CONTRIBUTED PAPER

# A Comprehensive Review on Signal-Based and Model-Based Condition Monitoring of Wind Turbines: Fault Diagnosis and Lifetime Prognosis

*This article reviews the state-of-the-art condition monitoring technologies used for fault diagnosis and lifetime prognosis in wind turbines.*

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**ABSTRACT** | Wind turbines play an increasingly important role in renewable power generation. To ensure the efficient production and financial viability of wind power, it is crucial to maintain wind turbines' reliability and availability (uptime) through advanced real-time condition monitoring technologies. Given their plurality and evolution, this article provides an updated comprehensive review of the state-of-the-art condition monitoring technologies used for fault diagnosis and lifetime prognosis in wind turbines. Specifically, this article presents the major fault and failure modes observed in wind turbines along with their root causes, and thoroughly reviews the techniques and strategies available for wind turbine condition monitoring from signal-based to model-based perspectives. In total, more than 390 references, mostly selected from recent journal articles, theses, and reports in the open literature, are compiled to assess as exhaustively as possible the past, current, and future research and development trends in this substantial and active investigation area.

**KEYWORDS** | Condition monitoring; fault detection and diagnosis (FDD); lifetime prognosis (LTP); wind farm; wind turbine.

## I. INTRODUCTION

While wind power production keeps rising worldwide, wind turbines are playing an increasingly major role in the present and future of renewable power generation. Yet, in the current wind production landscape, two trends seem to jeopardize the fulfillment of this global role. On the one hand, a significant share of the existing wind turbines has already reached its 20-year estimated lifetime, which requires additional maintenance services; on the other hand, new wind turbine technology is evolving toward larger wind turbines in remote offshore locations, which

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poses new accessibility issues for inspection and maintenance. Consequently, greater attention has recently been paid to the soaring operation and maintenance (O&M) costs of wind turbines (both onshore and offshore), which must be addressed for wind energy to remain financially viable [1]–[3]. From a technical point of view, wind turbines are complex aeroelectromechanical systems that are becoming larger and more flexible in design and increasingly digitalized and automated in operation. Unlike conventional power plants, they are often installed in remote locations and, thus, constantly undergo harsh weather conditions and largely variable aerodynamic, gravitational, centrifugal, and gyroscopic loads. Taken together, these elements induce a high frequency of faults and failures in wind turbines. In addition, access for maintenance is often troublesome and costly due not only to the large dimension of wind turbines but also their safety regulations, which restricts maintenance service to daytime hours, a relatively low air humidity, temperatures above 10 °C, and wind speeds below 8–12 m/s [4]. Such issues are exacerbated in offshore wind farms due to the harsh marine environment, which causes higher rates of failures in wind turbine components and additional maintenance complexities, whether in terms of difficult accessibility, higher logistic costs, or lower skilled manpower [5], [6]. As a result of poor equipment reliability and impaired wind turbine availability for power generation (unscheduled downtime/stoppages), O&M costs are quickly rising, now representing an increasingly significant part of the total wind energy generation cost [3], [7]–[9]. Currently, the O&M costs account for approximately 10%–30% of the total energy generation cost of an onshore wind farm after it has become operational [10]. In comparison, although offshore wind farms can generate wind energy more efficiently, their O&M costs can surge up to 25%–50% of the total energy generation cost, which is a considerable increase [5], [11]. Lowering the ever-soaring O&M costs in wind energy production requires improving the critical aspects of wind turbine reliability and availability (uptime) using appropriate condition monitoring solutions.

### A. Wind Turbine Condition Monitoring

Wind turbine condition monitoring involves the process of monitoring (and analyzing) the operating parameter(s) of condition in a wind turbine system or its components, aiming at identifying any abnormal change(s) in the condition or specific events that can indicate developing fault(s) in the system. Using the monitored change(s) in the parameter(s), the fault diagnosis (detection, isolation, and identification) and lifetime prognosis (LTP) (remaining useful life (RUL) estimation) can be accomplished before a failure or a critical malfunction occurs in the wind turbine. This allows a very cost-effective and optimal type of preventive maintenance (before a failure), which is often referred to as “condition-based maintenance” instead of resorting to costly time-based maintenance (fixed service intervals).

Currently, wind turbine condition monitoring can be performed either offline or online (in real time). Offline condition monitoring involves periodic inspections in which a wind turbine needs to be shut down and/or requires the attention of an operator. This condition monitoring method suffers from important shortcomings. It is, indeed, an expensive monitoring method since it requires the wind turbine to stop working, which results in energy production loss, not to mention the additional costs incurred during off-line inspections. Moreover, offline condition monitoring obviously falls short of detecting and reporting the faults or damages that happen between the inspection intervals. The mentioned shortcomings become increasingly serious, especially in offshore wind farms for which the inspection intervals are longer than those of onshore wind farms [12], [13]. Therefore, real-time (online) condition monitoring techniques are rapidly evolving to address the issues that come with offline techniques. Indeed, real-time condition monitoring continuously provides a deeper insight into the real-time health status of a wind turbine or its main components, while it is in service. It relies on appropriate sensors or data acquisition systems to obtain continuous raw measurements (e.g., vibration, strain, temperature, voltage, and current) from wind turbine components and may even incorporate onboard models and/or signal processing functionalities for enhanced data reduction and analysis. Thanks to the wide variety of sensors and data acquisition systems available for wind turbine components, real-time condition monitoring is highly customizable. Factors such as the wind farm’s environment (onshore/offshore, cold/hot, humid/dry, and so on), the size and design specifications of its wind turbines, the types, and characteristics of target components to be monitored, together with the capabilities, limitations, and costs of available real-time monitoring technologies, should all be considered when choosing a real-time condition monitoring system (CMS).

Given the significance, plurality, and evolution of real-time condition monitoring for wind turbines, this article introduces and discusses the details of well-known technologies and solutions in this area and provides an up-to-date comprehensive review of the available literature, covering both technical aspects of fault diagnosis and LTP in wind turbines.

### B. Bibliographical Status of Literature and Existing Reviews/Surveys

Wind turbine condition monitoring, including both aspects of fault diagnosis and prognosis, has become an active research area over the last two decades. Fig. 1 shows the number and trend of published articles in this area from 2000 to 2020. It should be noted that this information is extracted from the *Web of Science* (WOS), which only includes a part of the available literature in this area. Therefore, the number of the entire publications on wind turbine condition monitoring, including articles, conference proceedings, reports, press releases, and so on, is,

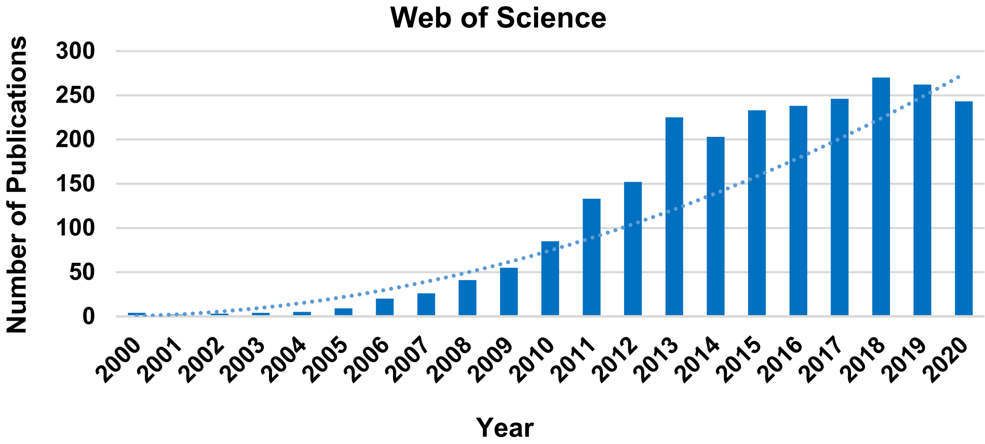


**Fig. 1.** ***Number and trend of published articles on wind turbine condition monitoring indexed in the WOS since 2000 (as of the beginning of 2021). Source: WOS.***

indeed, much higher than shown in the graphic in Fig. 1. Having said that, the reliable information extracted from the WOS and reflected in this graphic clearly indicates an overall rising trend for research articles on wind turbine condition monitoring by the end of 2020.

Given the rapid growth of research activities in this area, several literature reviews or survey papers have already been published on the different aspects of condition monitoring in wind turbines. For instance, Table 1 provides a chronological list of the existing review/survey journal publications in this area. Many of the reviews/surveys listed in the table are excellent in some facets and include very useful details. However, according to the indicated focus category and the brief description of each publication listed in Table 1, the following conclusions can be drawn regarding the existing reviews/surveys.

1) Some of them are relatively old, going back to 2006, which obviously obliterates the great advancement of wind turbine condition monitoring technology ever since (see Fig. 1).
2) Some are mainly focused on the monitoring of a particular wind turbine component, such as blade or gearbox, while a more comprehensive review/survey would provide broader knowledge of the appropriateness of technology, including its capabilities, limitations, and cost for monitoring different components at the same time.
3) Most of these reviews/surveys focus either only on the diagnosis or on the prognosis of wind turbines, not both together, which would enable a broader, more comprehensive perspective in the literature.
4) Those that discuss both aspects of diagnosis and prognosis in wind turbines are still limited in their attempts to offer a meaningful and comprehensive review of every available technique or solution, especially when it comes to prognosis.
5) The condition monitoring techniques reviewed are often restricted to those using either the signal-based (data-driven) approaches or mathematical model-based approaches but not both approaches in a broader perspective, nor using the hybrid methodologies that emerged out of the combination of the mentioned approaches.
6) The wind turbine nondestructive condition monitoring technologies (such as machine vision, ultrasound, and thermography) are often ignored, or, if reviewed, there is a tendency to only focus on a specific wind turbine component, such as blades, while providing little context about which component a technology is suited for, and with scarce details on capabilities, limitations, and costs.

In addition, as it came to the attention of the authors while reviewing the literature, the cited references in some of the existing reviews/surveys in this area are not always necessarily related to the problem of condition monitoring in wind turbines. For instance, some of the techniques or results reported for the condition monitoring of bearings or generators in engineering applications other than wind turbines were mistakenly cited and classified among the techniques specifically developed for wind turbines. This is not necessarily correct or reasonable since the problem of condition monitoring in wind turbines involves its own particular aspects and challenges that differ from those found in other engineering applications since they originate from the specific operating conditions and load variations of a wind turbine. Having said that, another problem with the references of some of the existing reviews/surveys is that, despite the new results and publications constantly emerging in this active research area, some recent reviews/surveys keep citing the same old or even obsolete references invocated in former reviews or surveys for years. This shortcoming has been carefully avoided in this review paper by citing the most important and relevant research papers with particular attention given to the recently published results, that is, in the last ten years.

**Table 1** Available Reviews/Surveys on Condition Monitoring of Wind Turbines

| Ref. No. | Author(s), Year | Focus Category | Brief Description |
|---|---|---|---|
| [12] | Hyers et al., 2006 | Diagnosis and prognosis | A relatively old review of the condition monitoring technologies in wind turbines but with an attention to the related technologies in other industries such as aerospace (helicopters and aircraft structures) |
| [13] | Wiggelinkhuizen et al., 2008 | Diagnosis | A relatively old survey-type investigation aimed at assessing the effectiveness of several online and offline techniques for wind turbine condition monitoring but it is limited to some signal-based techniques only and within the European Union project called “Condition Monitoring for Offshore Wind Farms (CONMOW)” |
| [14] | Hameed et al., 2009 | Diagnosis | A relatively old review of the signal-based and model-based diagnosis techniques for wind turbine condition monitoring, but it misses sufficient discussion on failure modes of different wind turbine components and the information regarding some important subsystems such as hydraulic systems and sensors |
| [15] | García Márquez et al., 2012 | Diagnosis | A review of diagnosis techniques along with signal processing algorithms for the condition monitoring of wind turbines but it is limited to signal-based techniques and lacking a comprehensive literature review that would include the complete capabilities and limitations of the available techniques |
| [16] | Purarjomandlangrudi et al., 2013 | Diagnosis | A systematic but relatively brief literature review on signal-based diagnosis techniques used in wind turbine condition monitoring |
| [17] | Schubel et al., 2013 | Diagnosis | A relatively brief review of damage diagnosis techniques, specifically for structural health and cure monitoring in wind turbine blades |
| [18] | Kusiak et al., 2013 | Diagnosis, control and operation | A review of the diverse issues related to available methodologies and techniques for wind speed prediction, system control, and condition monitoring of wind turbines, whose main downside is to be limited to certain signal-based techniques and which fails to offer a comprehensive literature review on condition monitoring specifically |
| [19] | Chen et al., 2014 | Performance monitoring and diagnosis | A survey of commercially available supervisory control and data acquisition (SCADA) systems and associated analysis tools for SCADA-based condition monitoring and performance optimization of wind turbines but it is lacking a comprehensive review beyond the commercial SCADA-based systems alone |
| [20] | Tchakoua et al., 2014 | Diagnosis | A review of diagnosis techniques and maintenance approaches in wind turbines but it is restricted to the signal-based techniques without sufficient discussion on the failure modes of different wind turbine components |
| [21] | Yang et al., 2014 | Diagnosis | A review of diagnosis techniques along with signal processing algorithms for condition monitoring of wind turbines but it is missing a comprehensive review and is bounded to certain signal-based techniques |
| [22] | Welte and Wang, 2014 | Prognosis | A review of methods and models for prognosis and lifetime estimation of wind turbine components which is relatively brief and whose major content is general and not specific to wind turbines |
| [23] | Crabtree et al., 2014 | Diagnosis and prognosis | A survey of commercially available condition monitoring systems for wind turbines but it misses a comprehensive review of literature beyond the commercial condition monitoring systems alone |
| [24] | Wang et al., 2014 | Diagnosis and prognosis | A review of SCADA-based condition monitoring techniques in wind turbines, followed by the proposal of an intelligent framework for fault diagnosis and prognosis of wind turbines using SCADA data but it is limited to SCADA-based techniques alone, thus failing to offer a comprehensive review |
| [25] | Antoniadou et al., 2015 | Diagnosis | A survey of some of the appropriate techniques for signal processing and machine learning used in structural and condition monitoring of wind turbines with some application examples but it is not a comprehensive survey |
| [26] | Wymore et al., 2015 | Diagnosis | A component-by-component review of some diagnosis techniques used in structural and condition monitoring of the major components of a wind turbine but it is limited to some signal-based techniques only |
| [27, 28] | Qiao and Lu, 2015 | Diagnosis and prognosis | A relatively extensive literature review in two parts: 1) failure modes and their characteristics in major wind turbine components and subsystems [27], and 2) diagnosis/prognosis techniques and major signal processing methods used in the condition monitoring of wind turbines [28], but it mainly reviews the well-known signal-based diagnosis techniques, while the model-based techniques or non-destructive condition monitoring technologies are very briefly outlined |
| [29] | Kandukuri et al., 2016 | Diagnosis and prognosis | A review of diagnosis/prognosis techniques which is mainly limited to some signal-based techniques, and in particular, the condition monitoring of low-speed bearings and planetary gearboxes in wind turbines |
| [30] | Azevedo et al., 2016 | Diagnosis and prognosis | A review of diagnosis/prognosis techniques with an attention given to the technical, financial, and operational challenges but which is restricted to some signal-based techniques, and specifically, the condition monitoring of bearings in wind turbines |
| [31] | Yang et al., 2017 | Diagnosis | A review of structural health monitoring techniques which yet does not constitute a comprehensive review, being limited to some signal-based techniques for wind turbine blades |
| [32] | Uma Maheswari and Umamaheswari, 2017 | Diagnosis | A review of drivetrain condition monitoring in wind turbines, however limited to the vibration monitoring technique including non-stationary signal processing algorithms, and specifically for drivetrain components |
| [33] | Tautz-Weinert and Watson, 2017 | Diagnosis | A review of diagnosis techniques for wind turbine condition monitoring, however limited to SCADA-based techniques only |
| [34] | Marugán et al., 2018 | Forecasting, diagnosis and control | A review of artificial neural networks (ANNs) used in wind energy systems for forecasting, design optimization, fault diagnosis, and optimal control but it does not review the literature beyond the ANNs techniques nor condition monitoring comprehensively |
| [35] | Salameh et al., 2018 | Diagnosis | A review of diagnosis techniques for wind turbine condition monitoring but it is restricted to some signal-based techniques, and specifically, the condition monitoring of gearboxes in wind turbines |
| [36] | Abid et al., 2018 | Prognosis | A review of prognosis techniques in wind turbines along with an overview of different prognosis phases including health indicator construction, degradation detection, and remaining useful life (RUL) estimation but it does not discuss the failure modes of different wind turbine components nor some important components such as rotor blades |

**Table 1** *(Continued.)* Available Reviews/Surveys on Condition Monitoring of Wind Turbines

| | | | |
|---|---|---|---|
| [37] | Leite et al., 2018 | Prognosis | A review of prognosis techniques and RUL estimation methods for the critical components of wind turbines but it does not address the failure modes of different wind turbine components |
| [38] | Wei et al., 2019 | Diagnosis | A review of diagnosis and signal processing techniques for wind turbine condition monitoring but it is limited to some signal-based techniques, and specifically, the condition monitoring of gears, rotors, and bearings in wind turbines |
| [39] | Moeini et al., 2019 | Diagnosis | A review of diagnosis techniques for wind turbine condition monitoring but it only includes some signal-based techniques and the majority of non-destructive condition monitoring technologies are simply missing |
| [40] | Zhang and Lu, 2019 | Diagnosis | A review of diagnosis techniques for wind turbine condition monitoring within three aspects of energy flow, information flow, and integrated O&M system but it does not constitute a comprehensive review, addressing some signal-based techniques without covering non-destructive condition monitoring technologies |
| [41] | Leahy et al., 2019 | Diagnosis and data quality | A review of issues related to data quality for enabling SCADA-based condition monitoring of wind turbines but it is limited to the discussions on data quality aspects, and addressing SCADA-based techniques alone |
| [42] | Habibi et al., 2019 | Diagnosis and fault-tolerant control | A tutorial-style review on diagnosis techniques and fault-tolerant control methods used in wind turbines which is limited to model-based techniques only |
| [43] | Madi et al., 2019 | Diagnosis and mitigation | A review of ice detection and active mitigation techniques for wind turbine blade surfaces but the main focus of the review, as its scope suggests, is the detection and mitigation of icing-related faults only |
| [44] | Stetco et al., 2019 | Diagnosis and prognosis | A review of machine learning methods for developing data-driven models used in wind turbine condition monitoring but the main focus of the review, as its scope suggests, is the signal processing algorithms based on machine learning methods when used under signal-based condition monitoring techniques |
| [45] | Wang et al., 2019 | Diagnosis | A review of gearbox condition monitoring in wind turbines which is limited to the vibration monitoring technique, and specific to planetary gearboxes |
| [46] | Du et al., 2020 | Diagnosis | A review of blade damage diagnosis techniques including a discussion on the fault indicators that are damage-sensitive but which only focuses on wind turbine blades |
| [47] | Liu and Zhang, 2020 | Diagnosis | A review of failure modes and diagnosis techniques for wind turbine bearings but it is limited to some signal-based techniques, and specifically for the bearings (main bearings, gearbox bearings, generator bearings, blade bearings and yaw bearings) |
| [48] | García Márquez and Peco Chacón, 2020 | Diagnosis | A review of non-destructive condition monitoring technologies for diagnosis of wind turbine blades but the main focus of review, as its scope suggests, remains on the non-destructive technologies, and specifically for wind turbine blades |
| [49] | Wei et al., 2020 | Diagnosis | A review of ice detection and mitigation techniques (anti-icing and de-icing technologies) for wind turbine blade surfaces but which predominantly focuses on the detection and mitigation of icing-related faults only |

The shortcomings and loopholes found in the existing literature reviews, along with the constant advancement of wind turbine condition monitoring technology that has inspired a considerable amount of new publications in this area, all together motivate the authors to present an updated and more comprehensive literature review in this article.

## C. Overview of the Present Comprehensive Review

This article aims at providing an up-to-date comprehensive literature review on real-time condition monitoring of wind turbines, spanning both fault diagnosis and prognosis aspects while exploring signal- and model-based approaches as well. Furthermore, the common fault and failure modes along with their root causes, traced to different wind turbine components, are discussed and categorized based on their severity; likewise, the updated results of recent reliability studies on both onshore and offshore wind turbines are carefully organized and presented. Compared with the existing literature reviews/surveys, the main features and contributions of this review paper specifically include the following.

1) A simple, straightforward language along with many informative and easy-to-understand figures, schematics, and tables is used to provide a systematic, comprehensive literature review in a way that is both appropriate and accessible to students, researchers, and any other practitioners, whether from academia or industry.
2) Both aspects of fault detection and diagnosis (FDD) and LTP are considered and reviewed for a deeper insight into the conditions of wind turbine components and subsystems.
3) All critical components of wind turbines are considered, and the advantages, disadvantages, limitations, challenges, costs, and trends of each condition monitoring technique or technology are carefully reviewed and explicitly discussed.
4) Given the in-depth literature in this field, and since a considerable share of studies has been published in the past ten years (see Fig. 1), the main focus is placed on the most recent journal publications, namely, those produced approximately between 2010 and 2021, unless the citation of some other references or recourses is utterly relevant to the area reviewed.
5) The most important, relevant, and up-to-date research results are carefully selected and cited to avoid the invocation of the same old references that used to be mentioned repeatedly in some of the existing reviews or surveys, disregarding the constant emergence of new results and publications in this active research area. That being said, this review paper explores various well-known and impactful papers that have significantly contributed to the development of this area since the 1990s.

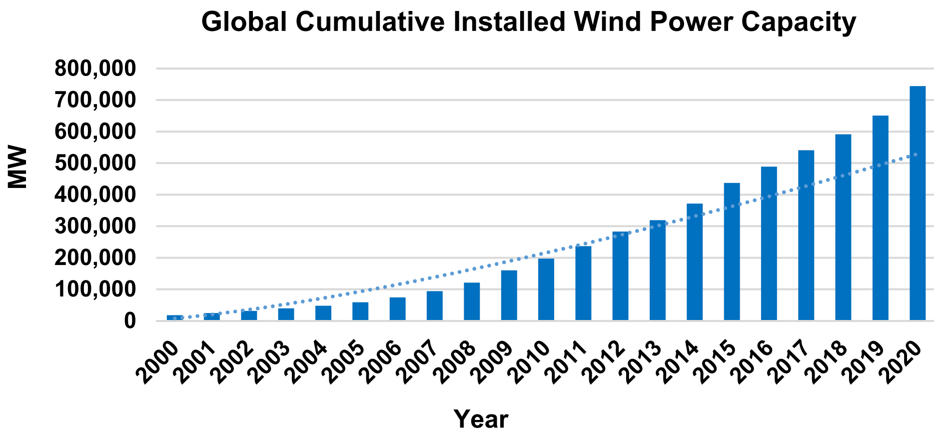


**Fig. 2.** *Trend of the global cumulative installed wind power capacity 2000–2020. Source: The World Wind Energy Association (WWEA), March 2021.*

6) A larger number of references are analyzed in order to achieve a more comprehensive literature review spanning an extended number of available techniques and technologies that include the SCADA-based techniques, 12 different varieties of dedicated condition-specific-based techniques (e.g., oil quality, vibration, and acoustic emission), mathematical model-based techniques, and the hybrid techniques as the combination of other techniques.
7) Throughout the review, the cited references are carefully selected and categorized with a special attention given to their true contents rather than the simple reformulation of their abstracts.
8) The cited references categorized in each table are sorted according to their publication dates to better represent the evolutive trend of a technology or approach over time and with respect to the monitored components.

The remainder of this article is organized into six different sections. The cutting edge of wind energy and wind turbines, with an emphasis on monitoring and control subsystems in wind turbines, is briefly discussed in Section II. The faults and failure modes, along with their root causes in different wind turbine components, are detailed and categorized in Section III. Wind turbine condition monitoring and condition-based maintenance techniques are described in Section IV. Hardware signal-based condition monitoring, including SCADA-based techniques and dedicated condition-specific-based techniques, is reviewed in Section V. Mathematical model-based condition monitoring is reviewed in Section VI. Finally, the summary, concluding remarks, and future trends are outlined in Section VII.

## II. STATE OF THE ART OF WIND TURBINES

### A. Wind Energy and Wind Turbines

In recent years, the demand for renewable/green energy has significantly increased. Among the different types of renewable energies, wind energy is the cleanest, a factor that contributes to making it the world's fastest-growing renewable energy source. Presenting the global cumulative installed wind power capacity from 2000 to 2020, Fig. 2 shows that, globally, the cumulative installed wind power capacity reached nearly 744 GW in 2020, which amounts to about 7% of the global electricity demand [50]. Following that trend, the mentioned wind power contribution is expected to increase up to 25%–30% by 2050 according to the Global Wind Energy Council [51].

As their names indicate, wind turbines harness the power of the wind. They do so by converting the wind's kinetic energy into mechanical energy, which is, in turn, converted into electricity using a generator. From a design viewpoint, wind turbines are classified into two different types: the vertical axis and the horizontal axis (see Fig. 3). Vertical axis wind turbines [see Fig. 3(a)] have a set of rotor blades that spin around a vertical axis, while other major components are located at the base of the wind turbine, which facilitates maintenance services. However, compared with horizontal axis wind turbines, they are known to be less efficient and are associated with higher O&M costs. This is partly due to the low rotor height that cannot harness greater wind speeds often found at higher levels, the less efficient rotor design that prevents the blades on the vertical axis rotor from receiving incoming wind at the same time, and more wind turbulence and structure vibrations that altogether cause higher component wear-down. On the contrary, with three rotor blades and presenting numerous advantages, such as access to the stronger wind (thanks to their tall towers), higher efficiency (since the blades always move perpendicularly to the wind), and receiving power through the whole rotation, the horizontal axis wind turbine [see Fig. 3(b)] has gradually dominated the commercial market of wind energy [52]. Given that, in Section II-B provides more details about the components and subsystems of this common type of wind turbine.

### B. Wind Turbine Components and Subsystems

A cross-sectional view of a typical three-bladed horizontal-axis wind turbine is shown in Fig. 4. The figure

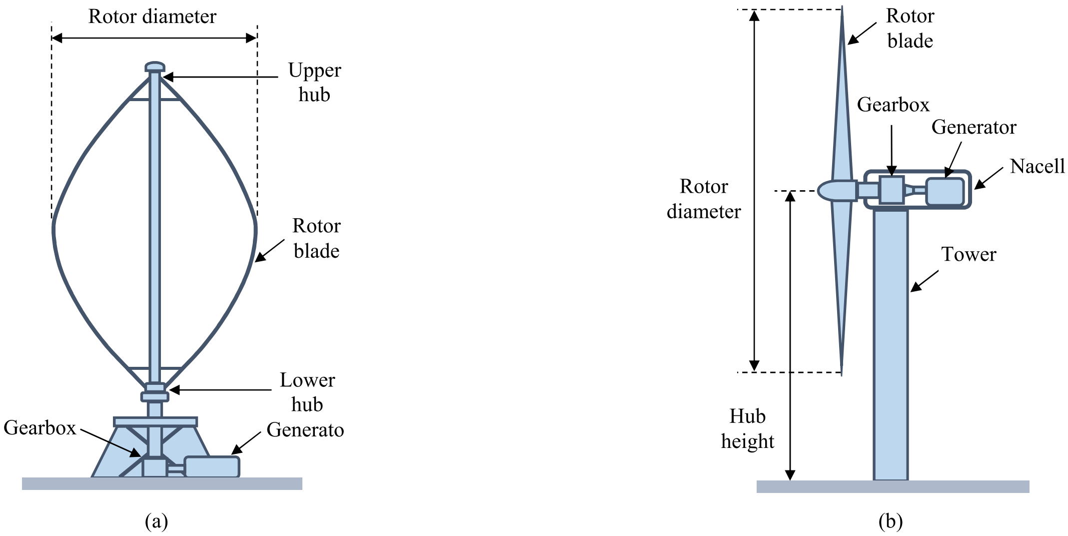


**Fig. 3.** ***Wind turbine designs: (a) vertical axis and (b) horizontal axis.***

depicts the most important wind turbine components and briefly describes their functionalities. Although absent from this figure, a large and strong foundation always finds itself under the wind turbine tower to withstand all the forces from the wind and hold the turbine upright. Section III provides detailed information about the significance, failure rates, and general reliability aspects of these wind turbine components. To further reinforce background knowledge of modern wind turbine systems, Fig. 5 shows the basic configuration of a wind turbine with its mechanical, electrical, and monitoring and control subsystems that are appropriately integrated for electricity generation in a controlled and reliable manner. Table 2 presents a more detailed list of major components under each category of mechanical, electrical, and monitoring and control subsystems. Note that some of the components in this list can be optional depending on the wind turbine's drivetrain design. As shown in Fig. 6, different alternative designs and arrangements for the drivetrains of wind turbines exist. As seen in this figure, depending on the type of the generator used and the design specifications of the turbine, the drivetrain can either be direct-drive (without gearbox) or geared-drive (with gearbox). The common alternative current (ac) generators are also categorized under two types of synchronous generators (which can be conventional or multipolar) and asynchronous (induction) generators with different rotor types, as also shown in Fig. 6. One should also mention that new designs can be expected as wind turbine technologies keep developing. Readers seeking further details on generators and power electronics for wind turbines are referred to [53] and references therein.

### C. Monitoring and Control: Critical Subsystems With Intertwined Functions

As they continuously ensure the safe and efficient operation of a wind turbine as a whole system, the monitoring and control equipment, among other subsystems, are of

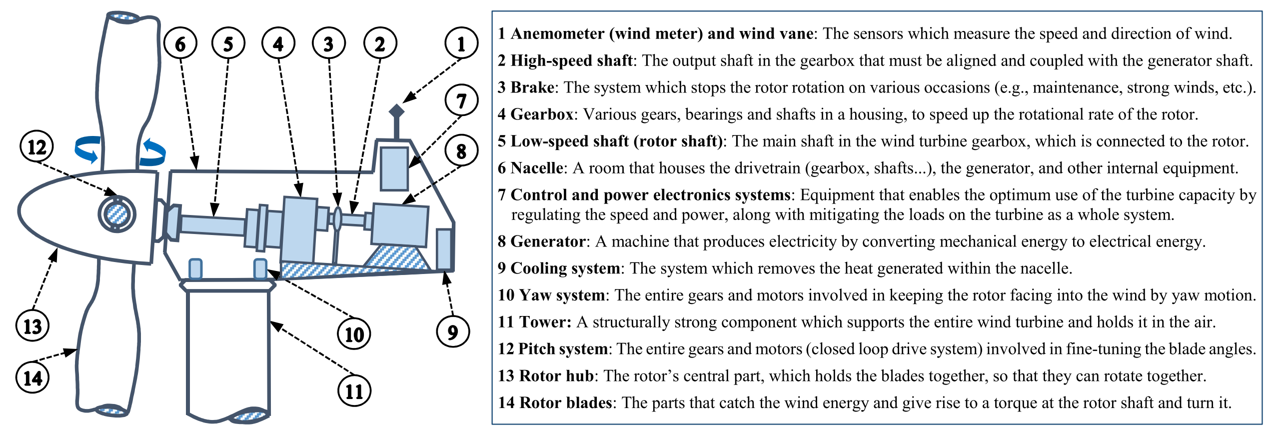


**Fig. 4.** ***Cross-sectional view of a typical three-bladed horizontal-axis wind turbine.***

**Table 2** Wind Turbine Major Components

| Mechanical | Electrical | Monitoring and Control |
|---|---|---|
| Tower and foundation | Generator | Sensors |
| Nacelle | Transformer | Actuators (pitch, yaw, and generator torque) |
| Rotor (a hub and blades) | Power electronic converter | Pitch controller |
| Gearbox | Space heaters for winter time (cold-climate wind farms) | Generator/Converter controller |
| Low-speed and high-speed shafts | Lighting system inside the nacelle | Yaw controller |
| Mechanical brakes | | |
| Cooling system for gearbox | | |

critical importance. They can be considered under each individual wind turbine and an entire wind farm (group of wind turbines) level. Fig. 7 illustrates this important classification of monitoring and control functionalities in wind turbines and wind farms. From a larger perspective, wind turbine condition monitoring, when conducted in real time, not only can enable condition-based maintenance (discussed in Section IV) but also the emerging concepts of "condition-based control" and "fault-tolerant control" to safely increase wind farm availability. This ultimately results in a health management scheme, as outlined in Fig. 8. One can see that the information obtained from real-time condition monitoring is used in a high-level supervisory control system, which accordingly determines if it is safe and reasonable for wind turbines to continue producing power in the event of faults and before the essential condition-based maintenance. In addition, wind turbines' operational uncertainties can be alleviated using condition-based and fault-tolerant control algorithms at the levels of any individual wind turbine or the entire wind farm. More precisely, condition-based control keeps track of the real-time condition of wind turbine components and adapts the control actions to modify the loading of components depending on their health condition and, thus, to delay/avoid failure. Fault-tolerant control, on the other hand, aims at accommodating the effects of noncritical faults in wind turbines by reconfiguring the control algorithms to avoid unnecessary shutdowns and missed production. When supported by a reliable and effective CMS, condition-based and fault-tolerant control mechanisms lower the probability of wind turbine unexpected maintenance and help enjoy improved supply certainty (availability). Let us note that such benefits come on top of the benefits from condition-based maintenance itself [54], [55]. Accounting for these benefits altogether leads to significant revenue improvements over the lifetime of a wind farm, especially if located in less accessible offshore regions.

## III. FAULT AND FAILURE MODES IN WIND TURBINES

Wind turbines constantly undergo a wide range of changing loads and operating conditions, which results in their components experiencing considerably high failure rates. The most common root causes of the fault and failure modes in wind turbines are shown in Fig. 9.

Unexpected faults may occur in any wind turbine components, such as sensors, actuators, rotor blades,

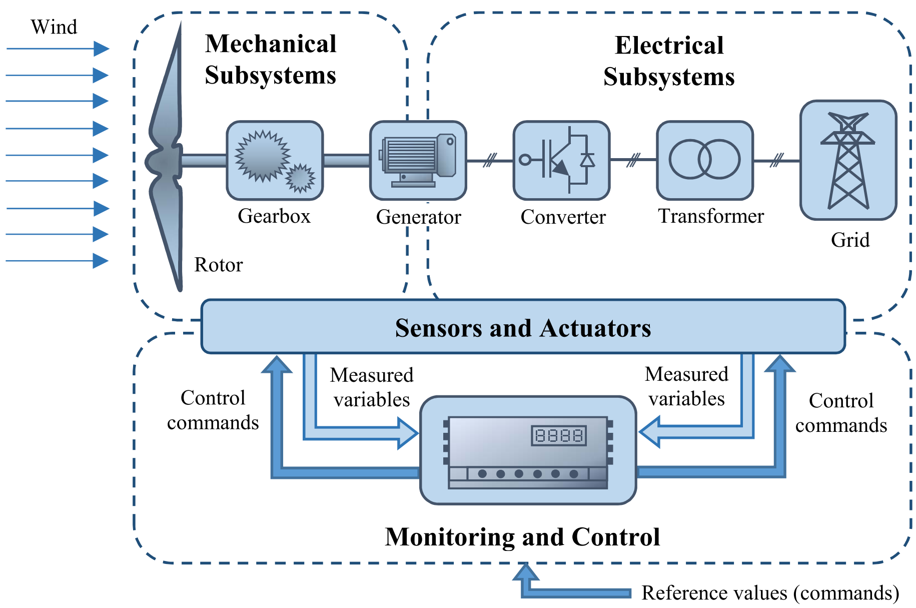


**Fig. 5.** *Basic configuration of energy conversion in a typical wind turbine.*

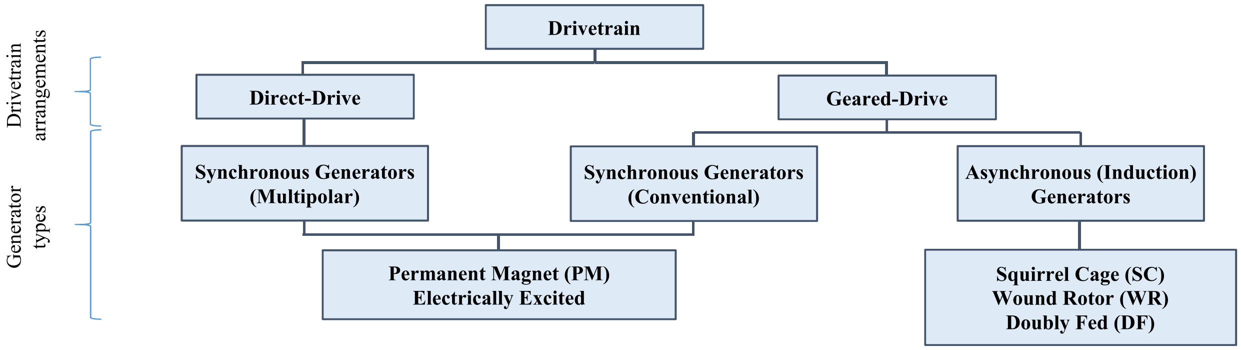


**Fig. 6.** ***Drivetrain arrangements and common generator types.***

generators, gearboxes, electric systems, and electronic control units, to name but a few. Fig. 10 shows the most important wind turbine faults and component failures according to their severity. The more damaging the ramification, the higher the level of severity assigned to the fault/failure effects. The most severe faults/failures can lead to the complete shutdown of the turbine. As for the severe and less severe faults, they usually partially affect the ability of a wind turbine to produce its nominal power, but urgent repairs may still be required. Notice that the low level of severity considered for sensor faults relates to the physical redundancy applied when installing sensors, which aims at facilitating the detection and accommodation of sensor fault effects. However, these sensor faults may become critical if their effects are not handled in a timely manner, which is before going through feedback loops into the wind turbine's control system. Indeed, a fault might not be severe in the first place, but its effects might quickly propagate in the wind turbine and lead to the catastrophic failure of its rotor, drivetrain, or power generation systems. Fig. 11 illustrates this process by showing how various components' fault effects can propagate through the wind turbine subsystems.

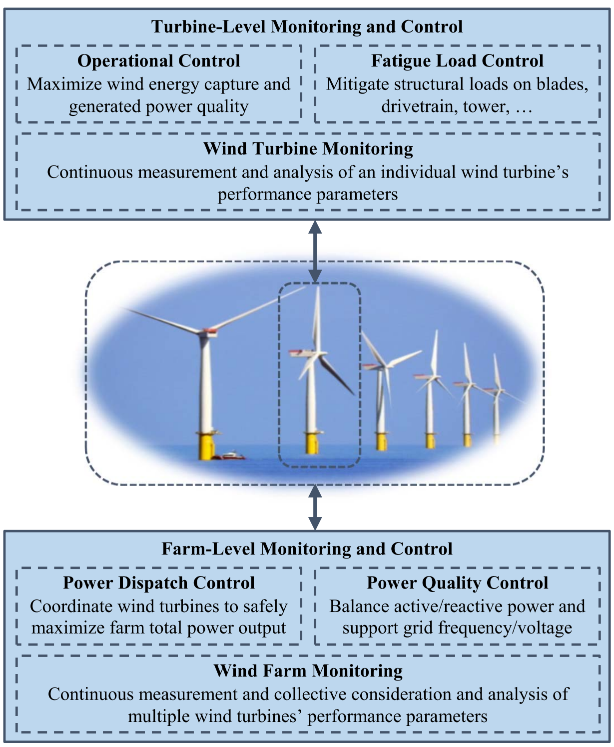


**Fig. 7.** ***Monitoring and control of wind turbines.***

Several independent studies on the reliability of wind turbines (mostly onshore) are already available in the literature (for instance, see [3], [9], and [56]). Also, relatively solid reviews, such as those in [7], [8], and [57], bring together and compare data from a selection of major studies in the literature. Table 3 presents the main results and conclusions extracted and compiled from these studies for both onshore and offshore wind turbines. According to reliability studies, as wind turbines are becoming larger, more flexible, and located further from shore, their O&M costs rapidly rise unless their reliability is improved through effective condition monitoring solutions.

## IV. WIND TURBINE CONDITION MONITORING AND CONDITION-BASED MAINTENANCE

It is quite important to detect, diagnose, and prognose any types of abnormalities and faults as early as possible before they propagate to major damage or severe failure. As shown in Fig. 12, the advanced techniques for FDD and LTP, included in a CMS, enable a very cost-effective type of preventive maintenance (before a failure), which is often referred to as "condition-based maintenance." When a fault occurs, depending on its type and location, it takes a certain time to develop before it can interrupt or stop the operation of the wind turbine. To be effective, CMS must take into account that time span. For instance, some faults occur within a very short timeframe, in the order of seconds, to grow from inception to failure (e.g., generator earth fault), whereas others may take up to months before causing a failure (e.g., fatigue and fracture). Thus, the former may provide sufficient time for detection

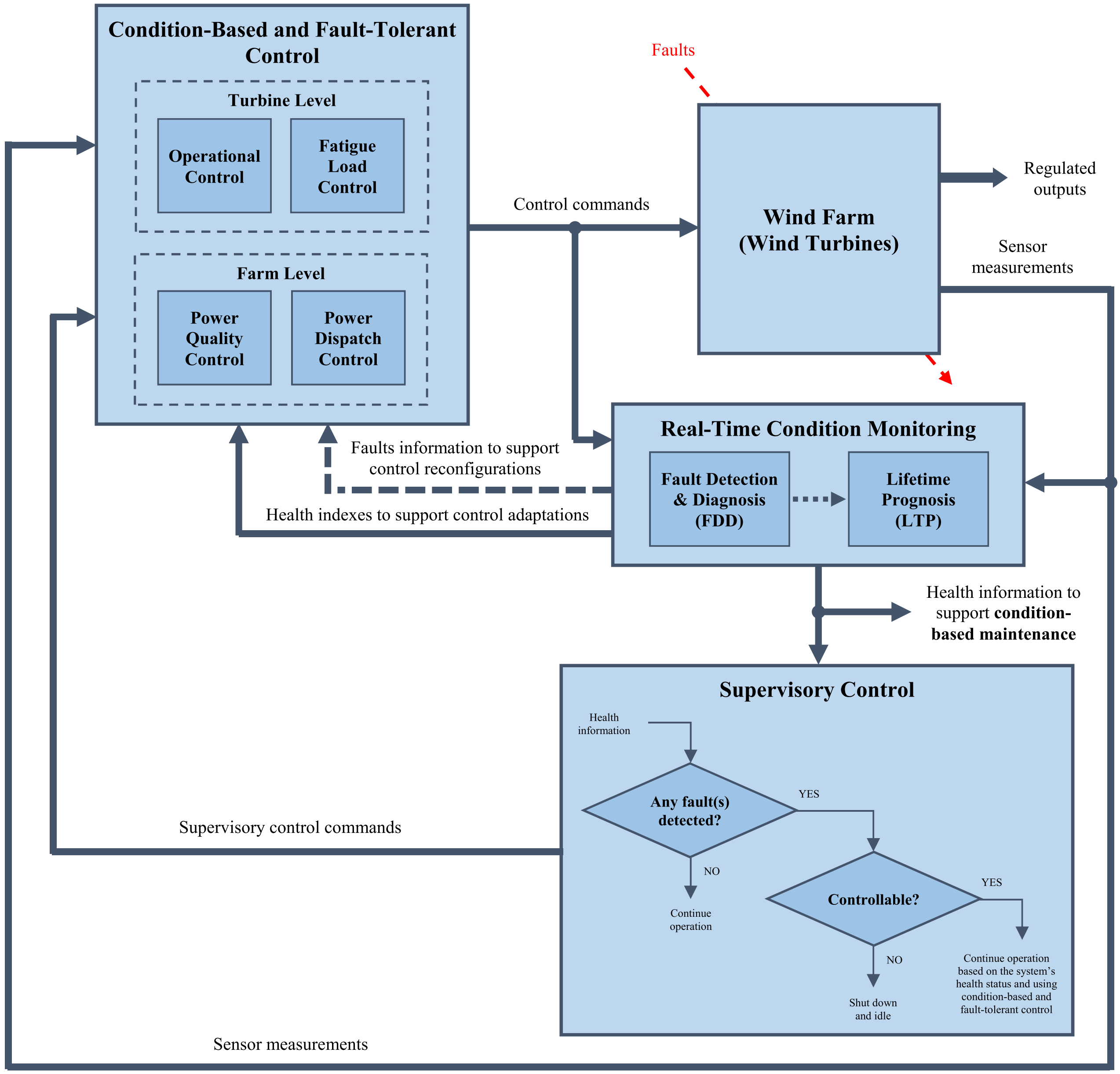


**Fig. 8.** *Schematic representation of an integrated health management scheme for wind turbines.*

but probably not for complete diagnosis, prognosis, and maintenance action, while the latter provides enough time not only for detection but also for effective diagnosis, prognosis, and successful maintenance action. The time period from fault detection to maintenance action is usually referred to as the "prognostic horizon." It is important to accomplish the FDD and LTP as effectively and automatically as possible to alleviate manpower and enable efficient condition-based maintenance. Fig. 13 exhibits the general maintenance objectives and a refined classification of the existing maintenance strategies, including condition-based maintenance. Compared with other maintenance strategies, condition-based maintenance reduces the number of maintenance visits and ensures that the overall maintenance is necessary and truly worthwhile. As a result, O&M costs decline in terms of labor, materials, and machine downtimes.

As aforementioned and shown in Fig. 13, CMS plays a key role in implementing condition-based maintenance. In recent years, efforts to develop efficient and cost-effective CMS for wind turbines have increased significantly. Several commercial systems for wind turbine monitoring, most of them developed based on existing techniques from other rotating machine industries, are already available on the market (for instance, see [23] and [58]). Also, many innovative projects and techniques have been introduced and are being explored in both academia (for instance, see [59] and [60]) and industry

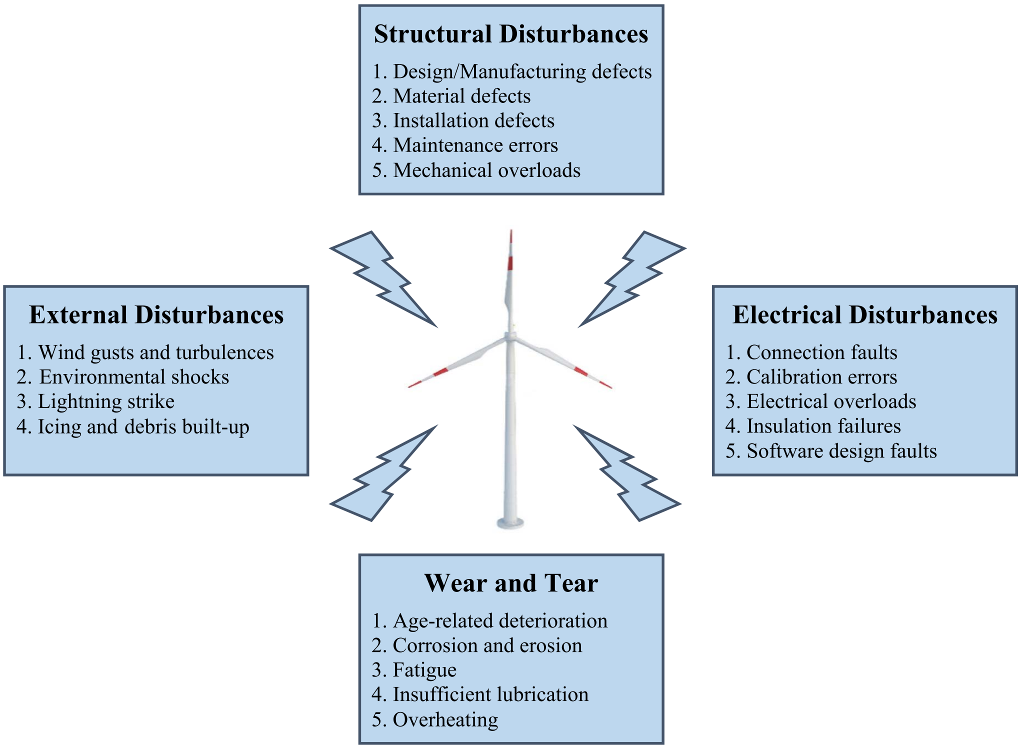


**Fig. 9.** ***Common root causes of faults and failures in wind turbines.***

(for instance, see [61] and [62]). In general, the monitoring techniques for wind turbines can be divided into two categories: 1) *offline* and 2) *online* (in real time). On the one hand, off-line techniques involve periodic inspections during which the machine needs to be shut down, and/or the attention of an operator is necessary. Although these techniques are suitable for the design and certification process of new wind turbines, they often require the attention of an operator and are unable to determine the real-time condition of a working wind turbine [12]. On the other hand, real-time condition monitoring based on online techniques is becoming increasingly important, especially for offshore wind farms where the inspection intervals are longer than those in onshore wind farms [13]. These online techniques continuously provide the real-time monitoring of a machine during its operation. They can automatically report continuous raw measurements and may even incorporate onboard models and/or signal processing functionalities for enhanced data reduction and analysis. Although there is no unified categorization of online techniques in the literature, they can generally be further categorized as: 1) *hardware signal-based techniques*; 2) *mathematical model-based techniques*; and 3) *hybrid techniques* that refer to any combinations or integrations of both hardware signal- and mathematical model-based techniques together.

Hardware signal-based techniques refer to any techniques utilizing the output signals from hardware sensors

| Less Severe | Severe | Most Severe |
|---|---|---|
| 1. Control malfunction due to faults in:<br>• Generator/Rotor speed sensor<br>• Pitch sensor<br>• Generator power sensor<br>• Wind speed/direction sensor<br>• Measurement cables/connections<br>2. Hydraulic system fault<br>3. Mechanical brake fault | 1. Shaft misalignment<br>2. Rotor blade misalignment<br>3. Cracks in rotor blades<br>4. Ice/Debris built-up on rotor blades<br>5. Hub spinning on shaft<br>6. Blade pitch system fault<br>7. Power converter fault<br>8. Yaw system fault<br>9. Power cable twist | 1. Rotor blade/hub catastrophic failure<br>2. Main shaft and coupling failure<br>3. Main-shaft bearing failure<br>4. Gearbox failure<br>5. Shaft-gearbox coupling failure<br>6. Generator failure<br>7. Electrical system failure<br>8. Premature brake activation<br>9. Metrological system failure<br>10. Tower/Foundation failure |

**Fig. 10.** ***Major faults and component failures in wind turbines.***

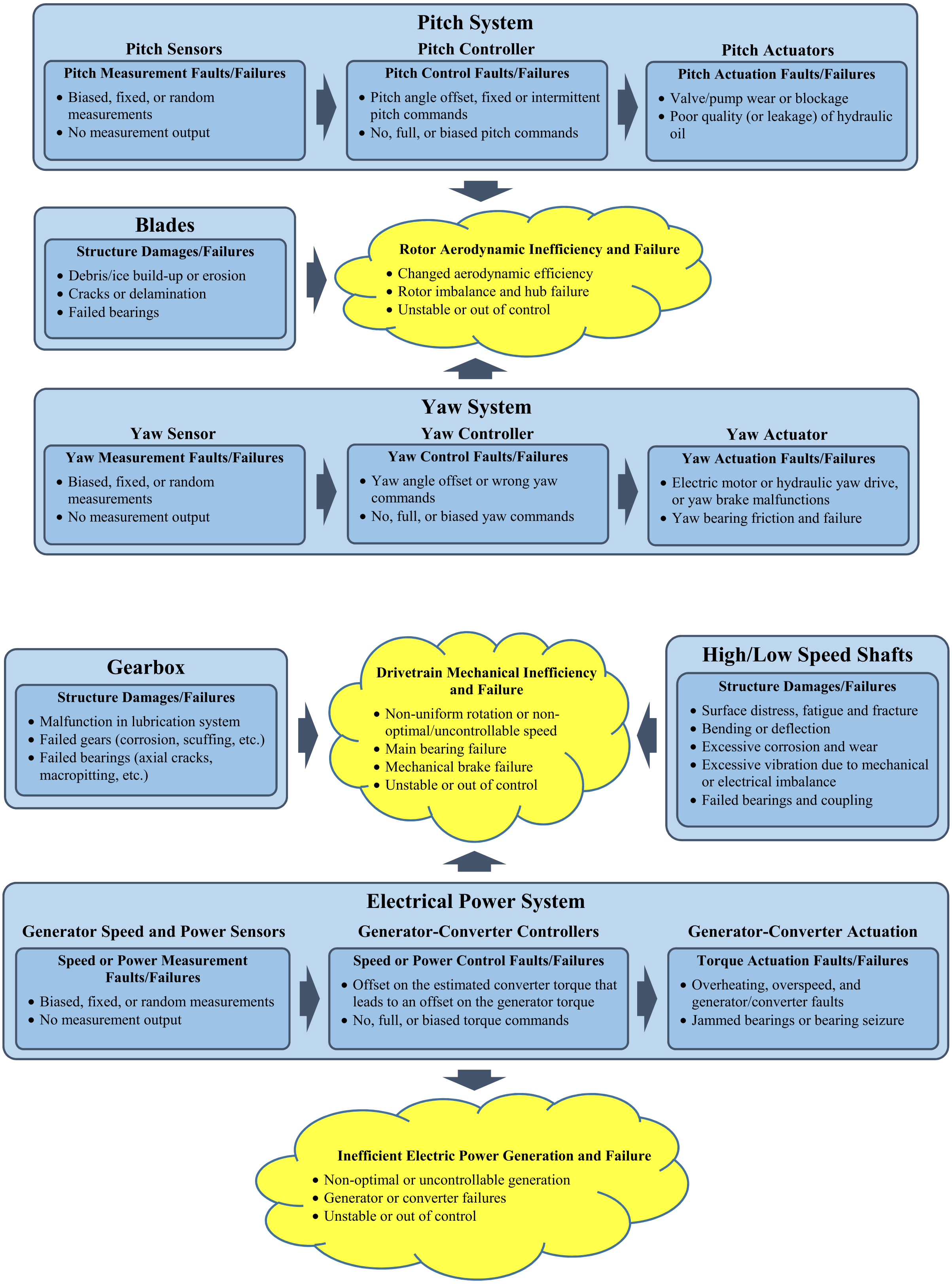


**Fig. 11.** ***Propagation of the fault/failure effects in wind turbine systems.***

in a wind turbine. These signals can come from either a "standard" supervisory control and data acquisition (SCADA) system or any "standalone condition-specific" sensing and data acquisition systems adopted to monitor the status of a specific condition variable (e.g., oil quality, vibration, and acoustic emission) using oil quality sensors,

**Table 3** Main Results and Conclusions of Reliability Studies on Wind Turbine Components

| Failure Rates | | Downtimes | | Top Contributors | | Reliability | |
|---|---|---|---|---|---|---|---|
| **Lowest** | **Highest** | **Lowest** | **Highest** | **Failure Rates** | **Downtimes** | **Least Reliable** | **Most Reliable** |
| Structure and drivetrain (shafts and bearings) | Electric system and control system | Structure and hydraulic system | Gearbox and rotor blades and hub | Electric system, control system, gearbox, rotor blades and hub, sensors, and pitch system | Gearbox, generator, braking system, electric system, rotor blades and hub, and drivetrain | Electric system, control system, gearbox, rotor blades and hub, and generator | Structure (foundation, tower and nacelle) |

**Important Findings**

- A wind turbine's reliability largely depends on the particular machine model/design, the technology and quality of manufacture, and the specific environment under which the machine operates.
- Higher mean wind speeds result in increased wind turbine failure rates.
- Larger and more flexible wind turbines (over 2.5 MW) tend to experience more failures and maintenance costs than small ones, mainly since most of larger machines employ new technologies with increased complexity in terms of operation and loadings.
- The average failure rates in offshore wind turbines is greater than that in onshore wind turbines, and the downtime per stop of an offshore wind turbine is approximately double that of an onshore wind turbine. The reason mainly relates to the harsh offshore conditions that bring about higher complexities and limited accessibility of offshore wind turbines.
- As offshore wind turbine technology has been directly derived from onshore technology, similar types of faults can be expected.
- Condition monitoring systems improve the reliability of wind turbines by enabling the detection, diagnosis and prognosis of faults at an early stage. This will eliminate or significantly reduce unplanned or unscheduled repair and maintenance costs.
- Identifying and ranking the reliability of components (across all technologies, sizes and locations) are the initial key steps of the effective design and development of condition monitoring solutions. Almost 90% of maintenance costs originate from the critical (less reliable) components.
- According to reliability studies, it is inferred that condition monitoring systems can rank and monitor the same components for both onshore and offshore wind turbines.

strain sensors, thermal sensors, infrared sensing devices, acoustic emission sensors, and so on. Therefore, signal-based techniques can be further categorized as: 1) *SCADA-* and 2) *condition-specific-based* techniques.

Mathematical model-based techniques employ the "mathematical models" of a wind turbine or its major components without requiring the high-resolution condition-specific signals used in signal-based techniques. Indeed, model-based techniques mainly require the mathematical models of the process and the input–output (I-O) information commonly available from a wind turbine and mainly related to the wind turbine's control system.

Conceived from the reviewed literature, Fig. 14 shows the important milestones in the evolution of the mentioned wind turbine condition monitoring techniques since 1990. In addition, Table 4 classifies a detailed list of fault and failure modes associated with wind turbine components and their relevant condition monitoring

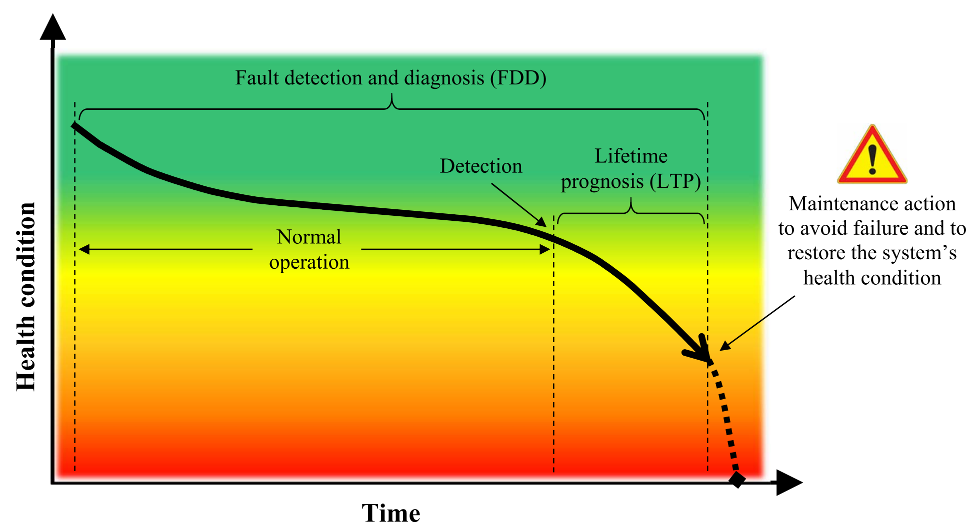


**Fig. 12.** ***Condition monitoring to enable condition-based maintenance.***

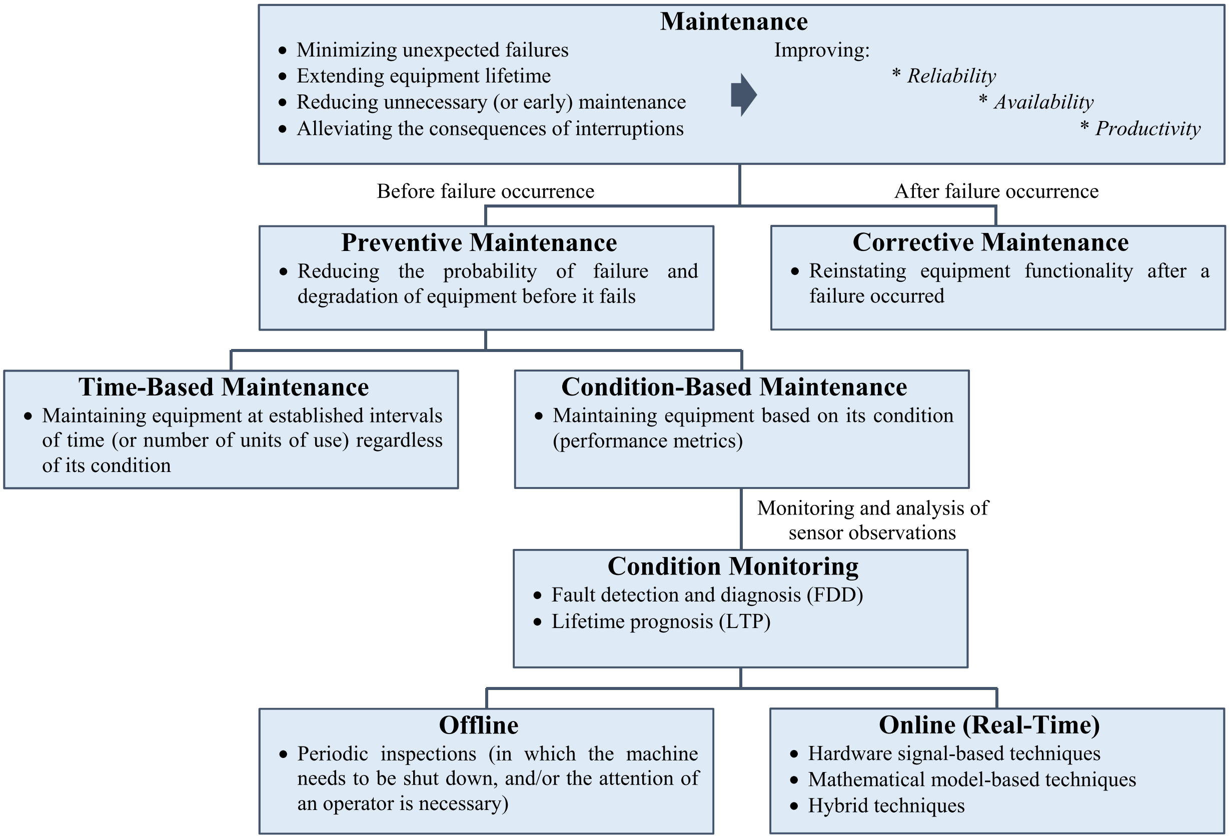


**Fig. 13.** ***Maintenance objectives and strategies.***

techniques. As observed in the table, although SCADA- and model-based techniques are potentially (or rather ideally) applicable to most wind turbine components, some other techniques, especially the condition-specific-based ones, can only be used for certain wind turbine components. Sections V and VI are devoted to the comprehensive review of each technique, individually.

## V. HARDWARE SIGNAL-BASED CONDITION MONITORING

As its name suggests, signal-based condition monitoring usually involves measurement signals and signal processing methods under a *data-driven approach* designed to obtain useful FDD and/or LTP information from a large amount of observed data. Data-driven approaches typically

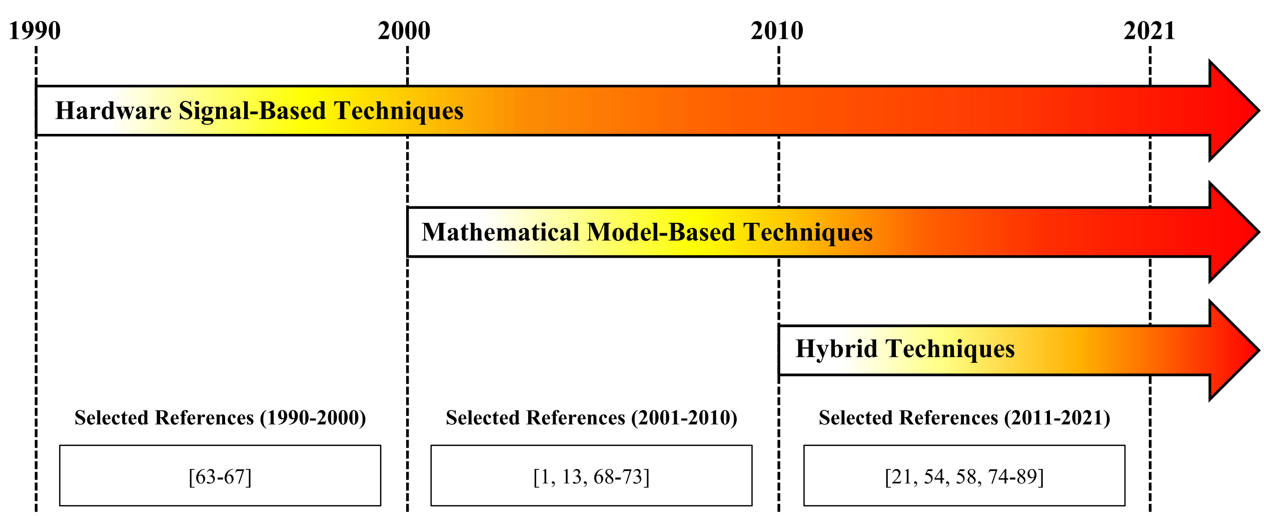


**Fig. 14.** ***Evolution and milestones of wind turbine condition monitoring techniques.***

**Table 4** Fault and Failure Modes of Components and Condition Monitoring Techniques

| Major Components | Fault and Failure Modes | Causes | Condition Monitoring Techniques | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Signal-Based | | | | | | | | | | | | | Model-Based |
| | | | SCADA-Based | Condition-Specific-Based | | | | | | | | | | | | |
| | | | | V | S | Tq | SP | AE | Tm | OP | EE | MV | U | Tg | R | |
| **Rotor** | Blade failure (fractures, cracks and delamination, debris build-up/erosion, failed bearings)<br>Hub failure (failed bolt and structure) and rotor imbalance<br>Pitch system failure (failed actuation, motor malfunction, failed bearings and gears) | Extreme loads/wind conditions, stress corrosion, harsh environmental conditions (icing, hail, dust…), impact by objects (e.g. birds), and lightning strikes<br>Pitch actuator overloading and excessive vibration, poor calibration and wrong pitch angle measurement (pitch sensor fault)<br>Manufacturing, installation and maintenance errors, and poor material quality | √ | √ | √ | √ | | √ | | | √ | √ | √ | √ | √ | √ |
| **Generator and Power Converter** | Overheating, fault, over-speed, jammed bearing, bearing seizure | Extreme loads, excessive vibration, no excitation, faulty cooling system, harsh environmental conditions, fatigue, mechanical failure, loss of drivetrain control<br>Manufacturing, installation and maintenance errors | √ | √ | | √ | | √ | √ | √ | √ | | | √ | | √ |
| **Drivetrain (including Gearbox)** | Gearbox failure (malfunction in lubrication system, failed bearings and gears)<br>Shafts failure (fatigue and fracture, surface distress, failed bearings and coupling)<br>Mechanical brake failure (low/high brake torque on high-speed shaft) | Misalignment and irregular grooving, welding defects and sudden shocks/loads above design limit<br>Poor lubrication, due to aged oil, lubricant contamination (presence of water or debris in the lubricant oil), and pump failure<br>Accelerated wear or excessive pressure on hydraulic lines<br>Manufacturing, installation and maintenance errors, and poor material quality | √ | √ | √ | √ | √ | √ | √ | √ | √ | | √ | √ | | √ |
| **Yaw System** | Increased bearing friction, motor malfunction and yaw angle offset, leakages of hydraulic system | Cracked roller, galled surface, poor lubrication and overheating, fittings issues, and sensor fault or misalignment<br>Manufacturing, installation and maintenance errors, and poor material quality | √ | √ | | | √ | √ | √ | √ | | √ | | √ | | √ |
| **Sensors, Actuators and Control System** | Faults or failures of sensors and actuators<br>Failed control and faulty control output | Design errors, short circuit, moisture penetration, harsh environmental conditions, and lightning strike | √ | | | √ | | | | | √ | | | | | √ |
| **Substructures (i.e., Nacelle, Tower, Foundation)** | Excessive corrosion, fatigue, fracture, deformation, buckling, displacement, broken bolted connections | Underestimation of environmental and operational conditions (e.g. extreme events, grid faults), excessive loading, buckling, and crack formation<br>Manufacturing, installation and maintenance errors, and poor material quality | √ | √ | √ | √ | | √ | √ | | √ | √ | √ | √ | √ | √ |

**Note: V:** Vibration; **S:** Strain; **Tq:** Torque; **SP:** Shock pulse; **AE:** Acoustic emission; **Tm:** Temperature; **OP:** Oil parameters; **EE:** Electrical effects; **MV:** Machine vision; **U:** Ultrasound; **Tg:** Thermography; and **R:** Radiography

rely on the *time domain*, the *frequency domain*, or the *time–frequency domain* data analyses to extract the fault-related *features* in the signals (observed data) and enable FDD or LTP without using a physics-based (or an explicit I-O) model. It is worth noting that, although a physics-based model is not used here, data-driven approaches may still

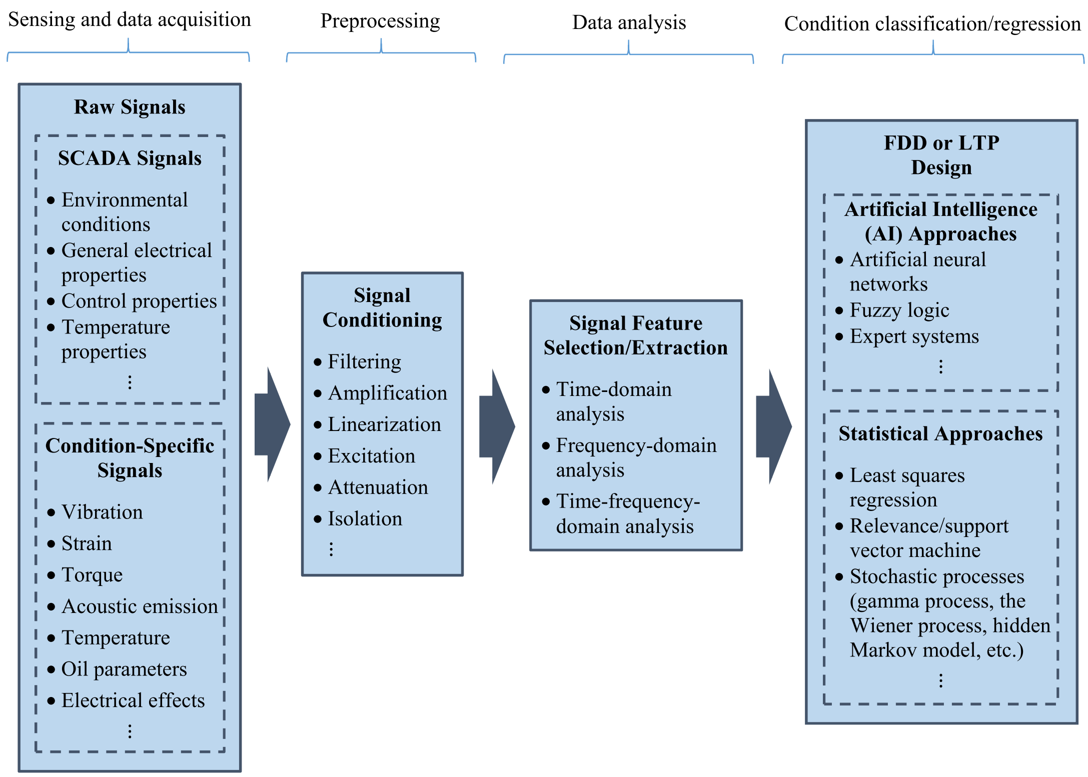


**Fig. 15.** ***Signal-based condition monitoring steps.***

use some sort of data-based models (in terms of mathematical functions/relations), which work only for a particular system under monitoring.

The major steps typically involved in the signal-based condition monitoring process and data-driven approaches are shown in Fig. 15. As seen in this figure, a set of (raw) signals is first obtained from either a standard SCADA system (i.e., the SCADA signals in Fig. 15) or other standalone condition-specific sensing and data acquisition systems (i.e., the condition-specific signals in Fig. 15). Typically, for data acquisition, the signals need to be simultaneously collected from several sensors installed at different locations and various wind turbine components. The collected signals are then preprocessed using appropriate methods for *signal conditioning*. Signals from multiple sensors and different sources are integrated (*sensor fusion*), and their features necessary to relate the process signals to the system conditions are generated. In most cases, *data analysis* using signal feature extraction/selection is needed to extract more useful (informative) features and reduce the dimensionality of data that are highly sensitive to the system's conditions (see Fig. 15). Often, choosing an optimal method for "feature extraction" is a challenging task that depends on the problem and classifier design. The main objective is to achieve independent and discriminative features. In general, the methods can be categorized into time, frequency, and time–frequency domains.

1) In time domain (time-domain analysis), the methods deal with extracting signal features directly from the time-domain representation of signals. These time-domain methods usually involve time-domain indices, such as peak level, variance, root mean squared (rms) value, shock pulse counting, kurtosis, crest factor, envelope analysis, time series averaging, and many more.
2) In the frequency domain (frequency-domain analysis), the methods focus on extracting signal features from the frequency-domain representation of signals, which is obtained from the Fourier analysis or fast Fourier transforms (FFTs). These frequency-domain methods usually involve frequency-domain indices, such as mean frequency, rms frequency, root variance frequency, spectral skewness, spectral kurtosis, spectral entropy, the Shannon entropy, and many more.
3) In the time–frequency domain (and the analysis of the same name), the methods deal with extracting signal features from the time–frequency domain representation of signals obtained from the mapping of 1-D time-domain signals to a 2-D function of time and frequency. The said mapping can be achieved using some common techniques, such as the short-time Fourier transform (STFT), the wavelet transform, and the Wigner–Ville distribution.

It should be noted that, due to their inherent dynamic nature, and particularly under the time-varying operating conditions, most of the signals encountered in engineering applications are nonstationary and vary over time. The time- or frequency-domain analysis alone is not ideal to deal with those nonstationary signals because they cannot reveal the important features in both time and frequency domains simultaneously. To overcome this problem, the joint time–frequency analysis is an effective solution, which has been used as the main feature extraction method in wind turbine CMS [44]. A detailed review of time–frequency analysis methods for signal feature extraction is presented in [90].

Beside feature extraction, another useful approach for feature dimensionality reduction (reduction of the number of features) is referred to as "feature selection." Unlike feature extraction that involves the transformation of features into a higher dimensional space, feature selection works by sorting out a subset of the existing features to remove those that are not relevant or that are redundant. Feature selection techniques are divided into three categories.

1) *Filters* that work by ranking the features according to some characteristics of the data, such as distance, correlation, information gain, and fisher score. The filter techniques are computationally efficient since they are independent of the classifier performance [91]. However, this results in a feature subset, which is not tuned to a specific type of classifier and usually gives lower prediction performance.
2) *Wrappers* that work by searching for a useful subset of the features according to a learning algorithm, which involves the classifier itself as part of the evaluation function. Compared to the filters, the wrapper techniques tend to perform better in selecting features. However, these techniques are computationally intensive, especially as the feature space grows [92].
3) *Embedded techniques* that are introduced to bridge the gap between the filter and wrapper techniques. They work by embedding feature selection with classifier construction to attain the benefits of wrappers (as they involve the interaction with the classification model) and filters (as they are computationally efficient) [93].

A comprehensive review of feature selection techniques in each of the abovementioned categories is presented in [94].

In continuation of the steps shown in Fig. 15, the signal features obtained from the process of data analysis are accordingly considered by the concluding process of *condition classification/regression*. In this process, the classification-based and/or regression-based data-driven approaches are used to predict a categorical variable (classification) or a numeric variable (regression), respectively. More precisely, a classification-based data-driven algorithm leads to a *mapping* (called classifier) from some input space (the space of feature values) to a discrete output in the form of *class labels*, while a regression-based data-driven algorithm results in a mapping (called regressor) from some input space to a continuous output in the form of *real numbers*. Indeed, the data-driven algorithm utilizes an adequate set of data to understand (learn) and evaluate the mapping relations between the input and output spaces. The set of data is representative of various operating conditions and is typically split into training (usually, about 65% of the data) and testing (usually, about 35% of the data) sets [44]. After parameter adjustment and learning from the training set, the performance of the resulting mapping relations should be evaluated using the testing set. In the case of classification, the performance is typically evaluated according to several measures, such as accuracy, sensitivity, specificity, and F1-measure. However, the evaluation measures for regression are different and may include measures, such as the mean absolute error, rms error, and r-squared. When a classifier or regressor is accurately trained and evaluated, it can be eventually used in the FDD or LTP process.

As seen in Fig. 15, for classification or regression purposes, there is a whole variety of algorithms in data-driven approaches that are generally included under two main categories: 1) *artificial intelligence* (AI) *algorithms* (e.g., artificial neural networks (ANNs), fuzzy logic, and expert systems) and 2) *statistical algorithms* (e.g., least-squares regression, relevance/support vector machine, and the stochastic processes, such as the gamma process, the Wiener process, and the hidden Markov model). Among these algorithms, the AI ones based on different types of ANNs have been widely used for both classification and regression in different fields and applications. Comprehensive reviews on various data-driven algorithms with general application to FDD and LTP can be found in [95] and [96], respectively.

Fig. 16 shows a typical schematic of a signal-based condition monitoring scheme but from a *machine learning* perspective. Indeed, a signal-based condition monitoring scheme can be designed using either a *machine-learning-based* approach (also known as a *knowledge-based* approach) or a simple *nonmachine-learning-based* approach. The nonmachine-learning-based approach only relies on a plant's measured outputs whose signal patterns under healthy conditions are "*a priori.*" Since the faults are reflected in the measured signals whose features are extracted, the fault diagnosis is simply carried out by checking the consistency between the known healthy signal pattern and the real-time signal pattern/feature of the plant, which is extracted from real-time monitored data by signal processing methods. However, the machine-learning-based approach deals with more complicated cases where a large amount of historical data (rather than *a priori* signal patterns) is available. In those cases, various AI algorithms are applied to the available historical data to extract patterns and the underlying knowledge of the plant (which implicitly represents the dependence of the plant's I-O variables). Finally, a diagnosis decision is made by checking the consistency between the obtained underlying knowledge base and the real-time signal pattern of the plant, which is extracted from real-time monitored data. It is important to note that the mentioned design approaches for signal-based

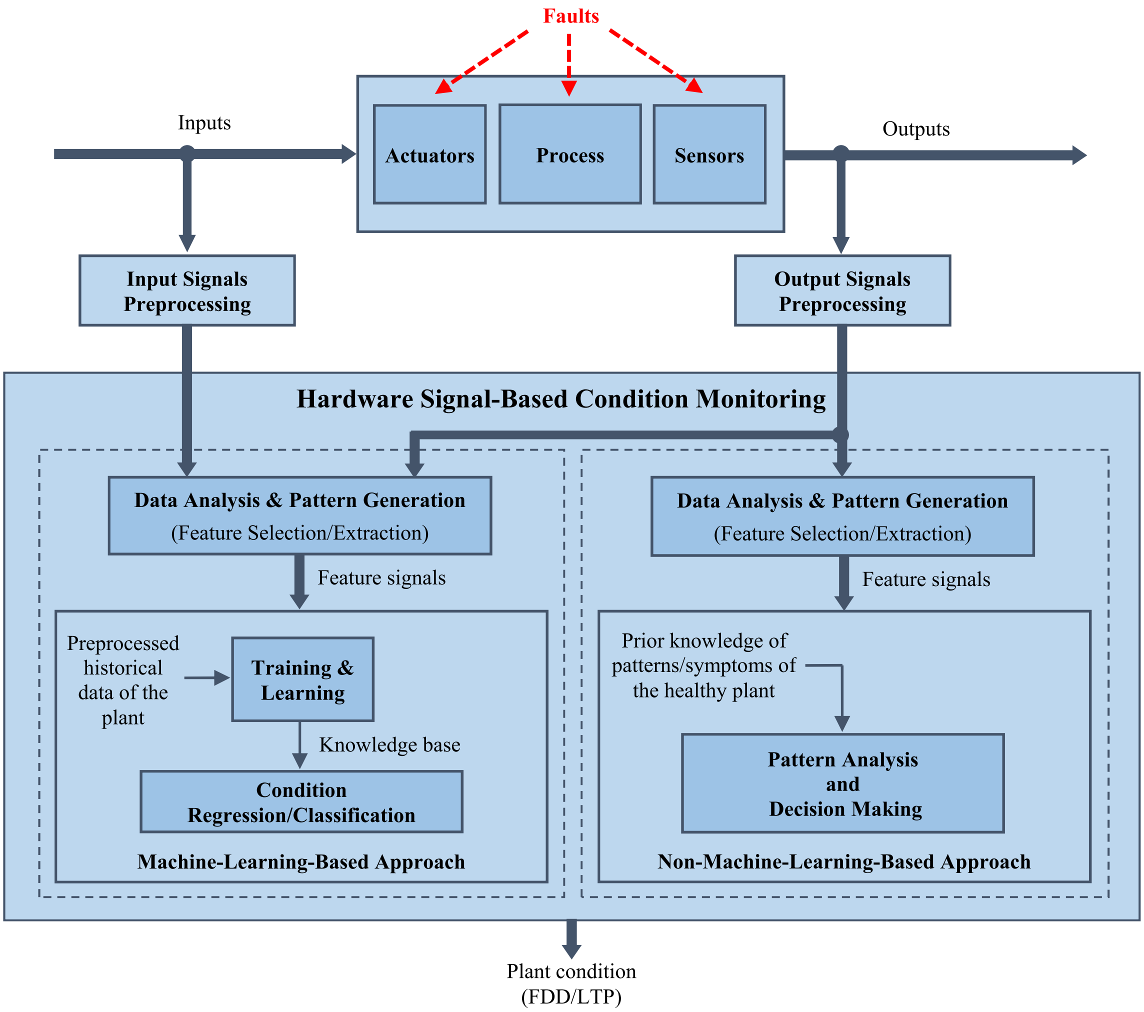


**Fig. 16.** ***Typical schematic of a signal-based condition monitoring scheme.***

condition monitoring can be appropriately applied for both FDD and LTP purposes according to similar principles but with different objectives and considerations. Indeed, to estimate the RUL under signal-based condition monitoring, LTP typically depends on the availability of the historical data, which captures the patterns of measured signals or extracted features from the equipment degradation process from incipient fault stage to failure. In other words, when a specific fault has occurred, the degradation trend of data can be classified under that specific fault, and the prognosis knowledge base can be trained to check the fault behavior patterns (as opposed to normal behavior patterns in FDD) and to estimate the RUL of a degrading plant or its components.

It is worth emphasizing that the schematic shown in Fig. 16 is for illustration purposes only. Depending on the specific requirements and circumstances of the problem addressed, the shown schematic may vary in some parts or steps (e.g., pattern recognition methods may act directly on the raw data without signal preprocessing and/or feature extraction).

With respect to the type of signals used in the signal-based condition monitoring of wind turbines, Sections V-A and V-B review the SCADA-based techniques and condition-specific-based techniques, respectively.

### A. SCADA-Based Techniques

All large utility-scale wind turbines use a SCADA system, mainly for monitoring the overall performance of wind turbines and their major components. A standard SCADA system provides an important source of information at both wind turbine and wind farm levels. This information includes operational and availability data (typically recorded at 10-min intervals), as well as instantaneous alarms data (whenever alarms or warning messages are generated). Although the exact information (and data configuration) obtainable from the SCADA system depends on the supplier, a list of signals typically recorded by such a system is given in Table 5 [23], [33], [79]. Note that several additional parameters, such as vibrations, oil pressure levels, and filter status, can also be recorded

**Table 5** Typical SCADA Signals for Wind Turbines

| Environmental Conditions | Electrical Properties | Control Properties |
|---|---|---|
| Ambient (outdoor) temperature | Active power output | Pitch angles of each blade |
| Wind direction | Reactive power | Yaw angle |
| Wind speed (measured at the top of nacelle (anemometer) and different heights of a metrological mast) | Power factor | Rotor speed (low-speed shaft) |
| | Generator currents (phases 1, 2, 3) | Generator speed (high-speed shaft) |
| | Generator voltages (phases 1, 2, 3) | Control set points/values |
| | Transmission-line frequency | Status messages/warnings and operational status code |
| | | Number of starts and stops |
| | **Temperature Properties** | |
| Nacelle (housing) temperature | High voltage transformer temperatures (phases 1, 2, and 3) | Gearbox bearing temperatures (for geared-drive machines) |
| Hub temperature | Inverter temperatures (generator side; phases 1, 2, and 3) | Gearbox oil temperature (for geared-drive machines) |
| Generator stator temperatures (phases 1, 2, and 3) | Inverter temperature (grid side) | Hydraulic oil temperature (used for pitching blades) |
| Generator bearing temperatures (gearbox end and transformer end) | Hub (pitch) controller temperature | Converter cooling water temperature |
| Generator slip ring temperature | Converter controller temperature | Converter choke coil temperature |
| Main shaft bearing temperature | Top (turbine) controller temperature | Grid busbar temperature |

by some up-to-date SCADA systems. However, in order to reduce the transmitted data bandwidth from a wind farm, the recorded data are generally 10-min averages of 1-Hz sampled values, while other forms, such as minimum, maximum, or standard deviation of live values recorded in a 10-min period, are also possible [97].

Despite the basic idea of using the SCADA system, rigorous analysis of SCADA data can potentially result in an efficient understanding of wind turbine's health condition. Indeed, using appropriate algorithms, the basic idea of "overall performance monitoring" by the SCADA system can be matured into efficient condition monitoring schemes with FDD and LTP capabilities for both rotating and nonrotating subassemblies of wind turbines. More precisely, "performance" is described in connection with the underlying process physics of a system—in this case, a wind turbine and its components. As wind turbine components deteriorate over time, the efficiency with which wind kinetic energy is converted to useful electrical energy decreases, and the performance of the wind turbine degrades. Therefore, the performance degradation can be a sign or symptom of many diverse problems in the wind turbine and its components, ranging from aerodynamic degradation of rotor blades (due to erosion, dirt, or ice buildup on blades) to any other component malfunctions due to faults, damages, or wear and tear.

Since condition monitoring of wind turbines using SCADA data is a potentially low-cost solution, requiring no additional sensors, several SCADA-based performance monitoring systems are already researched and developed in both academia and industry (for instance, see [19], [21], [33], and references therein). From a design viewpoint, a suitable performance parameter is first computed according to the measured SCADA signals [84]. This could be any performance-representative parameter or fault indicator chosen from raw sensor signals (or their features), sensor signals corrected for environmental conditions, component efficiencies or aerodynamic parameters, and so on. Then, using different methods, one or more such parameters are carefully considered to assess a wind turbine's condition and determine whether the wind turbine is behaving within its normal bounds. Several methods can be used for this purpose. Indeed, one of the first steps in the evolution of condition monitoring with SCADA data was based on simple *trending* methods, for instance, using regression lines in scatter diagrams of temperature versus power or 3-D visualizations, including the ambient temperature. Past studies involved such trending methods trying to detect faults or early signs of degradation (i.e., the evolution of damage) (e.g., see [98]–[100]). However, the main challenge lies in how to accurately interpret "trends" of SCADA parameters given the variability of the operating conditions of modern wind turbines, as a change in the value of a SCADA parameter is not necessarily evidence of a fault. Most studies have shown that automated online monitoring based on trending methods will most likely fall short of required accuracy since the problem is highly case-specific and usually requires an off-line visual interpretation of the trends. Such a problem can be very difficult to tackle, especially when dealing with monitoring a large farm of wind turbines that operate under very different conditions. To address this shortcoming of trending methods and as another step in the evolution of condition monitoring with SCADA data, *clustering* algorithms are introduced to automate the classification of "normal/healthy" and "faulty" observations (for instance, see [101]–[103]). Yet, according to the reviewed literature and compared with trending methods, the overall idea of clustering the observations does not exhibit a clear or noticeable advantage since the interpretation of results for condition monitoring is again difficult [33]. In addition, extensive historical fault data are required for training purposes—the data of faulty operation, which ideally include the full range of fault dynamics. However, it is not necessarily feasible to access such fault data in practice. To avoid such problems, more advanced methods, such as *normal behavior modeling* or *damage modeling,* are proposed in the literature. In normal behavior modeling methods, models of normal behavior, empirically "trained" on historical data (under normal conditions), are used to generate an error or residual signals with respect to the measured performance parameters. Accordingly, any serious deviations of the residuals (from the vicinity of zero) indicate the occurrence of faults or failures in a wind turbine component. For instance, SCADA data can be used to model and monitor the wind turbine "power curve" that relates the power output to the wind speed, thus giving an important measure of power generation performance by the wind turbine (e.g., see [104]–[107]). In addition, there are several other examples based on modeling approaches but for monitoring other wind turbine operational parameters (e.g., see [108]–[111]). From a design viewpoint, the normal model can be created based on either the Full Signal ReConstruction (FSRC) concept, for which only the signals other than those of a target parameter are used to predict the target, or AutoRegressive with eXogenous (ARX) input modeling, for which past values of the target are used as well. According to the reviewed literature, models created using polynomial equations, ANNs, adaptive neurofuzzy inference systems (ANFISs), or nonlinear state estimation techniques (NSETs) have demonstrated more satisfactory condition monitoring results [33]. However, there is no solid study comparing these modeling techniques in terms of their true value for the provided modeling accuracy in return for the imposed computational burden. This could help conclude which technique has superior performance over others for normal behavior modeling purposes. In addition, the majority of studies in this area are focused on modeling the normal behavior of "single-target" variables of interest. As a result, a growing number of models are developed to describe the normal behaviors of wind turbines' specific components (e.g., a normal model for the temperature behavior of the main bearing, a second model for the generated active power, and so on). In practice, one needs to both keep track of and maintain all of these models and to update them and/or their related threshold values when required, as the normal behavior may change over time due to sensor recalibrations, part replacements, software updates, and so on. Therefore, each additional normal behavior model further increases the burden for wind farm operators. To address this issue, multitarget normal behavior modeling approaches (such as the one recently proposed in [112]) can be considered. Such approaches enable, at once, simultaneous SCADA-based monitoring of multiple state variables using a single (multitarget) normal model. In contrast to the normal behavior modeling approach that presents a "black-box" solution with little or no insight into the physical processes that drive faults and failures, the damage modeling approach focuses on developing a damage model based on a physical understanding of one particular failure mode of interest. Thus, the latter approach can potentially better represent damage development and provide more accurate results. However, the development of reliable and sufficiently accurate damage models for all failure modes of a wind turbine will be very demanding. This is especially due to the lack of knowledge needed on the sufficiently large numbers of failures, which themselves can vary depending on the type, manufacturer, or location of wind turbines. Table 6 presents an updated summary of the literature produced on the so-called SCADA-based condition monitoring techniques.

In summary, motivated by the lower costs offered by the system not requiring additional hardware investment, a large number of studies in the literature have been devoted to SCADA-based condition monitoring in wind turbines. However, since not initially designed for condition monitoring purposes, the provided monitoring performance by SCADA-based CMS is limited, mainly due to the following concerns and shortcomings.

1) Although SCADA data provide relatively extensive information that can be useful to identify abnormal wind turbines in a wind farm, the data usually do not include all the necessary information for a full (detailed) condition monitoring of wind turbine subsystems and components.
2) The distribution of SCADA data is generally imbalanced, and the anomalous data mining is usually insufficient. This means that the amount of normal data is typically much higher than that of abnormal data, which might result in poor condition monitoring performance, since the data-driven models tend to be biased toward the majority class (i.e., normal data).
3) The sampling frequency of SCADA data is much slower than those required for some condition monitoring techniques.
4) Data quality is usually a concern. For instance, 10-min logs of SCADA data are commonly affected by problems such as "missing values," "NULL entries," or "zeros," "plausibility limits exceeded," "statistical outliers," "large blocks of identical values consecutively," "incorrect data format," and so on. Accordingly, any necessary corrections made to the data, such as those using linear or exponential interpolation, extreme values to limit value, or even removing the problematic channels of data, can decrease the required level of accuracy.
5) Given the variability in the operating conditions of modern wind turbines, rapid fluctuations of environmental conditions (wind speed/direction, air density, turbulence, and so on), and the low sampling frequency of typical SCADA systems, it is difficult to detect, diagnose and prognose incipient faults in a timely manner.

**Table 6** Summary of Existing Literature on SCADA-Based Wind Turbine Condition Monitoring

| Ref. No. | Author(s), Year | Focus of Monitoring | Brief Description of Major Contributions |
|---|---|---|---|
| [78] | Kusiak and Li, 2011 | Wind turbine power generation performance (power curves and status/fault codes) | Fault data provided by SCADA is explored through data-mining algorithms to achieve fault prediction (60 min before they occur) at three levels including i) fault/no-fault prediction, ii) fault severity, and iii) specific fault prediction. |
| [113] | Kusiak and Verma, 2011 | Pitch actuators | A data-mining prediction model is built to monitor the performance of blade pitch actuation against two actuator faults. Among five algorithms, the genetic programming resulted in the best results. |
| [81] | Gill et al., 2012 | Blades, yaw, and pitch actuators | Copula analysis is discussed and used for early recognition of incipient faults such as blade degradation, yaw and pitch errors. |
| [114] | Qiu et al., 2012 | Pitch actuators and converter system | Time-sequence and probability-based analysis methods applied to SCADA alarm data to rationalize and reduce the data and provide valuable fault detection, diagnosis, and prognosis information. |
| [115] | Kusiak and Verma, 2012 | Multiple components and operational parameters | A comparative analysis of various data-mining algorithms for constructing prediction models of wind turbine faults is reported. Among the studied algorithms, models derived by the random forest algorithm provided the best results. |
| [98] | Yang et al., 2013 | Blades and drivetrain | Data analysis is applied to process raw SCADA data and investigate the correlations among relevant data for the quantitative assessment of the health condition under both laboratory and site verifications. |
| [116] | Chen et al., 2013 | Pitch actuators | A fault prognosis approach, in terms of early fault detection rather than RUL prediction, is proposed using a-priori knowledge-based adaptive neuro-fuzzy inference system (APK-ANFIS). |
| [79, 80] | Schlechtingen et al., 2013 and 2014 | Multiple components and operational parameters | A two-part series of papers on methods and applications of adaptive neuro-fuzzy interference system (ANFIS) models combined with fuzzy-logic reasoning to the detection and diagnosis of faults. |
| [99] | Wilkinson et al., 2014 | Drivetrain | Three SCADA-based monitoring methods including signal trending, self-organising maps, and physical model are analyzed. The physical model is found to be the most reliable at predicting impending component failures. |
| [117] | Chen et al., 2015 | Pitch actuators | A priori knowledge-based adaptive neuro-fuzzy inference system is developed to achieve automated detection of significant pitch faults. |
| [118] | Papatheou et al., 2015 | Wind turbine power generation performance (power curves) | A machine-learning approach is applied to produce individual and population-based power curves and then predict the power output of each wind turbine. For monitoring, control charts with robust thresholds calculated from extreme value statistics are used. |
| [119] | Long et al., 2015 | Wind turbine power generation performance (power curves) | Multivariate and residual approaches are applied to monitor the variations of wind power curve profiles over time. |
| [120] | Qiu et al., 2016 | Drivetrain (gearbox and generator) | A thermophysics-based method is applied for drivetrain fault diagnosis. The method derives relationships between various SCADA signals and reveals variations in the wind turbine's thermophysics operation. |
| [121] | Sun et al., 2016 | Multiple components and operational parameters | Neural networks (NNs) are used to establish prediction models of the environmentally sensitive SCADA parameters. To improve the accuracy of anomaly identification, a fuzzy synthetic evaluation method is used. |
| [122] | Wang et al., 2017 | Gearbox | A deep neural network (DNN)-based framework is developed based on the lubricant pressure data. Results are compared with other data-mining algorithms (e.g., the k-nearest neighbors, ridge regression, and support vector machine (SVM)). |
| [123] | Zhao et al., 2017 | Generator | Using SCADA data and principal component analysis, an unsupervised learning method is proposed for the diagnosis and prognosis of wind turbine generators. |
| [108] | Chen et al., 2017 | Multiple components and operational parameters | A hierarchical method based on Gaussian process (GP) and principal component analysis (PCA) is applied for wind turbine diagnosis and prognosis. The method can provide several months ahead alarm before severe failure happens. |
| [124] | Hu et al., 2018 | Bearings (drivetrain) | A data-driven prognosis methodology based on statistical approaches and Wiener processes is presented to predict RUL of wind turbine bearings. |
| [125] | Morshedizadeh et al., 2018 | Power output | A combination of feature extraction, imputation, and dynamic multilayer perceptron (MLP) and adaptive neuro-fuzzy inference system (ANFIS) networks fusion approach is developed to predict future power performance of wind turbines. |
| [100] | Dao et al., 2018 | Multiple components and operational parameters | A methodology based on cointegration data analysis is proposed to analyze the nonlinear data trends, and continuously monitor for fault and/or abnormal conditions. |
| [104] | Hu et al., 2018 | Wind turbine power generation performance (power curves) | A confidence boundary modeling procedure is used to model power curve and to identify abnormal data while an evaluation system is constructed for adaptive modeling with guaranteed performance. |
| [105] | Pandit and Infield, 2018 | Wind turbine power generation performance (power curves) | A Gaussian process algorithm (a non-parametric machine learning approach) is applied for monitoring power curve to detect yaw misalignment fault which results in a loss of power generation. |
| [126] | Chen et al., 2019 | Blades | Data imbalance phenomenon is analyzed theoretically. An intelligent fault diagnosis technique is proposed based on exquisitely designed deep neural network (DNN). |
| [127] | Carroll et al., 2019 | Gearbox | Machine learning techniques and labelled data are used to predict failure and remaining useful life (RUL) of gearboxes. This is achieved using enough failure examples and data from one of the world's largest wind turbine operational and reliability databases. |

**Table 6** *(Continued.)* Summary of Existing Literature on SCADA-Based Wind Turbine Condition Monitoring

| | | | |
|---|---|---|---|
| [107] | Pandit et al., 2019 | Wind turbine power generation performance (power curves) | Three non-parametric approaches including Gaussian process (GP), random forest (RF), and support vector machine (SVM) are evaluated for power curve modelling and performance monitoring. |
| [128] | Gonzalez ET AL., 2019 | Wind turbine power generation performance (power curves) | A methodology using high-frequency SCADA data is proposed which features multivariate non-parametric methods for power curve modelling and monitoring. |
| [111] | Lebranchu et al., 2019 | Multiple components and temperatures | A multi-level (turbine and farm level) strategy combining a mono- and a multi-turbine approach is proposed to create fault indicators which are insensitive to both operating and environmental conditions. |
| [129] | Marugán and Márquez, 2019 | Multiple components and operational parameters | A correlation matrix (between SCADA variables) is used for pattern recognition, and a method based on curve fittings is applied for detecting false alarms and anomalies or faults in the wind turbine components. |
| [130] | Zhang and Lang, 2020 | Generator | A dynamic model sensor method is proposed for the SCADA-based wind turbine fault detection. |
| [106] | Guo and Infield, 2020 | Wind turbine power generation performance (power curves) | The drawbacks of the standard binned power curve modeling method are pointed out, and a multivariable power curve model is constructed using a modified Cholesky decomposition Gaussian process (GP). |
| [131] | Qiu et al., 2020 | Alarm data | Dempster-Shafer (D-S) evidence theory is applied for the fault diagnosis of wind turbine based on SCADA alarm data. |
| [132] | Ruiming et al., 2020 | Wind turbine output power | A multi-node network reflecting wind turbines' state is constructed based on digital twin theory and SCADA data. In addition, a dynamical network marker (DNM) is constructed for warning signal under wind turbine defects. |
| [109] | Pang et al., 2020 | Multiple components and operational parameters | A spatio-temporal fusion neural network (STFNN) is developed to automatically learn spatio-temporal dependency from the raw data and provide the fault diagnosis results. |
| [110] | Kong et al., 2020 | Multiple components and operational parameters | An approach based on fusing spatio-temporal features of SCADA data by convolutional neural network (CNN) and gated recurrent unit (GRU) is applied. |
| [133] | Renström et al., 2020 | Multiple components and operational parameters | Deep autoencoders are used to develop a single model which can detect anomalies or failures in multiple components. |
| [134] | Jin et al., 2021 | Generator | An ensemble approach is proposed. It uses historical healthy SCADA data of wind turbine generator to model the normal behavior and build a Mahalanobis space as a reference space to detect anomalies and diagnose faults in the generator. |
| [135] | Xiang et al., 2021 | Drivetrain (gearbox and generator) | An approach for fault detection is proposed, in which the CNN cascades to the long short-term memory network (LSTM) based on attention mechanism. |
| [136] | Liu et al., 2022 | Multiple components and operational parameters | An approach for fault detection and isolation is developed. A covariate-adjusted procedure is used to deal with working conditions of wind turbine. Accordingly, a global monitoring statistic is constructed based on SCADA temperature signals. |

Because of the abovementioned limitations, SCADA-based condition monitoring cannot currently replace a "professional" CMS, which is especially designed for condition monitoring purposes in wind turbines. As discussed in Section V-B, such a system employs additional hardware in the form of different standalone condition-specific sensing devices that are purposely dedicated to precisely monitor-specific condition variables, such as oil quality, vibration, and acoustic emission. Compared with SCADA systems, the measured signals are more precise and sampled at higher frequencies, which provide richer information, enabling greater insights into the wind turbine health condition. However, this comes with a higher cost, which depends on measurement accuracy, sampling frequency, system functionality, and application environment.

## B. Condition-Specific-Based Techniques

According to the additional hardware used in a professional CMS, a wide range of condition-specific signals is available for analysis. Table 7 provides a list of those signals and their related information, including the features of monitoring hardware, possible condition monitoring capabilities, and relevant components monitored in a wind turbine.

With respect to the condition-specific signals listed in Table 7, the following paragraphs briefly review the available literature for detection principles, development methods, pros and cons, and challenges and limitations of each technique.

*1) Vibration:* Many wind turbine components after being affected by faults or defects produce a new *vibration* behavior, which can be monitored using the signals obtained from vibration sensors. Thus, any abnormal variations in the measured vibration signals can indicate faults in a monitored component. For instance, in the case of moderate to high-speed bearings, each and every time a roller element passes over a defect, an impulse of vibration is generated, which can act as a fault indicator [29]. Also, the vibration signal's amplitude can indicate the fault's severity [28]. Indeed, appropriate signal processing methods can identify the fault frequencies and, accordingly, the location and type of fault [137].

Given the significance of vibration monitoring, most of the commercially available CMSs mainly rely on this type of monitoring using vibration sensors, often installed on the surfaces of rotor blades, and the casings of internal components, such as generator, gearbox, main shaft, and bearings. Depending on the frequency range and operating conditions of the monitored components, various types of vibration sensors are available, including: 1) displacement sensors in the low-frequency range; 2) velocity sensors in the middle-frequency range; 3) accelerometers in the

**Table 7** Comparison of Condition-Specific Signals for Professional CMS in Wind Turbines

| Signal | | Monitoring Hardware | | | Condition Monitoring Capabilities (FDD/LTP) | | | | Monitored Components |
|---|---|---|---|---|---|---|---|---|---|
| **Source** | **Name** | **Nature** | **Operation** | **Rel. Cost** | **Fault Detection** | **Fault Location** | **Fault Identification** | **Fault Prognosis** | |
| Process parameters monitoring | Vibration | Intrusive | Online | Low to medium | Yes | Yes | Yes | Yes | Rotor blades, generator, drivetrain (gearbox, bearings…), and tower |
| | Strain | Intrusive | Online | High | Yes | Yes | Yes | Yes | Rotor blades, tower, foundation, and drivetrain |
| | Torque | Intrusive | Online | High | Yes | Yes | Yes | Yes | Rotor, generator, drivetrain (gearbox, shaft…), and tower |
| | Shock pulse | Intrusive | Online | Low | Yes | Yes | No | No | Bearings (used in gearbox, yaw system or blades) |
| | Acoustic emission | Intrusive | Online | High | Yes | Yes | Yes | Yes | Rotor blades, generator, drivetrain (gearbox, bearings…), and tower |
| | Temperature | Intrusive | Online | Low to medium | Yes | Possible | No | No | Generator, converter, drivetrain (gearbox, bearings…), nacelle, and transformer |
| | Oil debris/quality parameters | Intrusive | Online /Offline | Medium to high | Yes | Possible | Possible | Possible | Generator and drivetrain (gearbox, bearings…) |
| | Electrical effects | Non-intrusive | Online | Low | Yes | Yes | Yes | Yes | Rotor, generator, converter, sensor, actuator, drivetrain (gearbox, bearings…), and tower |
| Non-destructive inspections | Machine vision | Non-intrusive | Online /Offline | Low to medium | Yes | Yes | Possible | No | Rotor blades, nacelle, tower, and foundation |
| | Ultrasound (ultrasonic scanning/readings) | Intrusive/Non-intrusive | Online /Offline | Medium to high | Yes | Yes | Yes | Possible | Rotor blades, nacelle, drivetrain, and tower |
| | Thermography | Non-intrusive | Online /Offline | High | Yes | Yes | Yes | Possible | Rotor blades, generator, converter, drivetrain (gearbox, bearings…), nacelle, and transformer |
| | Radiography (X-ray inspections) | Intrusive/Non-intrusive | Online /Offline | Medium to high | Yes | Yes | Yes | Possible | Rotor blades, nacelle, and tower |

**Note 1:** The provided information includes any technology readiness levels from R&D stage to already commercialized systems.
**Note 2:** Wind turbine's "bearings" refer to both transmission bearings (generator, gearbox, main bearings) and adjustment bearings (blade and yaw bearings).

high-frequency range; and 4) spectral emitted energy (SEE) sensors in very high frequencies (acoustic vibrations). Among them, accelerometers cover the widest working frequency range from 1 to 30 kHz, which makes them the most popular vibration sensors in the condition monitoring of wind turbines. In addition to the mentioned sensors, ground-based radar (GBR) is also used as a vibration-based noncontact remote sensor for structural condition monitoring of in-field wind turbine blades [138].

As listed in Table 7, the vibration signal-based technique is appropriate for monitoring the health condition of rotor blades, generator, gearbox, bearings, and other selected wind turbine components, such as a tower. Table 8 summarizes the advantages and disadvantages of this technology and provides a list of selected references categorized based upon the name of components being monitored by vibration in wind turbines. The main challenges of this technology relate to the complications that come with the components' different frequency ranges and the distinction of the acquired vibration signals generated by the faults from those caused by the environmental and operating conditions.

*2) Strain:* A wind turbine structure is made of materials that deform under applied loads. These structural deformations can be characterized by a dimensionless quantity known as *strain*. The measured strain signals can be effectively used to monitor structural health conditions against faults in the form of structural defects (e.g., blade icing and mass unbalance) or damages. Strain sensors are often mounted on the surface or embedded in the layers of a structure. Generally, there are two popular types of sensors for strain measurement: 1) traditional *electrical sensors* and 2) relatively modern *optical fiber sensors*. The electrical sensors include several types involving capacitance, inductance, semiconductor, or resistance. Among them, the *resistance strain gauge* is the most popular with a well-established mature technology. However, strain gauges can suffer from several issues, such as easy degradation and failure over long-term operations, and vulnerability to lightning strikes, electromagnetic interference, and variations in temperature, which necessitates careful compensations in the results [17], [46]. As modern alternatives based on fiber optics technology, optical fiber sensors are being developed [164]. Specifically, the so-called fiber Bragg gratings (FBGs) have become popular for offering high sensitivity through a direct physical correlation between wavelength and strain. They have long-term durability under hostile operating conditions and use nonelectrically conducting transmission lines, which ensures lightning safety and neutrality against electromagnetic interference [17], [165]. Having said that, FBG sensors are still expensive although efforts are made to make their application more cost-effective [15].

**Table 8** Vibration Signal-Based Condition Monitoring Technology

| Advantages | Disadvantages |
|---|---|
| • Good sensitivity with various types of vibration sensors<br>• Mature and standardized through years of application, especially for rotating equipment<br>• Possible for implementation in existing equipment<br>• Able to detect, isolate (locate) and diagnose/prognose faults, defects or damages | • Usually requires multiple intrusively mounted sensors on the surface or buried in the body of monitored components (wiring complications, increased complexity, etc.)<br>• Difficult to be accessed during wind turbine operation in case of sensor failure or system maintenance<br>• Inefficient to monitor low-frequency faults (low signal-to-noise ratio problem)<br>• Affected by variations in environmental conditions |

**References Based on Monitored Components**

| Ref. No. | Author(s), Year | Monitored Component(s) | Brief Description of Major Contributions |
|---|---|---|---|
| [139] | Zimroz et al., 2014 | Bearings (generator and gearbox) | An approach based on the analysis of online vibration data (root mean square and peak-to-peak features) and generator power is proposed for diagnosis. |
| [140] | Yang et al., 2016 | Bearings (generator and gearbox) | A de-noising and feature extraction approach based on empirical mode decomposition and correlation is presented, and a prototype system for vibration monitoring of bearings is developed. |
| [141] | Guo et al., 2017 | Bearings (generator) | Using vibration signals, a data-driven prognosis method based on a recurrent neural network is proposed for RUL prediction of bearings. |
| [142] | Teng et al., 2017 | Bearings (gearbox) | Signal processing and ANN methods are used to train data-driven models for vibration-based prognosis of bearings in a wind turbine gearbox. |
| [143] | Saidi et al., 2017 | Bearings (high-speed shaft) | A spectral kurtosis (SK) data-driven approach and a support vector regression (SVR) model are used to propose a vibration-based diagnosis and prognosis methodology for the wind turbine high-speed shaft bearing. |
| [144] | Ali et al., 2018 | Bearings (high-speed shaft) | An online data-driven approach based on unsupervised machine learning techniques is proposed to detect and diagnose high-speed shaft bearing faults. |
| [145] | Cao et al., 2018 | Bearings (generator) | A data-driven prognosis scheme, combining the interval whitenization with a Gaussian process algorithm, is developed to predict the bearings RUL. |
| [146] | Mauricio et al., 2019 | Bearings (gearbox) | Cyclo-stationary signal analysis is applied for vibration-based monitoring of rolling element bearings from their cyclo-stationary behavior. |
| [147] | Elasha et al., 2019 | Bearings (gearbox) | Two supervised machine-learning models (i.e., regression model and multilayer artificial neural network model) are developed for prognosis of an operational wind turbine gearbox using vibration measurements. |
| [148] | Inturi et al., 2019 | Bearings (gearbox) | Vibration, acoustic emission, and lubrication oil analyses are investigated by signal processing techniques, and an integrated condition monitoring scheme is developed for online diagnosis of bearing's outer/inner races faults. |
| [149] | Peeters et al., 2020 | Bearings and gear | A blind filter design approach based on envelope spectrum sparsity is applied for bearing and gear vibration-based condition monitoring. |
| [150] | Liu et al., 2020 | Bearings (blade pitch system) | An empirical wavelet thresholding method is applied to analyze noisy vibration signals and detect bearing faults in rotor-blade pitch systems. |
| [151] | Skrimpas et al., 2016 | Blades (structure) | Lateral vibration data from the nacelle and power performances analysis are used to detect icing (ice accretion) on wind turbine blades. |
| [152] | Joshuva and Sugumaran, 2017 | Blades (structure) | Machine learning algorithms (best-first tree and functional trees) are applied for vibration-based monitoring of rotor blades while considering crack, erosion, loose connection, pitch angle twist, and bend faults. |
| [153] | Tcherniak and Mølgaard, 2017 | Blades (structure) | An active vibration-based monitoring system using a semi-supervised learning algorithm is demonstrated on a Vestas V27 wind turbine for detecting blade damages such as cracks, edge opening, or delamination. |
| [154] | Moll et al., 2017 | Blades (structure) | Permanently installed radar sensors (with the frequency range of microwaves and millimeter-waves) are applied for remote/in-service blades monitoring. |
| [155] | Arnold et al., 2018 | Blades (structure) | A radar-based approach using a bistatic frequency-modulated continuous wave radar (33.4 to 36.0 GHz) is developed to monitor wind turbine blades, and a differential damage localization framework is presented. |
| [156] | Doliński et al., 2018 | Blades (structure) | An approach using finite element method and the laser scanning vibrometry is developed to diagnose delamination in laminated coatings of blades. |
| [157] | Oliveira et al., 2018 | Blades (structure) and foundation (onshore or offshore) | A vibration-based monitoring system based on the identification of the modal properties is developed, implemented, and validated for detecting damages in rotor blades as well as in onshore or offshore foundations. |
| [158] | Nguyen et al., 2018 | Tower (structure) | A vibration-based artificial neural network algorithm is designed for damage detection in a wind turbine tower. |
| [159] | Wang et al., 2020 | Tower (structure) | A comparative structural monitoring campaign adopting different tower vibration measurements (using contact and noncontact sensors) is performed. |
| [160] | Vamsi et al., 2019 | Gearbox (gears) | Signal processing techniques are used to investigate and compare the vibration, acoustic emission, and lubrication oil analyses to detect gearbox faults (tooth chip breakage and tooth root crack). |
| [161] | Teng et al., 2019 | Gearbox (planetary stage) | A vibration model and empirical wavelet transform are used for the fault diagnosis in the planetary stage of a wind turbine gearbox. |
| [162] | Elforjani, 2020 | Gearbox (gears) | Signal intensity estimator method and some machine learning algorithms are used to analyze vibration data for online diagnosis and prognosis of gears. |
| [163] | Pan et al., 2020 | Gearbox | Deep belief network, self-organizing map, and particle filtering are used to proposed a prognostic approach for the gearbox RUL prediction. |

As listed in Table 7, the strain signal-based technique is mainly appropriate for monitoring the health condition of wind turbine structures, including rotor blades, towers, and foundations. Table 9 summarizes the advantages and disadvantages of this technology and provides a list of selected references, which individually address

**Table 9** Strain Signal-Based Condition Monitoring Technology

| Advantages | Disadvantages |
|---|---|
| • Highly sensitive to minute structural changes (efficiency for incipient fault monitoring)<br>• Working at lower sampling rates compared with other techniques (e.g., vibration-, AE-, and electrical-signal-based techniques)<br>• No signal degradation with time or long transmitting distance (optical fibre sensors)<br>• No need for external power sources (optical fibre sensors)<br>• Able to detect, locate and diagnose structural defects/damages | • Always requires intrusively attached sensors to the materials being monitored (increased complexity, sensor-material separation under material deformations, etc.)<br>• Prone to failure due to sensor reliability concerns<br>• Requires initial knowledge of critical points and high-strain areas (sensor placement)<br>• Requires a large network of sensors as each sensor measures only at one local point (point strain)<br>• Relatively costly (especially using optical fibre sensors) |

**References**

| Ref. No. | Author(s), Year | Monitored Component(s) | Brief Description of Major Contributions |
|---|---|---|---|
| [166] | Yoon et al., 2015 | Gearbox | A strain analysis using a single piezoelectric strain sensor is used to diagnose gear faults on the sun gear, planetary gear, and ring gear of a planetary gearbox. |
| [167] | Wang et al., 2020 | Generator (shaft misalignment) | The potential of FBG frame strain sensing for detecting shaft misalignment in doubly fed induction generators (DFIGs) is investigated on a generator frame structure. |
| [168] | Yang et al., 2015 | Blades (structure) | Frequency response transmissibility analysis is applied to detect and locate damages in rotor blades when either FBG strain sensors or accelerometers are used for data acquisition. |
| [169] | Tian et al., 2015 | Blades (structure) | A methodology based on feature information fusion (FIF) is proposed to fuse the information of Chi-square distribution from FBG strain sensors and detect the blade damages. |
| [170] | Wu et al., 2015 | Blades (structure) | A large networks of flexible capacitive strain gauges are deployed to reconstruct a 2-dimensional surface strain map and deflection shapes of the surface for online condition monitoring. |
| [171] | Sierra-Pérez et al., 2016 | Blades (structure) | Real-time strain measurement and hierarchical nonlinear principal component analysis (h-NLPCA) are used to detect defects and nonlinearities in rotor blades during the certification testing of the blades, avoiding the premature failure of the structure. |
| [172] | Laflamme et al., 2016 | Blades (structure) | A novel strain sensing solution (based on a low-cost soft elastomeric capacitor technology) is employed, and its potential for blade damage detection, localization, and prognosis is demonstrated. |
| [173] | Downey et al., 2017 | Blades (structure) | An experimental study is performed for a hybrid dense strain sensor network (using soft elastomeric capacitor technology) and associated algorithms to detect, locate, and identify blade damages. |
| [174] | Lee et al., 2017 | Blades (structure) | Including a strain-based deflection estimation algorithm and a wireless sensor network, a deflection monitoring system that can be installed to already operating wind turbine blades is proposed. |
| [175] | Ovenden et al., 2019 | Blades (structure and misalignment) | The application of a laser displacement sensor (inside the tower) and a half-bridge type II strain gauge bridge (at the blade root) is investigated for the detection of blade icing, misalignment or bolt loosening. |
| [176] | Wen et al., 2020 | Blades (loading) | The feasibility of detecting blade loads using a sensing system based on FBG strain sensors and a fiber optical rotary joint (FORJ) is investigated for a floating wind turbine in wave basin tests. |
| [177] | Pacheco et al., 2020 | Blades and tower (loads) | An experimental structural monitoring campaign adopting strain gauges, clinometers, and accelerometers (distributed in the tower and blades) is performed at an onshore wind farm, called Tocha located in Portugal. |
| [178] | Soman et al., 2015 | Tower | A decision level data fusion method based on bi-axial neutral axis tracking is proposed to detect tower damages. To allow data fusion from the strain sensors and yaw mechanism, a discrete Kalman filter is used. |
| [179] | Bai et al., 2017 | Foundation (onshore) | A combination of two monitoring approaches (strain monitoring and ultrasonic testing) is proposed to detect and locate foundations defects in onshore wind turbine. |
| [180] | Perry et al., 2017 | Foundation (onshore) | The design, fabrication and field installation of subterranean FBG strain sensors meant to monitor the opening and lateral displacements of foundation cracks during wind turbine operation are outlined. |
| [181] | Mieloszyk et al., 2017 | Foundation (offshore support structure) | The application of strain sensors to structural monitoring of offshore wind turbine support structure (tripod) is experimentally investigated under environmental loadings. |
| [182] | Rubert et al., 2018 | Foundation (onshore) | A real-time strain monitoring campaign (including sensors design, characterisation and installation) is outlined for an operating wind turbine foundation. |
| [183] | Soman et al., 2018 | Foundation (offshore support structure) | A two-step methodology using strain measurements is presented for the damage detection and isolation in an offshore support structure accompanied by experimental results on a scaled tripod model. |
| [184] | He et al., 2019 | Foundation (onshore) | A strain monitoring system is employed to develop a real-time relationship between the behaviour of local concrete deformation and the characteristics of loads exerted on the wind turbine foundation. |

the monitoring of a specific component by strain in wind turbines. The main challenges of this technology relate to the need for a large number of sensors (as each sensor can measure at one local point) and enough initial knowledge of critical points and high-strain areas for effective sensor placement.

**Table 10** Torque Signal-Based Condition Monitoring Technology

| Advantages | Disadvantages |
|---|---|
| • Highly sensitive<br>• Possibility of using torque estimates in generator without torque sensors (transducers)<br>• Able to detect, isolate (locate) and diagnose faults and defects | • Usually requires additional space and intrusive installation of sensors (transducers) on the components being monitored (increased weight, complexity, etc.)<br>• Prone to failure due to sensor reliability concerns<br>• Relatively high cost when using torque sensors (transducers)<br>• Affected by variations in temperature |

**References**

| Ref. No. | Author(s), Year | Monitored Component(s) | Brief Description of Major Contributions |
|---|---|---|---|
| [185] | Djurović et al., 2014 | Generator | Shaft torque and frame vibration signals from a wound rotor induction generator are investigated for the detection of generator electrical faults. |
| [186] | Zappalá et al., 2019 | Generator | A harmonic time-stepped generator model is applied to analyze a wound rotor induction generator's electrical/mechanical signals (current, power, speed, mechanical torque and vibration measurements) for fault detection. |
| [187] | Perišić et al., 2015 | Drivetrain (shaft) | A multiple-model monitoring approach based on a set of different Kalman filters is designed for shaft torque estimation from measurements of generator torque and angular speeds of high-speed and low-speed shafts. |
| [188] | Zhang et al., 2018 | Drivetrain (shaft) | Two different methods of mechanical torque measurement and monitoring in wind turbine drivetrains are presented and analyzed taking into account their technical and economic feasibilities. |
| [189] | Zappalá et al., 2018 | Drivetrain (shaft) | A novel, contactless torque measurement system consisting of two shaft-mounted zebra tapes and two optical sensors mounted on stationary rigid supports is presented for rotating shafts in wind turbines. |
| [190] | Zappalá et al., 2019 | Drivetrain (shaft) | An experimental set-up is presented for the investigation of shaft dynamic transient loads through a contactless, low-cost torque meter designed by the authors for wind turbine performance monitoring/control purposes. |
| [191] | Zhang et al., 2020 | Drivetrain (shaft) | An enhanced transient feature selective validation (FSV) approach is used to validate a non-contact real-time torque measurement technique in wind turbine monitoring. |

*3) Torque:* Torque (also known as moment or moment of force) is the tendency of a force to cause an object to rotate around an axis or other point. It is a vector quantity with both a direction and a magnitude. The faults and defects in mechanical components usually leave signatures in measured torque signals. Thus, it is possible to detect and diagnose these faults and defects by monitoring the torque signals obtained from wind turbine components. For instance, malfunctions such as rotor imbalance and aerodynamic asymmetries can be diagnosed by analyzing the torque experienced by a wind turbine's tower [70]. Likewise, gear defects, especially for the low-speed gear in a gearbox, can be diagnosed using the envelope spectrum of the torque measurements in the gearbox [83].

A torque sensor is indeed a *transducer* that converts a torsional mechanical force into an electrical signal. Generally, there are two major types of torque sensors that can be installed on the components being monitored, such as rotor blades, gearbox, generator, and tower. The mentioned sensors include *rotary torque sensors* for measurement of rotational torque (when there is an axle or pivot to be turned around) and *reaction torque sensors* for measurement of bending moment (when there is an element to be bent). In the case of a generator, the torque can be also estimated based on the generator speed and electrical outputs without using torque transducers.

As listed in Table 7, the torque signal-based technique is available for monitoring the health condition of wind turbine components, including rotor, generator, drivetrain (gearbox, shaft, and so on), and tower. Table 10 summarizes the advantages and disadvantages of this technology and provides a list of selected references categorized based on the name of components being torque-monitored in wind turbines. This technology usually requires more complicated signal processing algorithms because of torque signal modulation problems with dominant components related to the load. Having said that, the main challenges still relate to the high cost and installation complexities of torque transducers, especially for new wind turbines with more compact designs.

*4) Shock Pulse:* Shock pulse monitoring, referred to as shock pulse method (SPM) technology, was first introduced in 1969 to determine the condition of rolling element bearings or any piece of machinery with continuous metal-to-metal contact, which gives off *shock pulse* signals [192]. In simple terms, at the instantaneous moment of mechanical impact between two masses, the molecular contact happens, and a compression (shock) wave/pulse develops in each mass. In a bearing (whether new or old), the mechanical impacts happen during the rotation of the bearing and due to its natural surface roughness or surface defects/damages. These mechanical impacts generate shock pulses in the interface between the loaded roller element and the race way, which, in turn, results in the bearing acting as a "*shock pulse generator*." The magnitude of shock pulses depends on the bearing's surface condition (i.e., roughness, stress, damages, and oil film thickness) and its peripheral velocity (i.e., rotational speed, size, and so on). These shock pulses have an ultrasonic frequency band and typically occur around a center frequency of 32 kHz [29].

In SPM, shock pulses are measured using specially designed piezoelectric accelerometers equipped with filters for reducing the influence of environmental factors, such

**Table 11** Shock Pulse Signal-Based Condition Monitoring Technology

| Advantages | | | Disadvantages |
|---|---|---|---|
| • Sensitive and simple to use with no need for advanced signal processing<br>• Straightforward display of results in Green/Yellow/Red scales<br>• Precision analysis of bearing lubrication condition (i.e., the lubricating oil film in the interface between the bearing's outer and inner races)<br>• Able to detect and isolate (locate) mechanical faults, defects or damages | | | • Usually requires the presence of a semiskilled personnel to conduct the monitoring in real time and interpret the results<br>• Fleet-level implementation might become complicated and expensive<br>• Direct demodulation may mistakenly estimate the shock pulse value<br>• Monitoring and detecting faults/damages might be less accurate at low speeds<br>• Unknown prognosis capabilities and limited published literature in general due to the proprietary technology nature |
| **References Based on Monitored Components** | | | |
| **Ref. No.** | **Author(s), Year** | **Monitored Component(s)** | **Brief Description of Major Contributions** |
| [194] | Zhang et al., 2014 | Bearings (gearbox) | Applied to bearings diagnosis, the effects of wind turbine's gearbox operating conditions on the shock pulse technique is analyzed through comparing the slope of dB values when the rotating speed or load changes. |
| [195] | Yang et al., 2014 | Bearings (gearbox) | Shock pulse signal-based technique is used to monitor several planetary gearbox bearings and detect/locate bearing faults through analyzing the signals' frequency spectrum. |
| [196] | Yang and Kang, 2016 | Bearings (gearbox) | Vibration and shock pulse signal-based techniques are used for the detection of bearings faults in a wind turbine gearbox. The obtained results indicate the superior monitoring performance of shock pulse technique. |
| [197] | Abouel-seoud, 2017 | Gearbox | Frequency spectrum analysis is applied to the shock pulse signals obtained from a gearbox testbed to detect gearbox component faults including the cracked planet gear tooth/carrier and the cracked main bearing inner race. |

as background vibration and noise. Such accelerometers are tuned mechanically and electrically to a resonant frequency of 32 kHz [192]. The measured shock pulses are typically recorded per second, and two amplitude levels are extracted: 1) the *decibel carpet* value of 200 shock pulses per second and 2) the *peak* value of incoming shock pulse under 2 s. The decibel carpet value provides an indication of the lubrication condition, and the peak value provides the extent of bearing damage. Indeed, the measured shock pulse amplitudes are subtracted from the expected shock values in a healthy bearing at a similar speed. Accordingly, an indication of the bearing health condition is obtained. Typically, there are three condition regions/scales, namely, "Green" for good condition, "Yellow" for warning, and "Red" for damaged condition. This provides the operator with the status information of the machine and the zone it belongs to.

As listed in Table 7, the shock pulse signal-based technique is mainly applied for the condition monitoring of wind turbine bearings used in the gearbox, yaw system, or blades. Unlike other alternative techniques, such as vibration analysis, SPM can uniquely analyze and display the state of bearing lubrication and bearing mechanical condition without needing baseline data development for trending [192], [193]. Also, this technology can isolate (locate) the faults/damages since the damaged bearings generate shock pulses with a pattern that corresponds to the frequency of the balls passing over the damaged part. Table 11 summarizes the advantages and disadvantages of SPM as referenced in a selected list of studies focusing on its implementation in wind turbines. Although the commercial SPM instrument is typically hand-held and simple to use in real time, the presence of semiskilled personnel for holding the device and pressing the sensor to the bearing cover with the probe is necessary. Therefore, the fleet-level implementation of this technology might become complicated and expensive compared with vibration monitoring. Finally, as a result of the technology's proprietary nature, the published literature on this subject, especially for wind turbines, is scarce, and there is almost no evidence of prognosis capabilities for SPM [29].

*5) Acoustic Emission: Acoustic emission* is a transient impulse caused by a rapid release of strain energy in the form of transient elastic waves within a solid material when it undergoes stress/strain conditions through mechanical or thermal loadings. According to this phenomenon, any alterations in a structure excite acoustic emission signals, which may be monitored by appropriate sensors. Indeed, the information about the occurrence and propagation of surface or subsurface structure damages can be extracted using the signals' waveform characteristics, such as acoustic energy, rise time, duration, amplitude, kurtosis, and rms values [17], [46], [198], [199].

Basically, acoustic emission monitoring is very similar to vibration monitoring in terms of the nature of the collected data, which, for both, originates from the alterations in a material structure. Indeed, the former employs acoustic sensors to "listens" to the material alterations using sound level meters, while the latter associates such alterations to the material vibrations measured using the vibration sensors [1], [30]. In contrast to the vibration sensors that are rigidly mounted to the monitored components, the acoustic sensors are flexibly attached to the components using a viscous couplant (i.e., a coupling medium, such as silicone grease or adhesive) and a mechanical clamp offering a constant coupling pressure [30], [200]. To widely monitor the whole structure and identify the location of a damage or fault, multiple acoustic emission sensors (i.e., sensor arrays) are required. The frequency of acoustic emission signals typically lies between 100 kHz and 1 MHz recorded by a wide range of sensor types, such as piezoelectric, resonant, or wideband transducers [200], [201].

**Table 12** Acoustic Emission Signal-Based Condition Monitoring Technology

| Advantages | Disadvantages |
|---|---|
| • Highly sensitive<br>• Having a large frequency range with a relatively high signal-to-noise ratio<br>• Able to detect, isolate (locate) and diagnose/prognose faults, defects or damages at an early stage (especially the incipient ones) | • Requires multiple intrusively attached sensors on the surface of monitored components (wiring complications, increased complexity, etc.)<br>• Difficult to be accessed during wind turbine operation in case of sensor failure or system maintenance<br>• Inevitable attenuation of signal during propagation and the necessity to install the sensor as close to its source as possible<br>• Complicated signal processing due to high sampling frequencies and noisy background environments<br>• Possibly affected by variations in environmental conditions<br>• Costly and requires sensor calibration and maintenance to provide reliable measurements over time |

**References**

| Ref. No. | Author(s), Year | Monitored Component(s) | Brief Description of Major Contributions |
|---|---|---|---|
| [202] | Papasalouros et al., 2013 | Blades (structure) | Instrumentation, data processing and other technical apparatus related to the acoustic-based remote monitoring of composite blades of NM48/750 NEG-MICON wind turbine are investigated and discussed. |
| [203] | Han ET AL., 2013 | Blades (structure) | Acoustic emission technique along with a new source location method and energy-based contour mapping is used for damage assessment in wind turbine blades under static loads. |
| [204] | Zarouchas and Hemelrijck, 2014 | Blades (structure) | Acoustic emission and a frequency-based methodology is applied for the identification of damage mechanisms, and digital image correlation is used to measure displacements and deformations of wind turbine blades. |
| [205] | Bouzid et al., 2015 | Blades (structure) | An in situ wireless monitoring system based on acoustic emission and wireless technology is proposed and tested for wind turbine blades. |
| [206] | Tsopelas et al., 2015 | Blades (structure) | The application, recent developments, and summarized results of acoustic emission technique for real-time condition monitoring of wind turbine blades are presented. |
| [207] | Tang et al., 2016 | Blades (structure) | The feasibility of in-service monitoring of fatigue damage growth in wind turbine blades is experimentally studied and analyzed using the acoustic emission technique. |
| [208] | Gómez Muñoz and García Márquez, 2016 | Blades (structure) | A signal processing approach is applied to the acoustic emission signals measured by macro-fiber composite sensors to detect and locate the fiber breakage damages in wind turbine blades. |
| [209] | Bo et al., 2017 | Blades (structure) | The correlation between fatigue conditions and the recorded acoustic emission signals is obtained using the blind deconvolution separation method which allows fatigue crack identification in wind turbine blades. |
| [210] | Tang et al., 2017 | Blades (structure) | An unsupervised pattern recognition approach using acoustic emission data measured by internally mounted piezoelectric sensors is presented to classify different damage mechanisms for a long wind turbine blade. |
| [211] | Liu et al., 2019 | Blades (structure) | Machine learning and acoustic emission technique are experimentally investigated for damage mode identification of a 59.5-meter-long composite wind turbine blade under accelerated fatigue loads. |
| [212] | Xu et al., 2020 | Blades (structure) | Acoustic emission technique and clustering analysis by fast search and find of density peaks (CFSFDP) method are used to achieve damage mode identification of adhesive composite joints for wind turbine blades. |
| [213] | Mollasalehi et al., 2017 | Bearings (generator) | Acoustic emission and vibration signals measured at the bottom of a wind turbine tower are analyzed and the presence of generator bearing fault signatures in the monitored tower signals is shown and diagnosed. |
| [214] | Liu et al., 2020 | Bearings (blades) | Acoustic emission and signal processing techniques are used to propose a monitoring methodology for the detection of faults in slow-speed wind turbine blade bearings. |
| [215] | Liu et al., 2021 | Bearings (blades) | A diagnostic framework is proposed based on a general linear and nonlinear auto-regressive model and the sparse augmented Lagrangian algorithm. |
| [216] | Qu et al., 2013 | Gearbox | A heterodyne-based frequency reduction method with time synchronous averaging and spectrum kurtosis are used to analyze acoustic emission signals and to extract fault indicator features for gear fault detection. |
| [217] | Ferrando Chacon et al., 2016 | Gearbox | An experimental study is presented on the application of acoustic emission technique and envelope analysis to the wind turbine gearbox diagnosis. |
| [218] | Zhang et al., 2017 | Gearbox | A methodology based on continuous wavelet transform, which allows to obtain the precise time of arrival of acoustic emission signals, is proposed to detect and locate the faulty planet gear in a wind turbine gearbox. |
| [219] | Leaman et al., 2019 | Gearbox | Aimed at locating acoustic emission sources in ring gears from planetary gearboxes, an easy-to-use methodology is proposed and tested in two different real-sized wind turbine gearboxes. |
| [220] | Tziavos et al., 2020 | Offshore wind substructures (grouted connections between the tower and foundation) | Acoustic emission technique and a parametric analysis of the measured signals are experimentally investigated to monitor damage evolution and failure mechanisms within grouted connections of offshore wind turbines. |

As listed in Table 7, the acoustic emission signal-based technique is mainly applied for the condition monitoring of wind turbine components, including rotor blades, generator, drivetrain (gearbox, bearings, and so on), and tower. Table 12 summarizes the advantages and disadvantages of acoustic emission monitoring and provides a list

**Table 13** Temperature Signal-Based Condition Monitoring Technology

| Advantages | | Disadvantages | |
|---|---|---|---|
| • Mature and standardized through years of application<br>• Cost-effective<br>• Able to detect and possibly isolate (locate) faults | | • Requires intrusive installation of sensors on the components being monitored (increased complexity)<br>• Prone to failure due to sensor reliability concerns, especially in harsh environments<br>• Difficulty in analyzing the exact source and root causes of temperature variations<br>• Unable to provide early detection due to the slow temperature development<br>• Easily affected by variations in environmental temperature and operational conditions (rotational speed and loads) | |
| **References** | | | |
| **Ref. No.** | **Author(s), Year** | **Monitored Component(s)** | **Brief Description of Major Contributions** |
| [221] | Tonks et al., 2017 | Drivetrain (shaft misalignment) | An infrared thermometer is employed to design a temperature monitoring technique for use on wind turbine shaft couplings. The shaft misalignment can be detected through monitoring the temperature rise at the couplings. |
| [222] | Guo et al., 2018 | Bearings (gearbox) | Aimed at detecting gearbox bearing over-temperature faults, the temperature-power distribution of the gearbox bearings is analyzed using machine learning techniques applied to the data measured from a wind farm. |
| [223] | Ko et al., 2018 | Converters | The actual current profile in the dc-link capacitor of a wind turbine back-to-back converter is analyzed to derive a correlation between the current frequency and the temperature variation of capacitor. |
| [224] | Astolfi et al., 2019 | Generator | Aimed at detecting wind turbine generator slip ring damages, a principal component regression is applied to the measured temperature data collected at the generator slip ring. |
| [225] | Zhao et al., 2019 | Gearbox | A long short-term memory neural network and adaptive error correction are used to construct an online hybrid model for temperature prediction and condition monitoring of wind turbine gearbox components. |
| [226] | Zhang et al., 2020 | Blades (icing) | High-performance distributed fiber optic sensors are attached to the surface of an experimental wind turbine blade to measure the temperature variations on the blade's surface aimed at detecting and estimating the blade icing. |

of selected references categorized according to the names of the components being monitored in wind turbines. Compared with vibration monitoring, acoustic emission technology works with signals of much higher frequencies that can provide more effective monitoring performance, especially for incipient structure defects, damages, or faults at an early stage. Yet, such high sampling frequencies can complicate the required signal processing and increase its computational cost. In addition, this technology usually relies on the installation of a large number of sensors, including dedicated data acquisition devices (for signal sensing, processing, and transfer), which increases condition monitoring costs and causes additional reliability issues due to the use of supplementary sensors. Finally, it is also challenging to correctly distinguish signals from acoustic emissions and noisy background environments, not to mention the other factors, such as temperature, lubrication, and loading, which are found to have a significant influence on the acoustic emissions [28], [29], [198].

*6) Temperature:* By definition, the *temperature* is the degree or intensity of heat present in a material or object. It is especially expressed using a comparative scale and indicated by a sensor. A variety of different sensors, such as *optical pyrometers*, *resistant thermometers*, and *thermocouples,* are available for temperature measurement [15], [30]. Among them, thermocouples are widely used in wind turbines given their very low cost and good reliability [21].

During the normal operation of a wind turbine, each component's temperature must remain within its allowable range. An abnormal temperature can possibly indicate faults due to problems such as equipment degradation, low lubrication oil or inefficient lubricant properties (excessive frictions), generator winding short circuits, and shafts over speed. Therefore, measurement and monitoring of temperatures in a wind turbine are among the most common techniques, which can provide useful information on the machine's health condition. For this technique, measurement of temperatures in each individual component and subcomponent (e.g., bearings and shafts) is essential since it enables better diagnosis performance based on larger information available. Also, it should be noticed that the changes in component temperatures can be correlated with variations in surroundings temperature (e.g., nacelle temperature) or the wind turbine's normal operating conditions, including rotational speed and loads [21], [30].

As listed in Table 7, the temperature signal-based technique is mainly used in the condition monitoring of wind turbine components, including generator, converter, drivetrain (gearbox, bearings, and so on), nacelle, and transformer. Table 13 summarizes the advantages and disadvantages of this technology and provides a list of selected references categorized according to the name of the components being monitored by temperature in wind turbines. In addition to concerns related to the measurement accuracy of a component's temperature (due to environmental and operational effects), the main challenge of this technology lies in the fact that "temperature" (containing fault-related information) develops slowly and sometimes too late compared with other condition-specific signals. As a result, to enable early and precise detection and diagnosis of faults, the temperature

**Table 14** Oil-Debris/Quality Signal-Based Condition Monitoring Technology

| Advantages | Disadvantages |
|---|---|
| • Suitable for offshore wind turbines for which the limited accessibility of turbines complicates offline oil sample analysis<br>• Suitable for detecting internal cracks/defects in the oil-lubricated components, especially gearbox<br>• Able to detect, diagnose, and possibly prognose internal faults, defects, or damages at an early stage | • Requires intrusively installed sensors<br>• Not all oil parameters can be monitored in real time<br>• Affected by variations in wind turbine operating conditions which makes it difficult to correctly interpret the real-time measurements or negative changes in the oil properties<br>• Usually not effective for pinpointing damage locations or the root causes of faults/abnormalities<br>• Costly and needs maintenance to provide reliable measurements over time |

References

| Ref. No. | Author(s), Year | Monitored Component(s) | Brief Description of Major Contributions |
|---|---|---|---|
| [227] | Zhu et al., 2015 | Gearbox | Commercially available viscosity and dielectric constant sensors along with particle filtering method are used for online wind turbine gearbox lubrication oil condition monitoring and remaining useful life prediction. |
| [230] | Liu et al., 2016 | Gearbox | A modified oil-line sensor and electrostatic sensing technique are applied in a real oil-lubricated wind turbine gearbox for monitoring the gearbox health condition and detect early faults. |
| [234] | Sheng, 2016 | Gearbox | Aimed at oil condition monitoring in gearboxes, onsite/offsite experimental results are presented from real-time oil and wear debris monitoring using both inline and online sensors as well as offline oil sample and wear debris analysis. |
| [235] | Sanchez et al., 2016 | Gearbox | Three different optical fiber refractometers are fabricated and characterized using the deposition of indium oxide thin-films and lossy mode resonances for gearbox synthetic lubricant oil degradation detection. |
| [228] | D. Coronado and Wenske, 2018 | Gearbox | Aimed at monitoring lubrication oil condition in wind turbine gearboxes, two sensors are used to determine the oil condition using dielectric constant and conductivity measurements as well as laboratory tests. |
| [229] | Macián et al., 2018 | Gearbox | An experimental assessment and validation of a family of oil ferrous wear debris sensors is performed for wind turbine gearboxes, and a satisfactory detection of amount and size of wear debris (in all ranges) is achieved. |
| [232] | Chitra, 2019 | Gearbox | Internet of things (IOT) and smart sensor technology are reported for IOT-based oil condition monitoring of wind turbine gearboxes. |
| [236] | López de Calle et al., 2019 | Gearbox | SCADA and additional measurements of online optical oil debris sensors are presented and analyzed for three wind turbines with faulty gearboxes in different damage stages. A methodology is used to identify regimes of operation and an oil debris-based health index for gearbox condition. |
| [237] | Nutakor et al., 2019 | Gearbox | A methodology is presented to experimentally characterize a family of friction coefficient formulas for predicting friction coefficient values of wind turbine gearbox lubrication oil based on contact conditions. |

signal is rarely used alone but rather often with another source of information such as vibration signals [15].

*7) Oil Debris/Quality Parameters:* The *lubrication oil* plays an important role in reducing the friction, heat, and wear between mechanical components that are in contact, especially those inside the wind turbine's rotating subsystems and components, such as gearboxes, generators, and bearings. The aims of the oil monitoring and analysis are twofold: 1) to ensure an appropriate oil quality to optimize oil changing schedule and prevent equipment damage caused by poor oil quality and 2) to monitor and estimate the health condition and wear of the oil-lubricated equipment. Besides monitoring the oil pressure and temperature, its samples can be analyzed to assess the oil debris/quality parameters, such as viscosity, levels of contaminants (e.g., water content, coolant, and fuel), and the size, shape, composition, and count of solid particles (debris). Indeed, an excessive number of particles, the presence of large particles, or those of a particular shape can indicate abnormal wear conditions, faults, or an impending failure [26], [227]–[229]. Therefore, the precise monitoring and analysis of oil debris/quality parameters can provide very useful information about the health condition of the wind turbine's oil-lubricated components and their potential faults at an early stage [227]–[230]. Although such an analysis is typically performed offline by taking periodic samples, recent advances in online oil sensing technology have enabled continuous online oil analysis tools [231], [232]. For online oil condition monitoring, there are several sensors available, such as the oil humidity (water) sensor, sensors for viscosity, particle concentration, quality and properties, conductivity, thermometer, and level sensor [35], [227], [233]. Indeed, the sensors' applicability depends on the oil type and the sensor measurement range and accuracy.

As listed in Table 7, the oil-debris/quality signal-based technique is mainly used for the condition monitoring of oil-lubricated wind turbine components, including generator and drivetrain (gearbox, bearings, and so on). Table 14 summarizes the advantages and disadvantages of oil debris/quality monitoring and provides a list of selected references categorized according to the names of the components being monitored in wind turbines. For this technology, the well-chosen monitored oil parameters, the relevant set of sensors, and their accuracy all together play a vital role in the reliability of detection and diagnosis results. However, the use of additional oil sensors not only is intrusive in terms of installations but also increases condition monitoring costs and leads to additional reliability issues caused by supplementary sensors. In addition, since the operation of a wind turbine has various impacts on the oil condition, it is usually challenging to correctly interpret the real-time measurements or determine the root causes of faults or abnormalities.

*8) Electrical Effects:* Electric current and voltage signals constitute the electrical effects (signatures) of the wind turbine generator. On the basis of electromechanical coupling between the generator and other wind turbine components/structures, several studies (e.g., Schoen *et al.* [238], Marzebali *et al.* [239], and Douglas *et al.* [240]) demonstrated that vibrations inside the mechanical components (shaft, gearbox, bearings, and so on) appear in the electrical effects of the wind turbine generator as well. More precisely, these electrical effects can include stator current, stator voltage, rotor current, and so on. Having said that, as listed in Table 7, the electrical effects' analysis provides a unique and nonintrusive signal-based technique to monitor wind turbine components and structure since their faults usually induce vibrations; such fault-induced vibrations appear in the electrical effects accordingly [241], [242]. For instance, Kia *et al.* [243] analytically derived the relationship between the characteristic frequencies of gearbox faults in vibration and electric current signals. With respect to the bearing faults in the wind turbine's gearbox or generator, Gong and Qiao [244] analyze the amplitude and phase spectra of electric current signals to diagnose bearing faults from an early stage. Another work in [245] studies the effectiveness of this technique in the detection of wind turbine rotor blade imbalances.

Table 15 summarizes the advantages and disadvantages of this technology and provides a list of selected references categorized based on the name of components being monitored by electrical effects analysis in wind turbines. The key advantage of this technology is that it does not need any additional sensors or costly data acquisition systems since the current and voltage signals used for signal analysis can be the same as those used in the wind turbine's existing control/protection schemes. This provides significant benefits in terms of system costs, hardware complexities, implementations, and overall reliability. Having said that, the real-life application of this technology in wind turbines is still challenging mainly due to the time-varying (nonstationary) nature and, thus, a low signal-to-noise ratio of the electric signals. Therefore, the fault information (i.e., fault signatures or features) hidden in a nonstationary signal obtained from the wind turbine cannot be directly extracted by the classical signal frequency analysis [28], [35].

*9) Machine Vision:* Machine vision inspection, also known as the *remote machine vision-based monitoring approach*, detects structure damages and defects externally visible: surface cracks, scratches, displacements, deformations, deflection, and so on. Obtaining the targeted object's information through sequences of 2-D or 3-D digital images from different locations and perspectives, this technology relies on principles similar to those of the stereoscopic view of human biological vision [46], [264]. For instance, two cameras can be located at known distances to take simultaneous images of the measured object from different positions. Based on the parallax principle and the geometrical relationship between the two cameras with respect to the object, the images can be combined and processed to obtain a clear sense of depth and surface geometry information [46], [265].

The machine vision-based technology typically consists of a sensing (measurement) system, including image acquisition devices (high-resolution digital cameras, lens, and so on) together with appropriate image processing and damage identification software/hardware platforms [266]. Online inspection and monitoring can be accomplished using remotely installed ground-based or airborne high-resolution image acquisition devices having sampling frequencies over 125 frames per second (i.e., >125 Hz), which would be much higher than those, for instance, typically adopted for strain measurement (about 20 Hz) in the commercial monitoring of wind turbine blades [31], [267]. Yet, the imaging results can be affected by weather conditions [31]. In this technology, especially for online applications, the digital image processing integrated with the damage identification algorithms plays an important role in the effective monitoring and detection of structure faults, defects, or damages [266], [268], [269]. The overall steps typically include: 1) capturing object images (either in 2-D or 3-D); 2) obtaining binary (gray scale) images from the original ones; 3) using edge segmentation techniques (e.g., threshold and edge detectors) and binary morphology to distinguish the defect/damage from the background; 4) extracting important fault indicator features, such as structure deformation, deflection, displacement, distributed strain, and modal parameters; and 5) analyzing the extracted features to assess the structural health [46], [266], [269]. Furthermore, the accuracy of feature extraction highly depends on the quality of image processing, which may involve a wide variety of techniques such as image restoration, reconstruction, segmentation, and recognition. Having said that, it would be yet necessary to comprehensively assess the knowledge behind the relationship between the extracted features and related damages [46].

As listed in Table 7, the machine vision signal-based technique is mainly applied for the condition monitoring of wind turbine structural components, such as rotor blades, nacelle, tower, and foundation. Table 16 summarizes the advantages and disadvantages of machine vision-based monitoring and provides a list of selected references categorized according to the names of the components being monitored in wind turbines. With the fast development of computer science and optics devices in recent years, machine vision technology shows a growing potential for structural health monitoring in the coming years [46], [266], [270], [271]. Also, through the power of AI and the latest autonomous system technologies, such as those using unmanned aerial vehicles (UAVs), new horizons for

**Table 15** Electrical Effects Signal-Based Condition Monitoring Technology

| Advantages | Disadvantages |
|---|---|
| • Non-intrusive with no need for additional sensors or data acquisition devices<br>• Cost-effective with the least hardware implementation difficulties<br>• Able to detect, isolate (locate) and diagnose faults and defects | • Low signal-to-noise (SNR) ratio of the electric signals<br>• Requires complex signal processing algorithms due to the nonstationary signatures of faults in electric signals |

References

| Ref. No. | Author(s), Year | Monitored Component(s) | Brief Description of Major Contributions |
|---|---|---|---|
| [246] | Gritli et al., 2011 | Generator | Currents frequency sliding preprocessing and discrete wavelet transform are used to design a diagnosis technique for DFIG's incipient faults (both stator and rotor faults) under speed transients and varying fault conditions. |
| [82] | Djurovic et al., 2012 | Generator | A methodology based on analysis of stator current and total power spectra is proposed for fault diagnosis in wind turbine wound rotor and DFIGs with rotor electrical asymmetries. |
| [244] | Gong and Qiao, 2013 | Generator | Current-based bearing fault diagnosis is designed for a direct-drive wind turbine with a permanent-magnet synchronous generator (PMSG) through modeling of the modulation effects of bearing faults on the stator currents. |
| [247] | Gangsar and Tiwari, 2017 | Generator | Aimed at predicting induction machine faults, both current signal monitoring and vibration monitoring, using multiclass support vector machine (MSVM) algorithms, are investigated and compared. |
| [248] | Artigao, et al., 2018 | Generator | A spectral analysis of current signature from a real DFIG in an in-service wind turbine is presented using a one-year measurement campaign. |
| [249] | Yang et al., 2019 | Generator | Aimed at detecting and identifying blade imbalance faults in wind turbine DFIGs, a current coordinate transformation is employed for the stator current characteristic analysis. |
| [250] | Brigham et al., 2020 | Generator | A combination of signal processing tools is applied to extract features from the machine stator current signal, and a linear classifier is used for fault detection in wind turbine induction generators with rotor electrical asymmetries. |
| [251] | Artigao et al., 2020 | Generator | Current signature analysis is performed on the data from two in-service wind turbine doubly fed induction generators (DFIGs) for diagnosis of excessive temperature in the generator rotor windings. |
| [252] | Hedayati Kia et al., 2015 | Gearbox | A non-invasive monitoring technique is proposed for the diagnosis of gear tooth surface damage faults in gearboxes based on the stator current space vector analysis. |
| [253] | Hedayati Kia et al., 2016 | Gearbox | Aimed at detecting gear tooth surface damage fault in a single-stage gearbox, a statistical analysis on a fault index computed based on the stator current space vector instantaneous frequency is presented. |
| [254] | Lu et al., 2017 | Gearbox | The nonstationary stator current signals measured from a generator are analyzed using signal processing algorithms for detecting gear faults in a multistage gearbox inside a variable-speed wind turbine. |
| [255] | Bravo-Imaz et al., 2017 | Gearbox | Wavelet decomposition and dual level time synchronous averaging are used to analyze the motor current signature for fault diagnosis of gearboxes operating under transient speed regimes. |
| [256] | He et al., 2020 | Gearbox | Aimed at diagnosing gearbox faults, a current-based unsupervised feature learning approach based on a two-layer sparse filtering algorithm is proposed. |
| [257] | Gao et al., 2021 | Gearbox | Three complementary analyses (Fourier spectrum, amplitude demodulated spectrum and frequency demodulated spectrum) of the PMSG stator current signals are used to diagnose planetary gearbox faults. |
| [258] | Whittle et al., 2013 | Bearings (generator) | Failures of wind turbine generator bearings due to bearing currents and electric stress on the generator is investigated and analyzed. |
| [259] | Amirat et al., 2013 | Bearings (generator) | An ensemble empirical mode decomposition (EEMD) approach based on the homopolar component of the generator stator current is used for bearing fault detection in wind turbine generators under stationary and non-stationary cases. |
| [260] | Wang et al., 2016 | Bearings (direct-drive wind turbine) | A current-aided vibration order tracking method is proposed to directly extract the shaft rotating frequency from the generator's stator current signal and enable fault diagnosis of bearing in direct-drive wind turbines under varying speed conditions. |
| [261] | Wang et al., 2017 | Bearings (direct-drive wind turbine) | Using the generator current signal, a multiscale filtering spectrum (MFS) method is proposed for fault diagnosis of bearing in direct-drive wind turbines under varying speed conditions. |
| [262] | Shahriar et al., 2018 | Bearings (drivetrain) | The generator current signal is used to estimate the bearing's rotational speed and resample the non-stationary current signal to diagnose drivetrain bearing defects based on the resampled signal. |
| [263] | Chen et al., 2020 | Bearings (generator) | Stator current analysis based on a modulation signal bispectrum (MSB) method is applied to diagnose bearing faults in wind turbine DFIGs. |

the autonomous machine vision-based monitoring of wind turbines are opening [4], [268], [271]–[273]. However, to improve detection accuracy, speed, and online computational efficiency, further studies need to focus on image processing algorithms, simultaneous localization and mapping (SLAM), and machine learning (pattern recognition) for correct damage recognition.

*10) Ultrasound:* Ultrasound, also known as *ultrasonic scanning/testing*, is a nondestructive inspection technique

**Table 16** Machine Vision Signal-Based Condition Monitoring Technology

| Advantages | Disadvantages |
|---|---|
| • Non-destructive and available/applicable for remote sensing/inspection of any wind turbines even the existing ones (no physical contact; suitable for offshore wind turbines)<br>• Good precision and available for visual interpretation of results<br>• Able to measure many points within a covered area simultaneously (i.e., full-range measurement capability)<br>• Able to detect, isolate (locate) and possibly diagnose faults, defects or damages which are visible on the surface of a structure | • Requires digital image processing with heavy computation<br>• Limited to the monitoring of faults or damages that are visible on the surface of a structure<br>• Although being available for on-line monitoring, the interpretation of results might become subjective since they depend on the personnel's own experience and judgement<br>• Unable to explain the physical mechanism of damages<br>• Affected by variations in weather conditions (e.g., proper lighting, etc.) |

**References**

| Ref. No. | Author(s), Year | Monitored Component(s) | Brief Description of Major Contributions |
|---|---|---|---|
| [274] | Ozbek et al., 2010 | Blades (structure) | The feasibility of photogrammetry for monitoring large wind turbine blades is investigated, and the monitoring results are discussed. |
| [265] | Yang et al., 2012 | Blades (structure) | A videometric technique is developed to monitor deformations of large-scale wind turbine blades during operation. |
| [275] | Baqersad et al., 2015 | Blades (structure) | Full-field dynamic strain prediction on wind turbine blades is achieved using a pair of high-speed cameras to measure the fixture and displacement of a series of optical targets distributed along the blades. |
| [276] | Carr et al., 2016 | Blades (structure) | To improve condition monitoring of blades, two methods based on digital image correlation and an expansion process along with finite element modeling are used to determine full-field dynamic strain on blades. |
| [277] | Poozesh et al., 2017 | Blades (structure) | A multi-camera measurement system using dynamic spatial data stitching is proposed for large-area photogrammetry-based inspection of blades. |
| [268] | Wang and Zhang, 2017 | Blades (structure) | An image-based data-driven framework is proposed to automatically detect and locate cracks on the wind turbine blades based on the processing of images taken by an unmanned aerial vehicle (UAV). |
| [278] | Sarrafi et al., 2018 | Blades (structure) | Phase-based motion estimation and motion magnification techniques are applied to estimate the structural motion from the captured sequence of images and damage detection in blades. |
| [279] | Mat Daud et al., 2018 | Blades (structure) | Visual condition monitoring and the piezoelectric sensors are used to assess lightning-strike damages on blades caused by lightning strikes. |
| [270] | Wu et al., 2019 | Blades (structure) | Three-dimensional digital image correlation is used to monitor the condition of wind turbine blades, and a fault detection method is proposed based on the relative deformation of the rotating blades. |
| [273] | Shihavuddin et al., 2019 | Blades (structure) | A blade surface damage detection technique using deep learning is used to automatically analyze the high-resolution images taken by UAVs. |
| [280] | Wang et al., 2019 | Blades (structure) | Using UAV-taken images, a two-stage data-driven approach is proposed for the detection of location and contour of blade surface cracks. |
| [271] | Xu et al., 2020 | Blades (structure) | Aimed at monitoring wind turbine blades, UAV-taken images are analyzed through image recognition using convolutional neural networks. |
| [272] | Khadka et al., 2020 | Blades (structure) | A digital image correlation system is installed on a UAV to obtain the vibration characteristics of rotating blades for their remote online monitoring. |
| [269] | Park et al., 2015 | Tower (bolted joints) | A vision-based monitoring technique including image processing is proposed to detect bolt-loosening faults at the bolted joints connecting tubular steel segments of wind turbine tower structure. |
| [281] | Fereshteh et al., 2020 | Tower (structure) | Using feature descriptors and deep learning, an intelligent and automatic vision-based monitoring system with UAVs is developed. |
| [282] | Peng et al., 2022 | Blades (structure) | An image processing method is applied to enhance the images captured under non-uniform illumination conditions, and a gradient threshold segmentation method is used to detect the blade surface damages. |

that relies on the propagation and reflection of ultrasonic waves within a material. Indeed, the amplitude attenuation and phase shift of the ultrasonic waves are affected differently depending on the differences of the material or any inner material discontinuities [43], [46], [283]. Therefore, structure faults cause different reflection, attenuation, resonance, and transmission patterns, whose analysis through signal processing algorithms enables effective detection and diagnosis of surface or subsurface material defects and damages.

Owing to its efficiency and reliability, ultrasonic scanning is one of the most common nondestructive inspection techniques used in the wind energy industry for the structural monitoring of wind turbine components [15], [46]. In general, the scanning mechanism can be based on the capture and quantification of either the reflected waves (known as the *pulse-echo* mechanism) or the transmitted waves (*known as* the *through-transmission* mechanism). Although each of these mechanisms is used in certain applications, the pulse-echo mechanism is usually more useful as it only requires one-sided access to the component being monitored.

As for the monitoring process, an ultrasound transducer (or probe connected to a diagnostic machine) is passed over the target component being monitored. A thin film of coupling materials (usually a liquid such as oil and grease) is typically used to remove the air gap between the ultrasound transducer and the component monitored. This facilitates the efficient transmission of ultrasonic energy from the transducer into the component. Ultrasound transducers are available in a variety of configurations depending on the application. To optimize the monitoring capability, it is important to select a proper type of transducer that suits the application requirements and has the required frequency, bandwidth, and focusing properties. In contrast to contact transducers, noncontact transducers (such as air-coupled transducers (ACTs), electromagnetic acoustic transducers (EMATs), and lasers) are especially suited to implement continuous remote monitoring of structures that are inaccessible or located in hostile environments [284]. This enables the noncontact automated ultrasonic scanning during which ambient air is the only acoustic coupling medium and the wind turbine is in operation. For instance, Park *et al.* [285], [286] employ the noncontact laser ultrasonic scanning in the structure monitoring of wind turbine blades.

As listed in Table 7, the ultrasonic signal-based technique is mainly applied for the condition monitoring of wind turbine structures: rotor blades, nacelle, drivetrain, and tower. In addition to the detection and diagnosis of material defects and damages, ultrasonic scanning is shown to be an effective tool to detect, locate, and characterize the icing on the rotor blades as well [43]. Table 17 summarizes the advantages and disadvantages of this technology as referenced in a selected list of studies focusing on its implementation in wind turbines. With respect to its main challenges and technological limitations, the ultrasonic scanning of some complex geometries may be challenging, and initial preparation and equipment calibrations are required especially for contact ultrasonic scanning. Also, more sophisticated signal processing techniques are usually needed to isolate signals from noise particularly in noncontact ultrasonic scanning using EMATs.

*11) Thermography:* Thermography, also known as *thermal imaging*, is a nondestructive inspection technique that uses a special camera (infrared-based camera) to produce thermal images, known as *thermograms*, showing patterns of heat (temperature) on the surface of objects [300]. It can be effectively used to detect (near-surface) "thermal transients" at a target material. These thermal transients may indicate faults due to different defects or problems, such as structural defects or damages, poor wiring or electrical connections, unbalanced loads, deteriorated insulation, or other potential problems in energized electrical components. More precisely, the faults can be detected, located, and characterized by the analysis of disturbances generated in the local thermal properties (e.g., temperature, thermal capacity, conduction, diffusion, and interface thermal resistance) of a structure or an object [300]. Another monitoring approach relies on the fact that any mechanical phenomenon is accompanied by correlated thermal effects (i.e., thermomechanical coupling), which can be reversible (linked to the strain (and stress) states of structure) or irreversible (linked to the occurrence of damages). Therefore, mapping the thermal state of a structure can also be a tool to detect abnormalities in the mechanical behavior of that structure [300].

As listed in Table 7, the thermographic signal-based technique is mainly applied for the condition monitoring of wind turbine components: generator, drivetrain (gearbox, bearings, and so on), tower, and especially rotor blades. In addition, thermography is shown to be an effective technique to detect and locate the accumulation of ice on a blade surface while distinguishing the types and conditions of icing on the blades [43], [301]. Table 18 summarizes the advantages and disadvantages of thermographic monitoring and provides a list of selected references classified according to the names of components being monitored by thermography in wind turbines. For this technology, "image processing" plays a vital role in the accuracy of detection and diagnosis results. However, it often encounters issues such as motion blurs of moving target objects (e.g., rotor blades when in service) and environmental conditions (e.g., wind speed, ambient temperature, air humidity, reflections, dirt, and prolusion) [302]. Other challenges relate to the nature of this technology, essentially sensitive to near-surface thermal transients (unable to detect or identify deep defects within a material). Also, it is difficult to detect thermal signals generated by incipient defects; the inspection speed is slow and still needs to be improved [303].

*12) Radiography:* Radiography, also known as *X-ray imaging*, is a nondestructive inspection technique that uses an X-ray scanner system to produce radiographic images (X-rays) of the interior structure of objects. This reveals structural variations of the materials, which are caused by changes in material properties, internal delamination, or cracks [15], [312], [313]. Indeed, X-ray transmission data provide quantitative information about those structural variations and enable effective detection and diagnosis of structure faults (i.e., surface or subsurface material defects and damages) in wind turbine components [69], [312]. Although there are some overlaps, the combined application of X-ray and ultrasound is proven to provide complementary capabilities, allowing the detection and diagnosis of a wider range of damages in wind turbine blades (e.g., cracks in adhesive joints, delamination, and laminate failure) [69].

Real-time radiographic inspection is a practical, accurate, and effective technique not only to detect and locate damage (especially laminate damage) but also to determine the size of the damage [69]. In contrast to film radiography, *real-time radiography* (also called digital radiography) employs a planer array of digital radiation-sensitive sensors (instead of a traditional radiation-sensitive film) and allows immediate image preview and availability [314]. Therefore, the radiographic images (X-ray data) can be quickly displayed, processed, and stored in digital format on a computer. Such a digital technology enables more advanced and flexible algorithms for image processing, real-time analysis, and storage. Recently, portable radiography equipment has been studied for wind turbines [315], [316]. When placed on a robot

**Table 17** Ultrasonic Signal-Based Condition Monitoring Technology

| Advantages | Disadvantages |
|---|---|
| • Non-destructive (also available for remote sensing/inspection when noncontact ultrasonic scanning is used)<br>• Non-hazardous to nearby personnel/human<br>• Only one-sided access is required when the pulse-echo method is used<br>• Its equipment can be highly automated and portable<br>• Highly sensitive with a high penetrating power, allowing the detection of very small defects or damages inside the object being monitored<br>• Able to detect, isolate (locate) and diagnose structure faults (both surface and especially subsurface (hidden) defects or damages in structure) | • Initial preparation and equipment calibrations are required, especially when contact ultrasonic scanning is used<br>• Extensive technical knowledge is required to implement inspection procedures when manual equipment is used<br>• Difficult to monitor parts which are rough, irregular in shape, very small, exceptionally thin, or nonhomogeneous<br>• Not very effective for inspection of some materials and possibly requires follow-up with other inspection techniques<br>• Linear defects oriented parallel to the sound beam may not be detected<br>• Requires advanced signal processing, especially when noncontact ultrasonic scanning is used |

**References**

| Ref. No. | Author(s), Year | Monitored Component(s) | Brief Description of Major Contributions |
|---|---|---|---|
| [287] | Lee et al., 2011 | Blades (structure) | A portable long-distance laser ultrasonic propagation imaging system is proposed for the visualization and evaluation of damages on blades. |
| [286] | Park et al., 2013 | Blades (structure) | A laser ultrasonic imaging and damage detection methodology is presented for rotating structures such as wind turbine rotor blades. A specially designed standing wave filter is used for damage visualization. |
| [285] | Park et al., 2017 | Blades (structure) | Aimed at expediting the detection of delamination in wind turbine blades, a noncontact laser ultrasonic measurement system is employed, and a two-level scanning strategy (coarse scanning and dense scanning) is proposed. |
| [288] | Tiwari et al., 2017 | Blades (structure) | Using ultrasonic guided waves, a hybrid signal processing technique based on cross-correlation analysis, wavelet transform, and Hilbert–Huang transform is proposed to detect and identify disbond-type defects on a wind turbine blade. |
| [289] | Tiwari and Raisutis, 2018 | Blades (structure) | Aimed at detecting and identifying disbond-type defects in wind turbine blades, discrete wavelet transforms, variational mode decomposition, and Hilbert transform are applied to process ultrasonic signals. |
| [290] | Zuo et al., 2018 | Blades (structure) | Using ultrasonic guided waves, a blade damage identification algorithm based on 2-dimensional multiple signal classification is proposed. |
| [291] | Shoja et al., 2018 | Blades (icing) | Numerical simulations and experimental validations are presented to investigate the application of ultrasonic guided waves for ice detection. |
| [292] | Jiménez et al., 2019 | Blades (dirt and mud) | Ultrasonic technique along with signal processing based on wavelet transform and pattern recognition using supervised learning classifiers are used for dirt and mud detection and diagnosis on wind turbine blades. |
| [293] | Jiménez et al., 2019 | Blades (icing) | Various feature extraction/selection methods and machine learning classifiers are applied to process ultrasonic signals for ice detection and diagnosis. |
| [294] | Li et al., 2019 | Blades (structure) | The quantitative relationship between ultrasonic parameters and blade debonding defects is investigated through time-domain analysis and short-time Fourier transform (STFT) time-frequency analysis. |
| [295] | Fierro and Meo, 2019 | Rotor hub (bolts) | Various nonlinear ultrasound methods are evaluated for in situ monitoring of the loosened state of a four-bolt structure found on large-scale wind turbines. |
| [296] | Galarza-Urigoitia et al., 2019 | Drivetrain (shaft) | An autonomous ultrasonic monitoring system based on root cause analysis (RCA) and related diagnosis/prognosis algorithms is developed to detect, identify, and prognose cracks on wind turbine low-speed shafts. |
| [297] | Oliveira et al., 2020 | Blades (structure) | Ultrasonic signals are preprocessed using wavelet denoising and principal component analysis (PCA), and damages in wind turbine blades are detected using different anomaly detection methods. |
| [298] | Marquez and Muñoz, 2020 | Blades (structure) | Using ultrasonic guided waves, an approach based on cross-correlation analysis and wavelet transform is used to detect and identify delamination in blades. |
| [299] | Jun et al., 2020 | Drivetrain (shaft) | Using ultrasonic diffracted waves, a quantitative method is proposed for the evaluation of position, depth, and size of surface cracks in the main shaft. |

platform, equipped with robotic arms, the X-ray system can climb wind turbine towers to deploy the X-ray inspection and scan a large area of structure automatedly [61], [317].

As listed in Table 7, the radiographic signal-based technique is mainly applied for the condition monitoring of wind turbine structures: rotor blades, nacelle, and tower. It is worth mentioning that, in addition to X-ray, Gamma-ray, as another radioactive source, can also be applied in the radiography of a wind turbine's structure [318]. Table 19 summarizes the advantages and disadvantages of this technology as referenced in a selected list of studies, focusing on its implementation in wind turbines. In addition to health safety concerns, this technology presents certain challenges and limitations, mainly regarding possible technical complications and equipment-related costs. These shortcomings make difficult the development of a complete, commercially viable system composed of an automated platform able to scan a large-scale wind turbine structure.

In summary, the signal-based condition monitoring when applied in wind turbines, using the reviewed standalone condition-specific sensing and data acquisition technologies, can provide highly precise and specialized condition monitoring capabilities that are usually much beyond those of the SCADA-based techniques. However, this requires additional hardware investment, which increases condition monitoring costs, not to mention the measurement reliability concerns and common complications of equipment calibration, installation, or implementation. In addition, it is worth noting that

**Table 18** Thermographic Signal-Based Condition Monitoring Technology

| Advantages | Disadvantages |
|---|---|
| • Non-destructive and available/applicable for remote sensing/inspection of any wind turbines even the existing ones (no physical contact; suitable for offshore wind turbines)<br>• Available for visual interpretation of results<br>• Able to measure many points within a covered area simultaneously (i.e., full-range measurement capability)<br>• Able to detect, isolate (locate) and diagnose faults, defects or damages | • Requires thermal image processing<br>• Unable to provide early detection due to the slow temperature development and inefficient to monitor incipient faults<br>• Although being available for on-line monitoring, the capabilities for continuous monitoring are limited<br>• Affected by variations in environmental conditions (e.g., ambient temperature, air humidity…) and motion blurs<br>• Relatively costly depending on thermal cameras |

**References**

| Ref. No. | Author(s), Year | Monitored Component(s) | Brief Description of Major Contributions |
|---|---|---|---|
| [304] | Galleguillos et al., 2015 | Blades (structure) | A feasibility study is reported on the application of infrared thermography and unmanned aerial systems for condition monitoring of blades. |
| [301] | Gómez Muñoz et al., 2016 | Blades (icing) | Remote sensing based on thermal infrared radiometry is used to detect icing on wind turbine blades. |
| [302] | Doroshtnasir et al., 2016 | Blades (structure) | A thermographic technique minimizing environmental disturbing influences on thermograms is proposed to enable the detection of subsurface defects in rotating wind turbine blades remotely. |
| [305] | Yang et al., 2018 | Blades (structure) | Photothermal thermal-wave radar with induction infrared thermography are used to monitor blade composites and diagnose subsurface delamination. |
| [306] | Traphan et al., 2018 | Blades (structure) | Infrared thermography for remote condition monitoring of rotor blades and for the detection of surface defects in operating wind turbines is investigated. |
| [303] | Sanati et al., 2018 | Blades (structure) | Various image processing algorithms are used for both passive and active pulsed and step heating and cooling thermography techniques to increase the image quality and the visibility of internal defects in rotor blades. |
| [307] | Zhou et al., 2019 | Blades (structure) | A method based on infrared imaging and rheological theory is proposed to detect air bubble defect evolution in wind turbine blades. |
| [308] | Hwang et al., 2019 | Blades (structure) | Remote continuous-wave line laser thermography along with a time–space-integrated coordination transform algorithm are used to monitor rotating wind turbine blades for damage detection and evaluation. |
| [309] | Hwang et al., 2020 | Blades (structure) | A continuous line laser scanning thermography system is proposed and experimentally assessed by laboratory and full-scale tests to remotely monitor rotor blades for internal delamination and surface damages. |
| [310] | Sousa et al., 2020 | Blades (structure) | A methodology based on position-triggered thermography, which enables the synchronization of thermographic images with the rotation of a target object, and thereby, online damage detection in blades, is presented. |
| [311] | Yousuf et al., 2021 | Blades (icing) | Thermal infrared imaging is used to study the ice accretion along blade profiles. The effect of blade geometry on ice accretion is explored as well. |

the full signal-based condition monitoring of a wind turbine, including all its components, would require a well-selected combination of several condition-specific monitoring equipment and technologies rather than only one. From a cost-benefit viewpoint, using standalone condition-specific monitoring equipment in onshore wind turbines can be justified if the costs associated with the equipment replacement, labor, and lost production are

**Table 19** Radiogeraphic Signal-Based Condition Monitoring Technology

| Advantages | Disadvantages |
|---|---|
| • Non-destructive with no necessity for direct access/contact to the target surface<br>• Available for visual interpretation of results<br>• Finely portable (especially for gamma-ray sources) with a very few material limitations<br>• Able to detect, isolate (locate) and diagnose structure faults (both surface and especially subsurface (hidden) defects or damages in structure) | • The health risk associated with the radiation for the operators and other nearby personnel<br>• Requires a two-sided access to the component<br>• Highly directional (i.e., sensitive to flaw orientation)<br>• Requires image processing and the overall inspection process is generally slow<br>• Relatively costly for a complete automated equipment and large-scale scanning process |

**References**

| Ref. No. | Author(s), Year | Monitored Component(s) | Brief Description of Major Contributions |
|---|---|---|---|
| [319] | Jasinien et al., 2009 | Blades (structure) | Both radiographic and ultrasonic techniques are adopted and compared when inspecting wind turbine blades. |
| [315] | Fantidis et al., 2011 | Blades (structure) | A simulation study using the MCNPX Monte Carlo code is conducted on a transportable radiography system for wind turbine blade inspection. |
| [314] | Körner et al., 2018 | Blades (structure) | Three non-destructive inspection techniques including X-ray imaging, infrared thermography, and terahertz inverse synthetic aperture radar, are investigated and compared when inspecting blades' spar caps. |
| [320] | Reid et al., 2019 | Bearings (gearbox) | Aimed at condition monitoring of wind turbine gearbox bearings, a measurement technique for subsurface strain evolution in operational roller bearings is proposed using energy dispersive X-ray diffraction. |
| [321] | Sattar et al., 2021 | Blades (structure) | A climbing robot system that deploys an X-ray source and detector around a blade is described. |

fully considered, especially if generator and gearbox failures are prevented. In the case of offshore wind turbines, using such condition monitoring equipment can be justified if the abovementioned costs plus the site access/logistic costs are considered, especially if large subassembly failures (e.g., rotor, foundation, gearbox, and generator failures) are prevented. Having said that, the ultimate investment justification in professional condition-specific monitoring systems highly depends on their practical capability in detecting incipient defects, damages, or faults at an early stage to avoid full subassembly replacements, which is the costliest aspect of failures.

## VI. MATHEMATICAL MODEL-BASED CONDITION MONITORING

Compared with signal-based techniques, model-based techniques require the "mathematical models" of a wind turbine or its major components. For this, one does not need to use high-resolution condition-specific signals, such as those used in signal-based techniques. Indeed, model-based techniques mainly require mathematical models of the process and the I-O information, commonly available from a wind turbine and mostly associated with the wind turbine's control system. The required mathematical models are typically developed either as the so-called "nominal models" to describe the fault-free process for FDD purposes or as "degradation models" to describe the degraded process for LTP purposes. As summarized in Fig. 17, both nominal and degradation models can be mathematically obtained using either the so-called "theoretical/physical modeling" or "experimental modeling" approaches. In the theoretical modeling approach, the process model is derived on the basis of mathematically formulated physical principles or laws of nature. However, in the experimental modeling, the model is identified from the process measurements using system identification techniques in a way that the process I-O relationship is expressed in a mathematical model [322]. Depending on the problem to address, one can choose between either of these modeling approaches.

Once the best-suited modeling approach is selected, different design approaches, as listed in Fig. 17, can be used to develop a model-based condition monitoring framework. The most important model-based design approaches for FDD and LTP are briefly reviewed in the following.

### A. Model-Based FDD Design

Model-based FDD schemes are commonly designed using the so-called *residual-based*, *fault estimation,* or *set-membership* approaches.

*1) Residual-Based Approach:* Residual (or symptom signal) is a fault indicator computed in real time as a deviation between measurements and outputs of the mathematical model. Most often, a model-based FDD scheme is developed based on *residual generation* to simply monitor the level (or trend) of the residual signal through the so-called *residual evaluation* and to act when the signal reaches a prescribed threshold value [322]. The residual evaluation is carried out by different methods, such as fixed or adaptive threshold testing on instantaneous or moving average values of the residuals, statistical methods (e.g., generalized likelihood ratio tests), and fuzzy logic approaches. Indeed, the residual is designed to be small ("ideally" zero if no noise and model uncertainty are involved) under fault-free (normal) conditions and to deviate significantly from zero when a fault occurs. The residual-based approach is relatively simple to implement although, when designing the residual generation, the main challenge is to address the process noise and modeling uncertainty, not to mention achieving the necessary disturbance decoupling (i.e., to ensure that the residual is not affected by unknown inputs other than faults) [322]–[324]. The most frequently used residual-based methods include parity equations, state estimation methods (observers in deterministic problem formulation framework and Kalman filters in stochastic/random process problem formulation framework), parameter estimation methods (e.g., least-squares or recursive least-squares and regression analysis), joint state-parameter estimation methods (e.g., a two-stage Kalman filter and an extended Kalman filter), and I-O representations (also known as "data-driven model-based") using neural network models, fuzzy models, neurofuzzy models, and so on. Most of the abovementioned methods are well established and extensively cited and explained in several reference books (e.g., see [322], [325], and [326]). In wind turbines, the residual-based FDD approach using the already mentioned methods has been largely studied. Table 20 presents an updated summary of the literature on the model-based FDD techniques, including the residual-based approach in wind turbines.

*2) Fault Estimation Approach:* In most cases, it is either difficult or inadequate to use residuals alone to determine the magnitude of faults. The fault estimation approach involves the online estimation of faults and is usually more challenging than the residual generation approach. Such an estimation approach not only can detect fault signals but can also effectively estimate their magnitudes to provide accurate fault information to active fault-tolerant control systems [327]. Fault estimation can be achieved using a variety of observers (e.g., an adaptive observer [328], a sliding mode observer [329], an unknown input observer [330], and an extended state observer [331]) or Kalman filters (e.g., a zonotopic Kalman filter [332], a two-stage exogenous Kalman filter [333], and a three-stage Kalman filter [334]). When appropriately designed for a particular fault scenario, a bank of observers or Kalman filters can be used to isolate the faults from each other in different components. For instance, the application of fault estimation in wind turbine diagnosis and fault-tolerant control has been recently studied using an adaptive sliding mode observer [335], the Takagi–Sugeno sliding mode

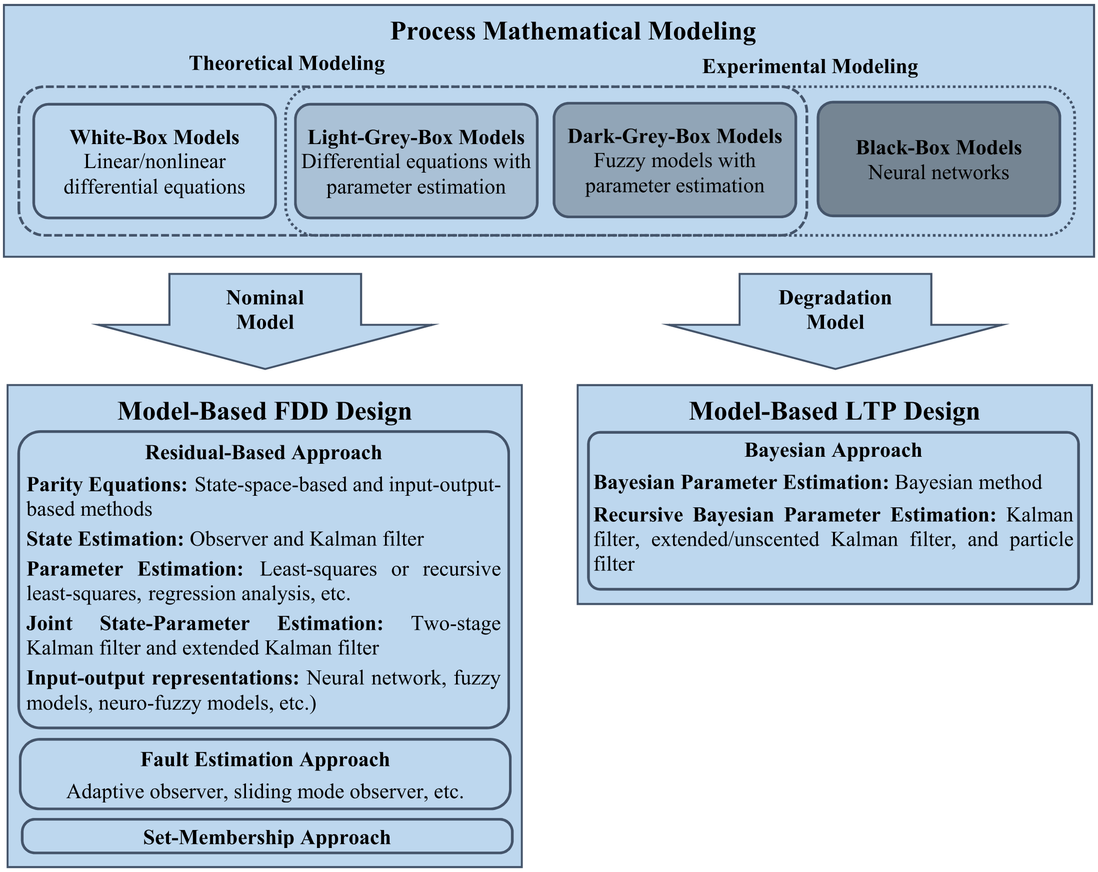


**Fig. 17.** *Classification of mathematical process models in model-based techniques.*

observer [336], and an extended state observer [337]. More references are also provided in Table 20. For further details on fault estimation methods, interested readers are referred to [327] and [338].

*3) Set-Membership Approach:* This approach, also known as the "error-bounded approach," relies on the assumption under which the noise, disturbance, and uncertainty in the model's parameters are unknown but bounded with *a priori* known bounds [339]. Accordingly, a set of mathematical models is generated for the system, in either state space or parameter space, with no need for a threshold design. If the measured sequence of system inputs and outputs available at every time instant is not consistent with any of the members of this set, a fault will be detected. Once the fault has been detected, the feasible state or parameter set can be reset to a set that contains all possible values even in a faulty condition. This enables fault isolation through the identification of the faulty feasible set. Also, fault estimation can be achieved by comparing the feasible set before and after the detection of the fault using the distance between the centers of these sets [339]. It is worth noting that the set-membership approach to design FDD produces no positive false alarms if the bounds applied on the uncertainties, noises, and disturbances are realistic. However, this approach usually suffers from its inherent conservatism due to the propagation of uncertainties and the overapproximations required in the set computations [339], [340]. As listed in Table 20, the application of the set-membership approach in wind turbine diagnosis has been recently studied in [340]–[343]. For further details on the set-membership approach, interested readers are referred to [339].

## B. Model-Based LTP Design

If the degradation model originates from the black-box modeling methods, such as neural networks, the obtained LTP is commonly classified under the data-driven LTP, as explained in Section V. However, when a degradation model other than black-box models becomes available, the measured monitoring data can be used to identify (or calibrate) model parameters. Once these model parameters are identified, it is possible to predict how faults or damages will grow in the future and thus obtain the RUL. In reality, however, the degradation model is not perfect, as the data used for model identification are always corrupted by measurement errors, noises, and variabilities; future loading or operating conditions are uncertain. These significant sources of uncertainty contribute to the ultimate uncertainty in estimated model parameters and, thus, the RUL prediction. Therefore, the key issue in model-based

**Table 20** Examples of Existing Literature on Model-Based FDD of Wind Turbines

| Approach Classification | Ref. No. | Author(s), Year | Technique(s) | Fault-Type Tackled | | |
|---|---|---|---|---|---|---|
| | | | | Sensor | Actuator | Process/System |
| Residual-Based | [344] | Pisu and Ayalew, 2011 | Parity equations | √ | √ | √ |
| | [345] | Tornil-Sin et al., 2014 | Parity equations | √ | √ | |
| | [346] | Blesa et al., 2015 | Parity equations | | | √ |
| | [347] | Dey et al., 2015 | Parity equations and Kalman filter | √ | √ | √ |
| | [74] | Wei and Verhaegen, 2011 | Observer | √ | √ | |
| | [348] | Gálvez-Carrillo and Kinnaert, 2011 | Observer | √ | | |
| | [349] | Li et al., 2012 | Observer | √ | √ | √ |
| | [350] | Laouti et al., 2014 | Observer | √ | √ | |
| | [68] | Wei et al., 2010 | Kalman filter | √ | | |
| | [351] | Cao et al., 2016 | Kalman filter | | √ | √ |
| | [352] | Cho et al., 2018 | Kalman filter | √ | √ | |
| | [353] | Borchersen and Kinnaert, 2016 | Extended Kalman filter | | | √ |
| | [85] | Ibrahim et al., 2018 | Extended Kalman filter | | | √ |
| | [354] | Noshirvani et al., 2018 | Unscented Kalman Filter | √ | √ | |
| | [86] | Wu et al., 2012 | Adaptive parameter estimation | | √ | |
| | [355] | Wu and Liu, 2017 | Recursive subspace identification | | √ | |
| | [356] | Badihi et al., 2014 | I-O representations via fuzzy models | √ | | |
| | [357] | Badihi et al., 2015 | I-O representations via fuzzy models | | √ | |
| | [358] | Simani et al., 2015 | I-O representations via fuzzy models | √ | √ | √ |
| | [359] | Simani et al., 2015 | I-O representations via fuzzy models | √ | √ | √ |
| | [360] | Badihi et al., 2017 | I-O representations via fuzzy models | | | √ |
| | [323] | Badihi et al., 2021 | I-O representations via fuzzy models | | √ | |
| Fault Estimation | [361] | Simani and Castaldi, 2014 | Adaptive filters via the nonlinear geometric approach | | √ | |
| | [336] | Schulte et al., 2015 | Takagi-Sugeno sliding mode observer | | √ | |
| | [337] | Shi and Patton, 2015 | Extended state observer | √ | √ | |
| | [362] | Witczak et al., 2017 | Joint state and fault estimation via a 2-stage combined adaptive and parameter estimation | | √ | √ |
| | [335] | Lan et al., 2018 | Adaptive sliding mode observer | | √ | |
| | [363] | Kim and Lee, 2019 | Adaptive fuzzy fading Kalman filter | | √ | |
| | [364] | Sedigh Ziyabari et al., 2021 | Observer-based estimation scheme using unknown input observer and sliding mode observer | | √ | √ |
| | [365] | Habibi et al., 2021 | Adaptive sliding mode observer | √ | √ | |
| Set-Membership | [341] | Blesa et al., 2011 | Parameter estimation based set-membership method (linear) | √ | √ | √ |
| | [340] | Tabatabaeipour et al., 2012 | State estimation based set-membership method (nonlinear) | √ | √ | √ |
| | [342] | Casau et al., 2015 | Set-valued observers (SVOs) for LPV systems | √ | √ | √ |
| | [343] | Blesa et al., 2016 | Zonotopic set-membership parity space method (linear) | √ | √ | √ |

LTP is to find ways to improve the accuracy of the degradation model while incorporating uncertainty in the future [366], [367]. To address this issue, parameter estimation algorithms based on the so-called *Bayesian approach* are often used for the real-time estimation of the degradation model parameters. A major advantage of the Bayesian approach over other parameter estimation methods, such as the least-squares method and the maximum likelihood estimation method, is its capability to estimate the uncertainty structures of the identified model parameters [366]. Such uncertainty structures depend on those of the prior information and likelihood functions. Indeed, the Bayesian approach employs the Bayesian statistics and measurement data to probabilistically identify unknown parameters of the degradation model and reduce their uncertainty in real time. Therefore, most model-based LTP schemes have their foundation in Bayesian statistics. Among Bayesian-based algorithms, the overall Bayesian method [368] and filtering-based techniques, such as a Kalman filter [369], an extended/unscented Kalman filter [370], [371], and especially the particle filter [372], are more commonly known. In the overall Bayesian method, the model's unknown parameters are estimated in the form of a posterior probability distribution, which is proportional to the likelihood of observed data multiplied by the prior probability distribution [368]. When applied, this method's main challenge is to appropriately choose the right options for the sampling process (e.g., the initial values of unknown parameters and the width of *proposal distribution* in the Markov chain Monte Carlo method) [366].

As for filtering-based techniques, they rely on a *recursive Bayesian update* process, under which model parameters are updated recursively by accepting one new measurement data at a time. The performance of the Kalman filter and its modern extensions highly depends on the initial condition and variance of model parameters, as well as the type of nonlinearity and errors in linearization. However, the particle filter is much more flexible and easier to design with no restrictions on the type of system (nonlinearity) or noise. Indeed, it employs particles (samples) to represent the prior and posterior probability density function (pdf) of model parameters. More precisely, when a new measurement becomes available, the posterior pdf at the previous time step is used as the prior pdf at the current time step. Accordingly, the parameters are updated by multiplying the prior pdf with the likelihood from the new measurement. Thus, particle filtering is also referred to as the "sequential Monte Carlo method," known to be the

**Table 21** Examples of Existing Literature on Model-Based LTP of Wind Turbines

| Approach Classification | Ref. No. | Author(s), Year | Technique(s) | Monitored Component(s) |
|---|---|---|---|---|
| **Bayesian** (Bayesian Parameter Estimation) | [373] | Herp et al., 2018 | Bayesian method | Bearing (gearbox) |
| | [374] | Ding et al., 2018 | Bayesian method | Gearbox |
| **Bayesian** (Recursive Bayesian Parameter Estimation) | [367] | Butler, 2012 | Particle filter | Main bearing |
| | [375] | Sharma and Mahto, 2014 | Particle filter | Main bearing |
| | [376] | Fan et al., 2015 | Particle filter | Gearbox |
| | [377] | Saidi et al., 2017 | Particle filter | High-speed shaft bearing |
| | [378] | Lu and Christou, 2019 | Particle filter | Power electronic converter |
| | [379] | Wang et al., 2019 | Particle filter | Bearing (gearbox) |
| | [380] | Cheng et al., 2019 | Particle filter | Bearing (gearbox) |
| | [381] | Valeti and Pakzad, 2019 | Particle filter | Rotor blades |
| | [382] | Wang et al., 2020 | Particle filter | Bearing (gearbox) |
| | [383] | Boutros et al., 2020 | Zonotopic Kalman filter | Rotor blades |

most popular method in model-based prognosis. Having said that, the computational cost and especially the so-called "particle depletion" phenomenon (i.e., accumulated sampling error during the updating process) have been major problems when using particle filtering [366], [372].

Compared with data-driven prognosis methods, model-based LTP has several advantages. First, model-based methods enable long-term prediction. Indeed, when the parameters of the degradation model are properly identified, the RUL can be well-predicted by propagating the model until degradation reaches a prescribed threshold. Second, the model-based methods mainly rely on the physics-based model and require a relatively small amount of data for the parameter estimation. However, the challenging issues to address include the adequacy of the degradation model, the accuracy and efficiency of parameter estimation, and the quality of required degradation data [366], [367].

In wind turbines, the application of model-based LTP is relatively recent and limited. This is mainly due to the particularly challenging aspects of prognosis in wind turbines. To name a few, the high nonlinearity and strong coupling of wind turbine components and their operation under the wide range of changing loads and operating conditions, along with the highly uncertain and variable onshore or especially offshore environmental conditions, are the most challenging problems to tackle. Table 21 presents an updated summary of the literature on model-based LTP techniques in wind turbines.

## C. Model-Based Condition Monitoring Framework

A complete condition monitoring framework involves all aspects of data acquisition, FDD, and LTP to provide the overall health assessment of a plant such as a wind turbine. For instance, Fig. 18 shows a typical schematic of a complete model-based condition monitoring framework, including the data acquisition and both model-based FDD and LTP schemes via the commonly used residual-based and Bayesian approaches, respectively. Under a mathematical model-based framework, data acquisition is achieved by collecting measurement data usually from the sensors of a wind turbine SCADA system (especially the sensors associated with the wind turbine's control system) and by processing them to obtain useful features for FDD. The model-based FDD is developed using an appropriate design approach (e.g., residual-based and fault estimation-based) to detect, isolate, and identify early symptoms of any fault or anomaly in the wind turbine components. According to the FDD information, the severity or size of a detected fault is usually quantified in the form of a normalized degrading health index (or health measure) for LTP purposes. Using such a health index, the model-based LTP is achieved based on the modeling of the degradation process in any wind turbine components while considering an appropriate Bayesian method to address the inherent large degree of uncertainty associated with the long-term predictions of a component RUL. As shown in Fig. 18, in addition to the FDD information, the LTP may also use some upcoming information expected about changes in the system's operating conditions in terms of variations in the environmental conditions, usage patterns, loadings, and so on.

In summary, the most important advantage of mathematical model-based condition monitoring is its low development and running costs since there is no need for any additional hardware components. In many cases, the measurement data used to control the process also suffice for the model-based FDD and/or LTP algorithms, meaning that no additional sensors must be installed. Also, the model-based algorithms can be finally implemented via software on a process control microcomputer [322], [325], [366]. Another advantage of the mathematical model-based approach compared with its signal-based counterpart is that the FDD/LTP information under a mathematical model-based scheme can be more useful for real-time control reconfiguration and fault-tolerant control purposes [322], [384]. This enables the timely accommodation/compensation of faults in such a way that they do not lead to wind turbine failures. Having said that, it is worth noting the particular challenges and limitations of the design and widespread adoption of mathematical model-based condition monitoring schemes. The high nonlinearity of wind turbine components—especially the aerodynamic subsystems—together with the stochastic wind fluctuations and turbulences, measurement noises, and external disturbances under harsh environmental

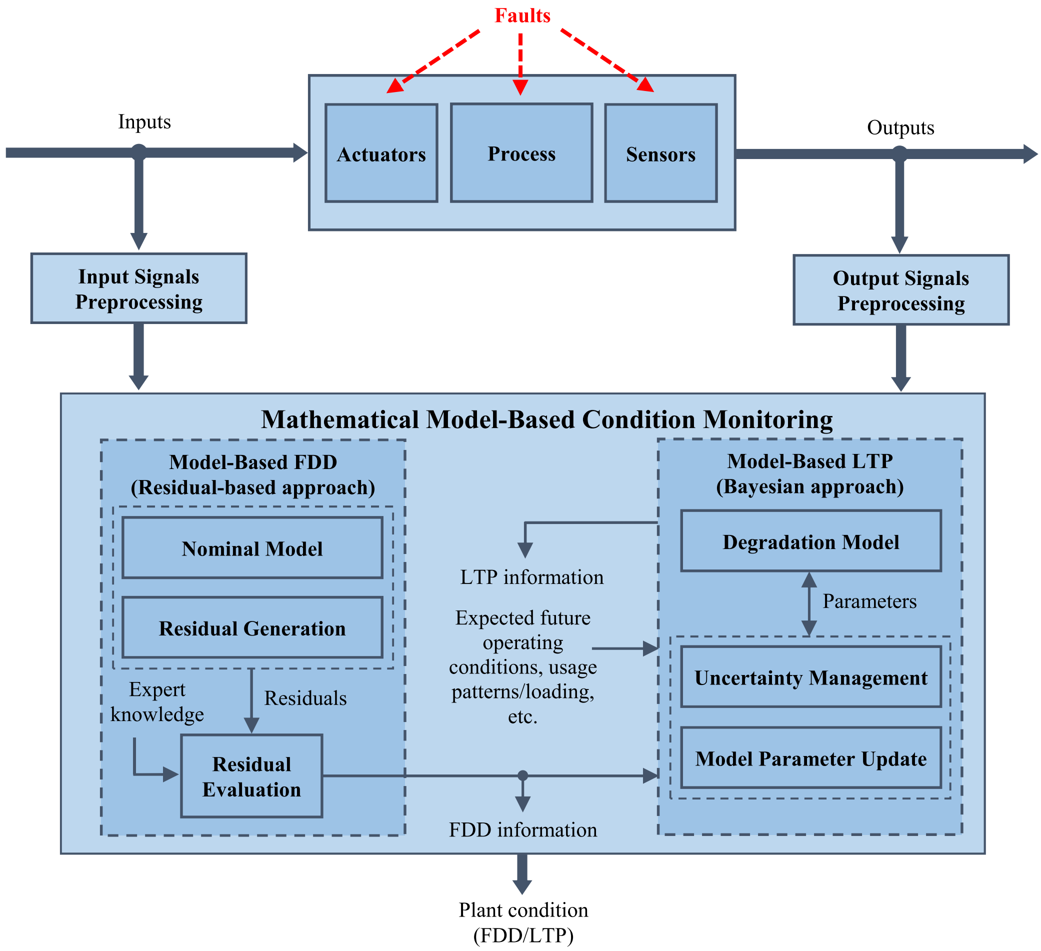


**Fig. 18.** ***Typical schematic of mathematical model-based techniques.***

conditions all make the model-based condition monitoring of wind turbines very difficult in practice. It is, indeed, challenging to derive robust and accurate models that can be used for FDD or LTP purposes. Given this main limitation of model-based approaches, various combinations of hardware signal-based and mathematical model-based techniques can also be considered. Such combinations are sometimes referred to as "hybrid" techniques, crossing the boundary between model- and signal-based techniques, in the hope of integrating both techniques' advantages to overcome the challenges and limitations of each technique alone. For instance, from a design architecture viewpoint, the knowledge of a system's physical behavior can be utilized to determine a mathematical model (e.g., determining the order of exponential or polynomial functions) in a data-driven framework. Also, it is possible to use a system's data-driven model along with a physics-based fault model or vice versa. It is worth mentioning that, when possible, the information used in hardware signal-based techniques can be added to the information about control signals and the wind turbine model to enable more optimized and comprehensive monitoring capabilities. This helps improve not only the reliability and performance of the CMS but also the feasibility of fault-tolerant control designs in wind turbines. Finally, a number of examples of hybrid techniques for wind turbine FDD and LTP are reported in [75], [385]–[388] and [76], [77], [389], respectively.

## VII. SUMMARY, CONCLUSION, AND FUTURE TRENDS

Due to their complex integrated nature and wide range of changing loads and operating conditions, onshore and especially offshore wind turbines are prone to component faults and premature failures that jeopardize their reliability and availability (uptime) for efficient energy production [3], [9], [57]. In order to detect, diagnose, and prognose any type of abnormalities or faults in wind turbines' components before they can propagate and cause major damage or severe failure, it is crucial to effectively monitor wind turbines' conditions in real time. Motivated by the significance of this issue and the ever-increasing role of wind turbines in the modern world's power grid, wind turbine condition monitoring has been at the forefront of both academia and industry over the past two decades. Considering the great diversity of approaches and techniques developed in wind turbine condition monitoring and the large number of results disseminated in this active research area as of 2020, this article aims at providing an up-to-date, comprehensive review of the available literature with particular attention paid to the results reported in the last decade.

This article summarized the major fault and failure modes observed in wind turbines and comprehensively reviewed the available techniques and strategies for wind turbine condition monitoring from signal- to model-based perspectives. Both aspects of condition monitoring, that is, fault diagnosis and prognosis, were considered, and the respective functionalities, capabilities, advantages, flaws, and challenges/limitations of each available technique were carefully outlined and explored, especially in view of wind turbine condition monitoring issue. According to the reviewed literature, the following holds.

1) *Signal-based condition monitoring:* This mainly involves measurement signals and signal processing methods under a data-driven approach designed to obtain useful FDD and/or LTP information from a large amount of observed data. Depending upon the measurement signals available from a wind turbine, this article categorized and reviewed the techniques for signal-based condition monitoring under the terms of "SCADA-based" and "condition-specific-based" techniques that rely on the signals coming from the SCADA and standalone condition-specific data acquisition systems, respectively. This article reviewed several SCADA-based techniques, such as trending, clustering, and data-driven normal/damage behavior modeling. In addition, this article outlined and reviewed a wide range of condition-specific techniques using vibration, strain, torque, shock pulse, acoustic emission, temperature, oil debris/quality parameters, electrical effects, machine vision, ultrasound, thermography, and radiography according to the additional hardware used in a professional CMS.
2) *Model-based condition monitoring:* This employs the mathematical models of a wind turbine or its major components without requiring high-resolution, condition-specific signals, such as those used in signal-based techniques. Indeed, the model-based techniques mainly rely on the processing of mathematical models and the I-O information that can be easily retrieved from a wind turbine as they are mostly associated with its control system. This article outlined the commonly used design approaches for both model-based FDD and LTP in wind turbines. Regarding the model-based FDD design, the so-called residual-based, fault estimation, and set-membership approaches were described and reviewed. Furthermore, this article examined the specific application of the Bayesian approach to the real-time estimation of the degradation model parameters in the model-based LTP design for wind turbines.

In addition, any combination of both signal- and model-based techniques was categorized under hybrid techniques, leveraging the monitoring performance by integrating together the advantages of both signal- and model-based techniques to overcome the challenges and limitations of each technique alone.

Drawing on the reviewed literature, the following challenges and shortcomings call for additional research and development in the future:

- *Data acquisition:* This is the first, thus essential, the step of any condition monitoring scheme. In wind turbines, a wide range of sensors and devices are used to measure the wind turbine's environmental, operational, and performance parameters. Optimal selection, placement, and implementation of these sensors and devices play an important role in the overall monitoring performance, and in both capital and O&M costs. Improper sensor selection or placement can easily degrade the monitoring performance. Likewise, inaccurate calibration or implementation/installation of sensors may cause measurement errors, serious reliability concerns, or even equipment failures. When designing any CMS, the sensor reliability issue and the possibility of sensor failures must be considered. When possible and appropriate, depending on the type of measurement, efficient utilization and management of redundancy (in hardware, software, or even communication networks) can be contemplated. In addition, the application of smart sensor technology along with the Internet of Things (IoT) can offer significant advantages for remote real-time data acquisition and transmission throughout large wind farms.
- *Data analysis:* To enable meaningful and effective condition monitoring, especially when based on data-driven approaches, it is important to collect and analyze a sufficiently large and representative (complete) amount of observed data. With an average lifespan of twenty years, systems such as wind turbines presumably offer huge amounts of easily collectable data, which makes the adoption of data-driven monitoring approaches all the more appealing. Having said that, beyond the challenges commonly posed by big datasets and the extraction of useful features, the quality and completeness of such data usually represent the major points of concern, particularly when originating from SCADA systems. These concerns become even more significant in new wind turbines, operating most often normally at the beginning of their operational life. In that case, the available historical databases are usually limited (incomplete) and do not cover the entire range of fault-related features useful for designing FDD and especially LTP solutions since the recorded data only characterize the wind turbine's normal operation without any information about other operating modes (i.e., faults and failures). When possible, using appropriate physical models, referred to as "digital twins," to generate the database that covers the system's useful features in normal and faulty operations can be considered a

potential solution to tackle this issue [390]. In addition, the emerging paradigm of *data-centric AI*, where giant databases simply do not exist, could be part of the solution [391].

- *Signal-based condition monitoring:* SCADA-based techniques are useful to identify abnormal turbines within a wind farm through the overall monitoring and tracking of key environmental, operational, and performance parameters but are usually limited when performing a full detailed) condition monitoring of a single wind turbine's subsystems and components. Given this shortcoming and the diversity of failure modes in wind turbine components, an integration approach starting with a digest of SCADA data and accordingly fusing several dedicated condition-specific-based techniques considering their capabilities, advantages, and disadvantages is recommended. With an ever-increasing number of offshore wind turbines and their inevitable accessibility limitations in harsh offshore conditions, it is crucial to embrace the power of AI and advanced machine learning capabilities (e.g., deep learning). Along with the latest advancements in robotics, UAVs or drones, and other autonomous system technologies, they remotely enable autonomous data collection, and fleet-wide condition monitoring and asset management using effective and fully autonomous condition-specific-based techniques, such as machine vision, thermography, and radiology, to name only a few.
- *Model-based condition monitoring:* Model-based techniques do not require any additional hardware components and can provide very cost-effective solutions for wind turbine condition monitoring. However, the diagnosis and prognosis performance obtained by model-based techniques is strongly tied to the accuracy, thoroughness, and robustness of their mathematical models, which are used to describe the nominal or degradation behaviors of a wind turbine or its major components. Since a wind turbine is an integrated complex system built with highly nonlinear components working under stochastic wind fluctuations and turbulences, external disturbances, measurement noises, and harsh environmental conditions, it is often challenging or even impossible to identify system dynamics across the entire wind turbine's operation regime. This makes the wind turbine modeling problem a serious challenge. Depending on the problem tackled, advanced modeling approaches, such as those using integrated multiple linear models or those based on hybrid modeling approaches (merging white and black-box modeling), can be considered as potential solutions to cover all possible system operating ranges. This does not mean that new modeling methods are no longer needed. In fact, recent studies have explored the design of model-based FDD with regard to nonlinear dynamic systems. However, it should be noted that most nonlinear designs are quite complicated and can only be applied to a very limited class of nonlinearities while relying on highly strict assumptions about the system nonlinearity to be implemented.
- *Hybrid approaches:* Given the limitations of signal- and model-based approaches, their various "hybrid" combinations can also be considered, crossing the boundary between the signal- and model-based approaches in the hope of integrating the advantages of both approaches together and overcoming the challenges posed by each approach alone. By establishing a promising framework to leverage the merits of different condition monitoring techniques, hybrid approaches can be more appealing to the industry in the short run while providing both companies and researchers with valuable practical experience in the long run when it comes to the real-life evolution of fully model-based solutions for wind turbine condition monitoring.
- *Monitoring system architecture:* A barrier to a hybrid application of different condition monitoring approaches under a truly integrated system is the common architecture, where available CMSs are segregated from each other. This phenomenon is mainly due to a dissociation between the original manufacturers of wind turbine components and those of their monitoring equipment. For instance, SCADA-based signals and alarms are both generated from within the industrial control system network of wind turbines, supplied by turbine manufacturers, whereas professional CMSs are purchased separately and installed on wind turbines independently of their control system. Therefore, it is physically difficult to integrate the SCADA-based and professional CMS signals, in spite of their different bandwidths. Having said that, some wind turbine control system manufacturers have been expanding SCADA and professional CMS signal facilities within their products, where fault monitoring algorithms and alarm handlers can operate based upon both SCADA-based and professional CMS signals data. As such, more flexible system architecture and integrated condition monitoring opportunities can be achieved.
- *Multiparameter monitoring:* An important aspect of condition monitoring that concerns wind farm operators is the reliability of the monitoring equipment/technique and the quality of its generated FDD/LTP information. The former can be addressed by experience and the appropriate selection of sensing and data acquisition systems, whereas the latter depends on the accuracy and the way the condition data (information) are presented to the outside world. It is obvious that, when a number of monitoring signals from different sources (e.g., both vibration and oil debris/quality for gearbox bearings) present confirmatory fault information, this is useful and builds confidence among operators and

O&M crew. Any type of condition monitoring sensor signal (e.g., vibration, strain, and temperature) has a probability of detecting and identifying faults in a wind turbine component. Indeed, the probability of accurate FDD/LTP depends in part on the sensor location and in part on the reliability and accuracy of the sensor. According to the reviewed literature, relying on more than one monitoring sensor (e.g., multiple sensors in different locations and of different types) or multiparameter monitoring often improves the chances of successful detection and diagnosis of incipient damages or faults at an early stage. However, this can result in a data overload (as commonly seen in the wind industry), not to mention that its benefits may diminish if more than a sufficient (optimum) number of sensors are used. For instance, although two sensors may improve the probability of accurate FDD/LTP results, increasing, say, from six to seven sensors provides a much smaller improvement. Therefore, wind farm operators are advised to reduce the number of sensors (when possible) but to increase their quality and reliability. Overall, it can be reasonable to explore higher integration of the interpretation of monitoring signals among different systems (e.g., between SCADA-based and professional CMSs, such as in [392]) with the objective of enabling accurate and early fault detections and enhancing the prognostic horizon.

- *Prognosis:* This will be an important function of future CMSs. Compared to wind turbine diagnosis, the studies on prognosis are still in their infancy. This is mainly due to the challenging nature of prognosis problems in the view of the high complexity, nonlinearity, and uncertainty of wind turbine systems, not to mention the technical challenges to obtain the useful historical data (especially up-to-failure data) needed to identify the degradation progress. This research area certainly deserves further attention and requires more research efforts since prognosis presents a huge potential for enabling more effective condition-based maintenance and the reduction of O&M costs in both onshore and offshore wind farms.
- *Evolving new technologies and offshore wind:* Wind turbine technology is rapidly evolving to reduce weight, control loads, and improve energy production. With the increasing tendency toward larger and more flexible wind turbines in offshore installations, the O&M costs will quickly increase unless reliability and availability are improved through the remote real-time condition monitoring and health management of wind turbines. Indeed, the harsh offshore conditions may impose unknown complexities and new challenges for the condition monitoring of wind turbines, especially in terms of accessibility and logistics. Therefore, adapting and tailoring wind turbines' condition monitoring solutions to specific offshore conditions need to be researched in an exclusive and extensive manner. Having said that, recent advances in wind farm digitalization, wireless communications, supercomputing technology, and sophisticated atmospheric measurement capabilities and large real-time streams of data (big data) collected from turbine-based systems (both the turbines and meteorological measurement equipment) provide excellent opportunities to significantly improve wind turbine condition monitoring and control as never before.
- *Farm-level condition monitoring:* Depending on the type of fault and failure modes, condition monitoring strategies can be carried out either at the levels of an individual wind turbine or an entire wind farm. However, thanks to the multiple measurements offered by the different wind turbines found in a wind farm and the simultaneous and collective consideration of those measurements in the condition monitoring process, some faults may be diagnosed more easily at the wind farm level (e.g., the rotor aerodynamic malfunctions or faults related to icing or debris built up on the rotor blades). An example of this approach is presented in [360] although there is much more room for future research in this area.
- *Cybersecurity:* Wind farms' cybersecurity is becoming increasingly important. While wind farm digitalization can offer various benefits, it can also make wind farms more vulnerable to "cyberthreats," which constitutes a new dimension of health risks associated with wind farms operation, the others being brought by physical faults or damages. As a matter of fact, cyberthreats in the form of cyberintrusions or cyberattacks on wind energy systems have been already reported in recent years. For instance, a cyberattack in March 2019 exploited a vulnerability within a firewall and resulted in a denial-of-service (DoS) condition and, consequently, the disruption of communications between a control center and wind and solar generation sites for a large wind owner/operator in Utah, USA [393]. Given the expansional role of digitalization of wind farms empowered by wireless communications that come with inherent cybervulnerabilities, such examples of cyberattacks will probably continue to increase in sophistication and number, resulting in severe cascading failures impacting not only the cyber and physical components and operations of a wind farm, but also the reliability of the entire power grid. It is worth noting that, although faults and cyberattacks originate from different sources, they both might have similar signatures that ultimately lead to the system's failure. Consequently, it is essential to consider appropriate technologies exclusively developed for the detection, identification, and mitigation of cyberattacks, especially in order to differentiate cyberattack- and noncyber-related/operational incidents in wind energy systems. This helps to correctly identify the type of incident and its root cause(s),

which is necessary to achieve effective and reliable condition monitoring, control, and health management of wind turbines. Additional considerations, requirements, and guidelines regarding the cybersecurity aspects of wind turbines and wind farms can be found in a recently published roadmap for wind cybersecurity in [394].

- *Condition monitoring and system protections:* Wind turbine system's protections are necessary to ensure safety and system integrity in the event of serious uncontrollable fault effects or emergencies. However, a very conservative application of system protections may shut down a wind turbine too early, even before it is necessary and justified by the condition-based maintenance enabled by the condition monitoring process. Such early shutdowns of wind turbines by system protections may potentially restrict the benefits obtained from condition monitoring and condition-based maintenance. To further explain, an effective and reliable condition monitoring scheme can detect, diagnose, and prognose incipient signs of degradation or faults before they propagate to major damage or severe condition where system protections are inevitable. In other words, wind turbine condition monitoring information provides wind farm operators with enough time span to plan condition-based maintenance actions (see Fig. 12) and even enables control adaptation and reconfiguration mechanisms (see Fig. 8) to safely increase wind farm availability. As a result, wind turbine condition monitoring can enhance confidence among operators to possibly further fine-tune the tolerance for activation of some protections and, thus, lower the probability of unnecessary wind turbine shutdowns to help enjoy improved production (availability).
- *Health management:* Finally, it is worth mentioning that the complete and autonomous health management of wind turbines can be fully realized through a smart and integrated design of condition monitoring, control, and intelligent decision-making strategies under a unified framework (see Fig. 8). Currently, the FDD and/or LTP information obtained from CMSs is mainly used for wind turbine general health assessment and possible maintenance recommendations after being analyzed and interpreted by expert assistance. Yet, the exploitation of real-time condition monitoring information when a fault happens in a wind turbine component still shows great potential to enable appropriate control reconfiguration under active fault-tolerant (or self-healing) control strategies [42], [323], [356], [357], [360], [361], [395]–[397]. This offers an inexpensive technology that enables large wind farm operators to monitor and extend their wind turbines' operations (availability) by accommodating fault effects before they propagate to failures, which improves reliability, productivity, and planning for condition-based maintenance. Although some studies have already initiated the exploration of the abovementioned potential to some extent, the research on wind turbine fault-tolerant control, particularly the robust integrated design of model-based FDD/LTP and control reconfiguration, is yet scarce and open. In addition, the research areas dealing with intelligent strategies for data interpretation, cautioning, and automated decision-making (e.g., using expert systems), which aim at delivering meaningful condition-based maintenance, are yet open to further explorations. □

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