High/Medium	High	No	No
Temp	Gearbox, generator, Bearing, power converter	Yes	Medium	Low	Online	Possible	Yes	Possible	No	High/Low	Medium	Yes	Yes
Oil parameters	Bearing, gearbox, generator	Yes	Medium	Low	Both	Possible	Yes	Possible	Possible	High/Low	Medium or high	No	Yes
Electrical signals	Bearing, Blade, gearbox, generator, motor, power converter, sensor, shaft, tower	No	Low	High/medium	Online	Possible	Yes	Yes	Yes	Low/ Medium	Low	No	Yes
SCADA signals	Blade pitch, control system, generator, hydraulic system, power converter, sensor, overall system	No	–	Medium	Online	Possible	Yes	Possible	Possible	Low/Low	Low	No	Yes
Infrared thermography	Blade , gearbox	Yes	Low	Low	Both	Possible	Yes	Yes	Yes	High/– low	High	No	No
Ultrasound	Bearing, blade, gearbox	Yes	Low	Low	Both	Possible	Yes	Yes	Yes	High/– medium	High	No	No

Table IV: recent studies summarizing (monitored component, data, methods)

Ref	Monitored Component(s)	Data Type(s)	Methods(s)
61	Bearing	Vibration	Randall model
62	breakage, crack in the Gearbox	Vibration, Acoustic	Wavelet
63	Gearbox Bearing	Vibration Current	Canonical Correlation Analysis
64	Fault-Related Harmonics	Dimensional Parameters, Electrical asymmetry	Correlation
65	Gearbox	Stator Current	Multiview Sparse Filtering
66	Drivetrains Bearing	Stator Current	Signal Model Based on Torsional Resonances
67	Bearing	Stator Current	Modulation Signal Bispectrum
68	Rotor eccentricity, Stator Winding Short Circuit	Electromagnetic Characteristics	Wavelet
69	Bearing	Acoustic	Envelope Autocorrelation, Adapted Spectral Coherence
70	Planetary Gears	Acoustic	Data Reduction Algorithm
71	pitch Bearings	Acoustic	Wavelet
72	Blade	Stator Current	Coordinate Transformation
73	Wind turbine	SCADA	Correlation of SCADA data
74	Wind turbine	SCADA	STMNN
75	Wind turbine	SCADA	AdaMTCN
76	Generator, Gearbox, Hydraulic System	SCADA	Density-Based Spatial Clustering
77	Wind turbine	SCADA	Semi-supervised Multivariate Time Series
78	Actuators, Sensors	Sensors	TBSM
79	Blades Actuators	Sensors	Load Reduction
80	Actuator	Sensors	RAFFNN
81	Blades, debris buildup	Sensors	Fuzzy Logic
82	Pitch System	Sensors	Adaptive Controller
83	Generator winding	Sensors	Controller
84	Sensors	Sensors	Observer-Based Approach

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