energies

Review

Fault Diagnosis and Fault Tolerant Control of Wind Turbines: An Overview

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Abstract: Wind turbines are playing an increasingly important role in renewable power generation. Their complex and large-scale structure, however, and operation in remote locations with harsh environmental conditions and highly variable stochastic loads make fault occurrence inevitable. Early detection and location of faults are vital for maintaining a high degree of availability and reducing maintenance costs. Hence, the deployment of algorithms capable of continuously monitoring and diagnosing potential faults and mitigating their effects before they evolve into failures is crucial. Fault diagnosis and fault tolerant control designs have been the subject of intensive research in the past decades. Significant progress has been made and several methods and control algorithms have been proposed in the literature. This paper provides an overview of the most recent fault diagnosis and fault tolerant control techniques for wind turbines. Following a brief discussion of the typical faults, the most commonly used model-based, data-driven and signal-based approaches are discussed. Passive and active fault tolerant control approaches are also highlighted and relevant publications are discussed. Future development tendencies in fault diagnosis and fault tolerant control of wind turbines are also briefly stated. The paper is written in a tutorial manner to provide a comprehensive overview of this research topic.

Keywords: fault detection and diagnosis; fault-tolerant control; robustness and reliability; data-driven and model-based approaches; signal-based schemes; wind turbine

Citation: Fekih, A.; Habibi, H.; Simani, S. Fault Diagnosis and Fault Tolerant Control of Wind Turbines: An Overview. *Energies* **2022**, *15*, 7186. https://doi.org/10.3390/en15197186

Academic Editor: Frede Blaabjerg

Received: 14 August 2022
Accepted: 21 September 2022
Published: 29 September 2022

1. Introduction

Wind energy is among the most promising and fastest-growing sustainable energy sources in the world [1]. It is projected that wind energy will generate 49% of all electricity produced by non-hydro power renewables by 2028 [2], as highlighted in Figure 1.

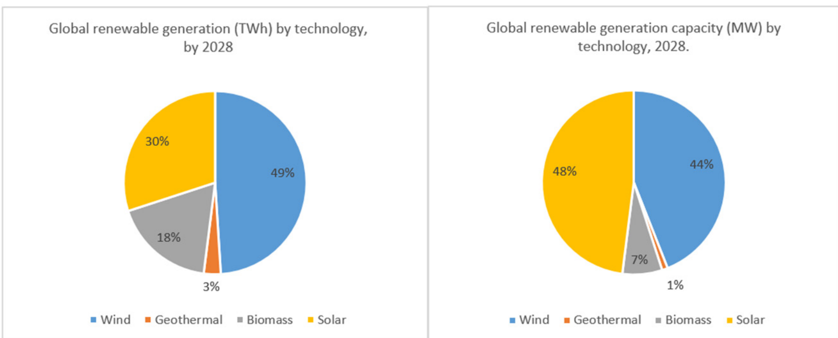

Figure 1. Global renewable generation and capacity by technology, by 2028 [2].

However, the operation and maintenance costs of Wind Turbines (WTs) are significant, especially for large-scale offshore WTs [2–4]. These latter are often installed in remote offshore locations and subjected to increased loads, especially on the rotors and drivetrain components. WT operational and maintenance costs are quite significant and range from 65–95% of the installation's investment cost [5]. Unscheduled maintenance resulting from malfunctions in system components such as the yaw system, rotor blades, rotor hub, gearbox, hydraulic system, gearbox, control and power electronic systems, generator/rotor speed/pitch sensors accounts for 30–60% of the total operational and maintenance costs of WTs and lead to prolonged downtimes and loss of electricity generation [5]. The reliability study reported in [6], found that electric components and control system faults resulted in half of WT failures whereas generator and gearbox failures were less frequent but resulted in longer downtimes. Mechanical brake systems are critical to the WT's integrity and safety since they perform two critical functions; retaining the nacelle stability when it turns and when it is oriented toward the wind. If mechanical brake systems are damaged, the repair process and component replacements are both challenging and costly.

Typical WT faults along with their severity and failure rate are illustrated in Table 1.

Table 1. List of typical faults, their occurrence and severity.

Fault	Failure Rate [7]	Potential Causes	Severity [8]
Generator	4%	Wind loading, extreme weather conditions, excessive vibration, voltage irregularities, mechanical and electrical failure of the bearings	Most severe
Gearbox	4%	Axial cracking in bearing, lubricant contamination, gears, filtration system problems	Most severe
Mechanical brake system	6%	Surface finish imperfection, damage to brake callipers, brake disc	Most severe
Yaw system	8%	Misalignment, fatigue, yaw bearing friction and failure	severe
Rotor blade	7%	Fatigue, corrosion, surface degradation, delamination, cracks, blade misalignment, lightning strikes	severe
Rotor hub	5%	Wind loading, weather extremes,	severe
Drive train	2%	Bearing failure, gear failures, axial cracking in bearings, lubricant contamination, overloading	severe
Electrical components	23%	Electric overload, insulation failure, connection faults, calibration errors, software faults	Less severe
Control system	18%	Voltage irregularities, electronic failure, software failure	Less severe
Sensors	10%	Biased, fixed, random or no measurements	Less severe
Hydraulic system	9%	Malfunctions, lubricant contamination, leakage	Less severe

Increasing the frequency of scheduled maintenance to prevent potential failure is counterproductive as it leads to higher maintenance and operational costs and results in less generated power as a result of downtimes [9]. Hence, to maintain the cost of generated power as low as possible, decrease downtime, and improve WTs reliability it is imperative to prevent faults from evolving into failures by devising mechanisms capable of ensuring fail-safe operations and continuous power generation until the next scheduled maintenance is conducted.

Fault-Tolerant Control (FTC) designs are control systems able to tolerate the possible malfunctions of the component and retain desirable performance and stability properties [10]. The key to FTC design is to prevent the propagation and development of local faults into system failures, and consequent safety hazards for man and the environment. FTC is a significant task to be fulfilled since faults in sensors, actuators and components are usually associated with increasing operating costs, unexpected shut-downs and possible detrimental environmental impacts. In general, a proper design of FTC system can add some beneficial characteristics to WT operations, including detection of faults in the early stages and conducting maintenance to prevent fault propagation and avoid failure, initiating the maintenance for the components, on which the fault has been isolated, optimizing the maintenance plan and schedule based on the Fault Detection and Diagnosis (FDD) information, the severity of faults based on the fault information, and planning if the maintenance may require the plant shutdown or if it can be conducted while the system is operating, based on the isolated and identified faults. It also provides a level of confidence for planning the maintenance, as it guarantees the required performance. Moreover, if the system shutdown is not required during the maintenance, then the system is kept operational, taking into account the FTC scheme. These characteristics, in turn, turn to improve availability, reliability, productivity, and sustainability and reduces operation and maintenance costs.

FTC techniques typically include different schemes, i.e., active and passive. The main difference between these two schemes is that active FTC requires timely and accurate FDD information to be fed into the controller structure, i.e., to adjust the available baseline controller to the current state of faults to compensate for fault effects completely and maintain the system stability and keep the performance objectives level as for the fault-free case. In contrast, in passive approaches, the baseline controller is predetermined and designed for the whole operation, whether fault-free or faulty conditions. Indeed, the baseline controller is designed to be optimally robust against a set of presumed faults, considered as the system uncertainties. The benefit of passive schemes is that the baseline controller is fixed and neither fault detection nor controller reconfiguration is needed, which increases the final system robustness, even though, it introduces some performance degradation in faulty conditions and limited fault-tolerant capability. Moreover, stability is not necessarily guaranteed for faults other than the considered set of presumed faults [7]. Several recent WT FTC designs [11–17] have been motivated by the benchmark model proposed in [11]. This model includes both faults for which the WT should be reconfigured to continue operation, as well as very severe faults which should result in a safe and fast shut down. As mentioned earlier, the baseline controller needs to be determined first, on which basis the FTC capability is augmented. Also, the operational objectives are defined to evaluate the designed FTC performance.

FDD methodologies are classified in the literature into model-based, data-driven and signal-based approaches [18]. Data-driven methods rely on the availability of a large amount of historical data, typically from a Supervisory Control and Data Acquisition (SCADA) system, with full fault scenarios. This latter is then transformed and presented as a priori knowledge to a diagnostic system using different spectrum analysis or vibration signal processing techniques such as Hilbert spectral analysis [19], support vector machines [20], Fourier transforms analysis [21], vibration-based analysis [22], thermal signal analysis [23], wavelet transform [24], and so on. A survey of the most relevant WT health monitoring and FDD techniques can be found e.g., in [25–28]. Signal-based techniques rely on available signals from WT sensor measurements such as electrical signals, vibration, sounds, and temperature which contain innumerable structural and electrical information. Signal processing, frequency analysis techniques and statistical methods are often used to extract fault signatures/features from the real-time measurements signal by comparing them to healthy signals and identifying fault frequency, type and location [29]. Signal-based fault diagnosis techniques are typically classified into frequency-domain, time-domain, and time-frequency techniques, as highlighted e.g., in [8,30–32].

Model-based FDD methods, on the other hand, rely on a dynamic model of the system under consideration [33]. Model-based FDD schemes are commonly designed using either residual signals [34], fault estimation techniques [35,36], or set-membership approaches [37]. Residual signals are fault indicators typically computed in real-time based on the difference between the measured output and the mathematical model. Faults are detected following residual evaluation either via fixed or adaptive threshold testing or by statistical methods and fuzzy logic approaches. Though residual-based approaches are relatively simple, ensuring the decoupling of the residual signal from noise and model uncertainties is a challenging problem. Fault estimation techniques rely on online estimation techniques to provide accurate information about the fault and its magnitude. Fault estimation can be achieved using Kalman filters [38,39], observers [40–47], interval parity equations [48], and fuzzy modelling and identification techniques [49] among others. A comprehensive review of signal-based and model-based condition monitoring techniques for WTs can be found in [8]. Set-membership-based FDD techniques rely on the generation of a set of mathematical models of the system without a need for a threshold design [50,51]. The FDD is achieved when there is any inconsistency between the measured inputs and outputs data with any of the members of the set. Fault isolation is achieved through the identification of the faulty feasible set. This method, however, suffers from the propagation of uncertainties along with the over-approximation required in the set computations [8].

One of the motivations of this paper comes from a real need to have a critical discussion and review of the challenges of FDD and FTC for very demanding systems, such as WTs, especially for their offshore and floating installations, requiring the so-called fault tolerance characteristic, also known as 'sustainable' feature. It is the main feature, i.e., tolerating possible malfunctions and, simultaneously, maintaining the operation, with power conversion efficiency. Especially for offshore and floating structures, those systems demand a higher degree of reliability and availability. Those deployments are to retain specified operable and committable conditions and to avoid costly maintenance processes. In this case, there exists a clear conflict, i.e., guaranteeing a high degree of availability and reducing costly maintenance. The latter factor may affect the energy conversion cost by up to 30%, due to unplanned maintenance services, especially if they are required in harsh environments.

Floating offshore WTs allow the extraction of wind resources from deeper offshore locations than the early shallow water fixed WTs [52,53]. One of the long-term goals of developing such devices is to generate electricity sustainably, which requires reducing the cost of the electricity produced [54] until it is comparable to that generated by bottom-fixed offshore and onshore WTs [55,56].

Larger size and higher output power lead to economy of scale for floating offshore WTs. Still, failures of floating devices tend to be hard to diagnose [57–59], even when they are limited to one component [60]. Moreover, the storm sea conditions can introduce damage to the floating structures, leading to more frequent failures and breakdowns than the onshore and bottom fixed offshore WTs [61–63].

The reduction of the floating wind energy generation costs and the electricity price calls for higher reliability, availability, and energy production efficiency of floating offshore WT. Reliability in this context is the probability that a floating offshore WT generates electricity as designed during a given time at sea. It represents the capability of a floating offshore WT to produce electricity without failures over a given time. Reliability analysis and assessment are foundations of lifecycle management, including reliability evaluation, reliability improvement, and reliability-based optimization design [64]. Moreover, the results of the mentioned works would directly support risk management, availability estimation, and maintainability investigations [58,59,65] of the floating equipment. The purpose of reliability analysis and assessment of such devices can be roughly divided into [57–59,66–68]:

(i) Prevent catastrophic failures;
(ii) Improve the robustness, reliability, availability, and electricity generation efficiency;
(iii) Support the optimal configuration design of subsystems.

This paper provides an overview of existing FDD techniques along with FTC designs for large onshore and offshore/floating WTs. A bibliographical review of some of the most relevant FTC techniques for WTs is carried out. FDD algorithms are also surveyed. A discussion on the future of diagnosis and FTC designs for WTs is also provided and the end of this paper.

The remainder of the paper is organized as follows. Section 2 briefly discusses the definition of faults and outlines existing FDD techniques. Section 3 outlines some of the existing FTC designs. Some concluding remarks and the future research directions are finally given in Section 4.

2. Faults and Fault Detection and Diagnosis

Faults are defined as an impermissible deviation of the system parameters or structure from the nominal situation [51]. Examples are a scaling error fault in the sensor reading, stuck sensor or actuators, biased actuator fault, fixed sensors, loss of actuator effectiveness, loss of a sensor, and disconnection of a system component. These faults can change the performance of the closed-loop system and result in degradation and potential loss of the system function. Faults are classified as sensor, actuator or plant faults. Actuator faults can affect the controller performance and can lead to either limiting or interrupting its influence on the plant. Erroneous sensor readings or their complete absence can drastically skew the performance of the controller. Plant faults, on the other hand, can change the dynamic properties of the system. Theoretically, a given fault is distinguished from another by the fault signal dynamic properties, described by the residual fault sensitivity, which should be different for each different fault.

FDD aims to detect and identify faults when they occur. This can be done by either using a residual generation approach or an online fault estimation approach.

Residual-based fault diagnosis algorithms typically consist of the following steps:

Residual generation: The process of generating a set of signals or residuals that react to a carefully chosen subset of faults as compared to the normal operating conditions.

Residual evaluation: The process of comparing residuals to some predefined thresholds according to a test and at a stage where symptoms are produced.

Decision making: The process of deciding based on the symptoms, which elements are faulty.

The general architecture of a residual-based FDD scheme is illustrated in Figure 2.

As illustrated in Figure 2, the FDD module is composed of a fault detection unit whose objective is to decide whether or not a fault has occurred. A fault diagnosis block that identifies in which component the fault occurred, and at the same time determines the exact location of the fault with its amplitude.

Existing FDD methods can be classified as (1) model-based techniques, (2) signal processing based-techniques, (3) data-driven techniques, and [8,9,69].

Model-based techniques rely on a model of the WT, this model can either be physics-based model or estimated using an observer, or another identification method. Faults are detected based on the residual generated by state variable or model parameter estimation. In signal processing-based techniques, information about the faults is extracted by either performing mathematical or statistical operations [70,71] or applying artificial intelligence techniques to the measurements [20,72].

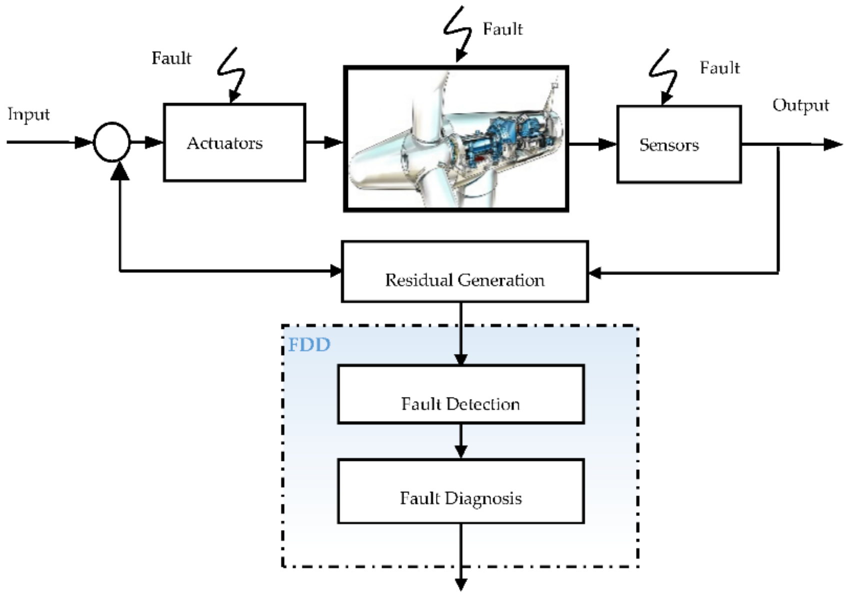

Figure 2. General architecture of an FDD module.

The following are the most commonly used techniques for FDD and FTC applications to WTs.

Kalman Filters: Kalman filters (KFs) are linear quadratic estimation techniques that use a series of measurements observed over time, including statistical noise to generate estimates of unknown variables via the estimation of a joint probability distribution of the variables over a given time frame. KFs are used for fault detection to estimate the system states using modelled information. The KF outputs are then compared with sensor measurements for fault detection. In normal operating conditions, the innovation sequence, which is the difference between sensor measurements and filter estimates, is used as a residual for FDD. The residual's mean value is zero under fault-free conditions and is changed from its initial zero mean value under faulty conditions when all hypotheses of the KF hold. The KF is designed in such a way that the sensor faults are considered exogenous output disturbances to be rejected, within the bound of noise properties defined with noise covariance matrices, providing an accurate/fault-free state estimate. Attributes of KF approaches are their ability to attenuate the effect of sensor noises on the residual. KF is the linear system optimal estimate with additive independent white noise in both the dynamics model and the measurement. The performance of KF strongly depends on how different the true probability distribution is from the ideal Gaussian case. Its computational time depends only on the number of samples, not model complexity. Robust applications of KFs for FDD of WT were shown e.g., in [73], where a model-based approach was addressed. The FDD scheme was so designed that the generated residual is guaranteed to be robust against stochastic uncertainty. For residual evaluation, a generalized likelihood ratio test was performed. The chi-square distribution table with one degree of freedom is used for the threshold testing to detect the fault occurrence.

Extended Kalman Filters (EKFs) are the nonlinear version of KFs often used for joint parameter and state estimation to provide an optimal estimation of the fault. The optimality of the method, however, relies on the a-priori choice of the covariance matrices. In practice, optimization is achieved by iteratively testing different values and evaluating the results over a test period. The parameter estimates can converge slower than the state estimates and in general, only local convergence can be expected. Also for the case of EKF, when considering safety-critical applications, continuous monitoring is necessary for improving availability and reliability. Therefore, the design of robust FDD and FTC systems is essential for such applications. Therefore, for example [74] described an FDD method to detect stator winding partial inter-turn faults with the percentage, using EKF and Unscented Kalman

Filter (UKF). Both simulation and practical implementation results were performed and validated with a prototype machine lab, highlighting significant responses for different operating conditions and different fault states.

Observer Designs: State observers are typically used to reconstruct or estimate state variables that are either unmeasured or not easily measured based on variables that can directly be measured. When robust state or output observers have to be designed for application to WT, different solutions can be adopted and they can be based e.g., on linear parameter varying tools or interval representations.

Linear Parameter Varying (LPV)-based observers yield models that are valid along the whole operating range.

Interval observers are a class of observers for robust state estimation, with the estimate of the upper-and lower-bounds. This attractive feature minimizes the unavoidable estimation errors resulting from disturbances or uncertainties by clearly defining an interval where the system state lies at any given time [20].

Table 2 provides a brief summary of some existing model-based techniques.

Table 2. List of some of the most relevant model-based FDD techniques.

Technique	Publication	Fault Detected
Kalman Filters (KF)/Extended KF (EKF)/Unscented KF (UKF)	[38]	Current sensor fault
	[75]	Pitch sensor bias
	[76]	Gearbox and generator faults
	[77]	Hydraulic actuator fault
	[34]	Pitch sensor and pitch actuator faults
	[78]	Pitch angle actuator fault/rotor speed sensor fault/generator speed sensor fault
LPV Observer/LPV extended Observer	[79]	Electric power fault/Generator speed/wind speed sensor fault/blade pitch angle
	[80]	Generator speed sensor fault/wind speed sensor fault
Interval Observer	[81]	Pitch actuator faults
	[40]	Generator power sensor/tower top accelerometer sensor/ sensor and actuator of the pitch sub-system
	[41]	State parameter anomalies
Unknown input observer	[42]	Rotor and generator speed sensor faults
	[43]	Sensor faults
	[44]	Converter faults
Fuzzy Takagi-Sugeno observer	[45]	Sensor faults
	[46]	Sensor fault in the DFIG Stator
KF and Artificial Neural Networks	[39]	Blade pitch system
Parity Equations	[48]	Debris build-up in the blades/blade misalignment/change if drivetrain damping
Takagi-Sugeno Sliding Mode Observer	[47]	Pitch actuator faults
Sliding Mode Observer	[82]	Pitch and drivetrain systems

It should be noted that the major problem in observer design for WTs is the considerable noise content of sensors and the poor measurement of wind speed. The former reduces the observer accuracy [83], while the latter is needed for drivetrain observer design [11]. To improve the observation performance [84] adopted an H-/H∞ optimization technique to minimize the noise effect. On the other hand, the application of the KF, as the optimal observer, has been considered on WT sensor FDD, in which it is guaranteed that the noise effect is minimized. In [85], a KF is designed to detect and isolate pitch sensor faults. Similarly, Ref. [86] used a KF for generating the residual generation, with a generalized likelihood ratio test, considering sensor faults of the pitch actuator and drivetrain. However, redundant physical sensors are required for fault isolation. Also, the applied aerodynamic torque was considered as a disturbance and the designed KF was shown to be robust against wind speed variations.

Data-driven techniques rely on data availability for the SCADA system. WT condition monitoring based on data available from the SCADA system is a relatively affordable solution. A brief summary of some of the most recent approaches is illustrated in Table 3.

Table 3. List of some of the most relevant *data-driven* FDD techniques.

Technique	Publication	Fault Detected
Artificial Neural Networks (NNs)	[87]	Gearbox bearings
Multiscale convolutional NNs	[88]	Gearbox faults
Multi-scale NNs	[89]	Bearing faults
Recurrent NNs	[90]	Converter Electrical faults
Fuzzy logic and Neural Networks	[91]	Wind speed sensor fault
	[92]	Pitch actuator fault
Deep Neural Networks	[93]	Gearbox faults
	[94]	Blade faults
Adaptive neuro-fuzzy inference system	[95]	Pitch actuator
	[96]	Component faults
Machine learning techniques	[97]	Gearbox faults
	[98]	Power generation performance monitoring
Convolutional Neural Networks	[99]	Component faults
	[100]	Gearbox and generator faults
	[101]	Gearbox Bearing Temperature
	[102]	Gearbox faults
Convolution NNs and signal-to-image encoding	[103]	Bearing faults
Gaussian Process	[104]	Power generation performance monitoring
Statistical Analysis	[105]	Drivetrain
	[106]	Downwind main-shaft Bearing
Hilbert spectral analysis	[19]	Drivetrain
Thermal analysis technique	[23]	Generator
Partial least square and regression Models	[83]	Generator/Gearbox/Rotor speed sensor fault
Hybrid intelligent approach	[107]	Gearbox fault
Cascaded SAE and LightGBM algorithm	[108]	Generator

Signal-based techniques rely on available signals from WT sensor measurements such as electrical signals, vibration, sounds, and temperature which contain innumerable structural and electrical information. Signal processing, frequency analysis techniques and statistical methods are often used to extract fault signatures/features from the real-time measurements signal by comparing them to healthy signals. Signal-based fault diagnosis techniques are typically classified into frequency-domain, time-domain, and time-frequency techniques. Signal-based techniques have extensively been reviewed in the literature [8,30,31]. Note that robust signal-based approaches are effective for FDD, as there is no need for system modelling and redundant sensor measurements. However, the model nonlinearity, disturbances and noise, and temporal dependence in time-series data impose challenges. To this end, as an example [109] proposed a new FDD solution based on a recently developed method, which led to robust nonlinear representations from data against noise and input fluctuation. A significant feature of this approach was the enhanced FDD performance, i.e., the ability to capture simultaneously the nonlinear correlations among multiple sensor variables and the temporal dependence of each sensor variable.

Only a few techniques are briefly reviewed in Table 4. The interested reader should refer to the above-mentioned review papers for further details.

Table 4. List of some of the most relevant *signal-based* FDD techniques.

Technique	Publication	Fault Detected
Vibration Signal Analysis	[110]	Generator and gearbox
	[111]	Tower structural faults
Wavelet transform	[112]	Gearbox
Wavelet transform and machine learning	[113]	Bearing Faults
Cyclostationary signal analysis	[114]	Gearbox
Machine learning	[115]	Gearbox
Operational Modal parameters	[116]	Blades structural faults
Statistical pattern recognition process	[30]	Blade, low-speed shaft and yaw joint
Statistical methods	[117]	Blade damage
	[118]	Pitch torque actuator faults/pitch sensor
Sensor Strain Analysis	[119]	Gearbox structural changes
	[120]	Blade loads

Albeit the wide variety of FDD techniques, the following challenges still exist:

- Most of the existing FDD techniques are often restricted to detecting faults for a specific component. Approaches that cover simultaneous faults in various components are rather scarce.
- The rapid fluctuations in WT's environmental conditions along with the low sampling frequency of SCADA systems make it difficult to detect and diagnose faults in a timely manner.
- Ensuring good data quality in data-driven techniques is not always guaranteed. For instance, data logs often suffer from missing data, statistical outliers, and larges sequences of identical values.
- Data-driven approaches provide higher diagnostic accuracy than model-based ones. However, their accuracy is highly dependent upon data availability. Optimal selection and placement of sensors and data acquisition devices are crucial in the overall performance of the FDD approach.

- The performance and accuracy of model-based techniques rely on an explicit physical or mathematical expression to accurately describe the performance degradation stemming from faults, whereas data-driven approaches rely on a historic run to failure data. However, in practice obtaining sufficient and reliable run-to-failure data for WTs is quite difficult, and obtaining an accurate model for such complex structures as WTs is quite impossible. Hence, considering a hybrid approach that integrates the data-driven and model-based framework can potentially alleviate the shortcomings of each individual approach while leveraging the merits of both approaches.

3. Fault Tolerant Control

The objective of FTC design is to maintain desirable performance and stability properties in the event of a fault and prevent local faults from developing into system failures that can end the mission of the system and cause safety hazards for man and the environment. FTC approaches are generally classified into two types: *passive* and *active* approaches. In the passive approach, the robustness range of the baseline controller is specified to be wide enough to accommodate specified faults within the accepted performance specification. The effectiveness of this strategy, with some restrictive assumptions on faults, depends upon the nominal closed-loop system robustness. This control exhibits a fast response and is simple to implement as neither fault detection nor controller reconfiguration is needed, however, it is challenging to consider several fault scenarios and it is unable to tolerate unforeseen faults. For some small changes in parameters and signal, a robust controller is able to achieve the FTC objective. However, in practical cases, using robust control alone may lead to substantial risk. This is due to the need for the known degree of fault insensitivity as a priori. This often results in some performance degradation in faulty conditions and limited fault-tolerant capability. Additionally, stability is not necessarily guaranteed for faults other than the considered set of presumed faults [7].

Active FTC approaches re-design a new control system taking into account the estimation of the fault, captured by the FDD filter, and the required specification to be met. Two active FTC methods are identified, including the projection-based methods and online automatic controller redesign methods. The former depends on using new pre-computed control laws based on the detected faults and severity. Hybrid or switching structure controls are common approaches. On the other hand, in the online automatic controller re-design methods, following the design paradigm typical of adaptive control, new parameters of controllers are computed when a fault is detected. This is potentially able to tackle a large number of fault scenarios and a certain number of unforeseen faults. However, it is more complex to implement and presents a real challenge in real-time decision-making. In addition to the drawbacks listed above for each approach, the following issues are of concern. The main issue with passive approaches is the high gain design with the required high bandwidth. This might lead to noise amplification, saturation and excitation of high-order modes. On the other hand, false alarms, false isolation, and false reconfiguration are the most reported issues with active FTC approaches.

The virtual sensor and actuator (VSA) FTC approach belongs to projection-based methods. In VSA, the information of fault is obtained from the FDD scheme and fed into a virtual (software) sensor/actuator module. This module is implemented between the actual sensor/actuator and the baseline controller, for fault effects compensation in the sensor/actuator. This can be seen as signal correction in the virtual sensor/actuator such that the effect of the fault is mitigated, as in Algorithm 1.

In Algorithm 1, s and a are outputs from the virtual sensor and actuator modules, respectively. Also, s_B and a_B are the baseline sensor and actuator of the WT, whose outputs are corrected in the virtual module. t_{DT} represents the time at which the fault is detected. The baseline controller is still in operation in this approach, which is an interesting industrial aspect because the existing baseline controller needs no modification and thus, can be used in both fault-free and faulty situations [121].

Algorithm 1: VSA FTC

If a fault is detected,
Then determine:
The fault detection time t_{DT},
The fault source, i.e., finding a faulty sensor or actuator,
The fault size $\hat{f}$,
If the fault source is a sensor, then $\underset{t \geq t_{DT}}{s(t)} = s_B(t) - \hat{f}(t)$,
If the fault source is an actuator, then $\underset{t \geq t_{DT}}{a(t)} = a_B(t) - \hat{f}(t)$,
Otherwise,
$s(t) = s_B(t)$ and $a(t) = a_B(t)$.

For some faults, their effects cannot be accommodated via VSA. For instance, for the power loss fault and process fault, modelled as the scaled power output, due to blade icing and debris built-ups, actuator abrupt faults, hydraulic actuators stuck and pump wear, it is better to tolerate by incorporation of a new scheme or reconfiguring the current control. Even if these faults are detected timely, the signal correction cannot remove their effects, because of the changing dynamics of the closed-loop system. Accordingly, in the Controller Reconfiguration (CR) approach, which belongs to online automatic controller re-design methods, the whole/part of the baseline controller is reconfigured to an alternative controller to guarantee stability and satisfactory performance. This alternative controller is obtained by either modification of the current baseline controller parameters, switching a new controller into the system, or using the available hardware/software redundant components [122,123]. Accordingly, in this approach, all available components should be considered in the baseline controller design. CR approach is summarized in Algorithm 2.

Algorithm 2: CR fault accommodation

If the fault is detected,
Then determine:
The fault detection time t_{DT},
The fault source, i.e., finding a faulty sensor or actuator or system fault,
The fault size $\hat{f}$,
Then $\underset{t \geq t_{DT}}{u(t)} = u_A(t)$ or $\underset{t \geq t_{DT}}{s(t)} = s_A(t)$ or $\underset{t \geq t_{DT}}{a(t)} = a_A(t)$.
Otherwise,
$u(t) = u_B(t)$ and $s(t) = s_B(t)$ and $a(t) = a_B(t)$.

In Algorithm 2, u, s and a are new control, sensor and actuator outputs, respectively. Also, $u_A \in U$, $s_A \in S_A$ and $a_A \in A_A$ are alternative controller, redundant sensor and redundant actuator, respectively. U is the achievable control set, whereas S_A and A_A are the available sets of redundant sensors and actuators, respectively. $u_B \in U$ is the baseline controller. CR approach has less industrial acceptability due to its complex implementation, but it shows promising performance for severe faults.

Several of recent and successful FTC designs [13,14,88,121–148] have been motivated by the WT benchmark model proposed in [11,12], which included sensor, actuator, and system faults, in the pitch, drive train, generator, and the converter systems. The need for robustness in WT control is motivated by WT nonlinearity between the generated power, the rotor and wind speeds. This stems from the fact that the turbine captures partially the wind energy based on rotor speed. This means that the maximum power generation and the maximum rotation speed are not concurrent. Moreover, the wind speed is essentially stochastic with continuous fluctuations. Also, there exists the system constraint on inputs (variation, the minimal and maximal values) and the outputs [149].

Different robust control schemes were proposed in the full load regime, which is more challenging than the partial load regime. Multiple SISO control was first used, e.g., the PI and LQG controllers [150]. The drawback is that the inputs are decoupled from the design, and the constraints are not considered. Therefore, MIMO control strategies have been developed, e.g., adaptive control [151–153] and feedback linearization controller [154]. Model Predictive Control (MPC) in WTs was first employed for gain scheduling, e.g., in [154,155]. It was also used for the FTC design of the pitch system by keeping the existing PI controller of the pitch angle [156,157].

MPC was later used for WT control, such as [158], where multiple linearizing models were employed, taking into account different operating points for variable wind speeds. Ref. [159] employed the same approach, but included the turbulent wind velocity. Ref. [160] developed variables change to transform the nonlinear dynamics into linear dynamics. Then, with convex constraints, MPC is used to control the pitch, generator torque, and charge/discharge rates for the storage device, aiming the total energy maximization. Also, limits of the time derivative of power delivered to the grid are considered. In [161] robust FTC was developed using min-max robust MPC, for variable speed WTs in the full load regime, tacking pitch actuator faults. Robust MPC has the advantage over conventional MPC to tackle parameter uncertainties in a structured way. For model uncertainties or process drift from the nominal one, e.g., actuators or in the system faults, along with an identification method, uncertainties can be suppressed. In [17] multiple LPV controllers were employed considering pitch angle fault. Ref. [162] employed robust MPC to tackle uncertainties in tower damping. Ref. [163] considered a min-max robust MPC approach to overcome fluctuations in the wind speed that was estimated using a KF.

Several other robust approaches have been considered in the design of FTC for WTs, including Sliding Mode Control (SMC) [164], nonlinear control, time delay control, robust fuzzy schedulers, adaptive control, fractional order SMC, control allocation, LPV control, and so on. For instance, an adaptive FTC strategy was proposed in [165] to mitigate pitch actuator faults in a large-scale WT. The approach considered a Linear Matrix Inequality (LMI)-based fault estimation algorithm and implemented a baseline multi-objective state feedback regulator. Linear Parameter-Varying (LPV) model-based control was proposed in [166] for the pitch and torque actuator faults in WTs. [167] considered an FTC scheme based on an adaptive CR approach augmented with a reallocation mechanism. Fuzzy Model Reference Adaptive Control (MRAC) was proposed in [168] to mitigate generator/converter torque actuator faults in large offshore WT benchmarks. [169] considered an FTC strategy based on a second-order fast non-singular terminal SMC to deal with actuator gain-bias faults and stochastic disturbances.

Table 5 provides a brief summary of the main existing robust FTC approaches along with their classification as passive or active techniques.

Table 5. Summary of the main FTC approaches for WTs.

Technique	Publication	Type
Observer-based FTC	[82]	Active
	[170]	Active
	[128]	Active
	[129]	Active
	[134]	Active
	[171]	Active
	[172]	Active
	[173]	Passive
	[174]	Passive

Table 5. *Cont.*

Technique	Publication	Type
Takagi–Sugeno (T–S) multiple models	[130]	Active
Takagi–Sugeno fuzzy model.	[131]	Active
Adaptive Sliding Mode Control	[123]	Passive
	[132]	Active
Fuzzy gain-scheduled PID control	[133]	Active
Fuzzy T-S multimodel and Fuzzy if-then control	[126]	Passive
Takagi–Sugeno Sliding Mode Observer	[175]	Active
	[47]	Active
Time Delay Control (TDC) and nonlinear disturbance observer	[134]	Active
Fuzzy if-then rules and fault estimation	[148]	Active
Fractional order SMC	[135]	Active
	[136]	Passive
Fractional order Nonsingular SMC	[137]	Passive
Fractional order Terminal SMC	[138]	Passive
Sliding Mode Control (SMC)	[139]	Passive
	[140]	Passive
	[141]	Passive
	[142]	Active/Passive
Integral Terminal SMC	[143]	Passive
	[176]	Active
Second Order ITSMC	[144]	Passive
Adaptive output feedback sliding mode control	[145]	Active
Control allocation	[146]	Active
Virtual sensors/actuators	[121]	Active
LMI based control	[147]	Passive
Model predictive control	[156]	Active
Gain scheduling and disturbance estimator	[177]	Active
Gain scheduling	[178]	Passive
	[179]	Passive
LPV-based control	[17]	Passive
	[16]	Active/Passive
Model reference adaptive control	[180]	Active
Fuzzy logic control	[181]	Passive
H_∞ norm	[182]	Passive
Adaptive PID control	[183]	Active
	[184]	Active
Takagi–Sugeno and sliding mode techniques	[175]	Active

According to the reviewed FTC literature, the following challenges still exist:

- Most of the existing FTC techniques have been developed to mitigate faults in specific components. Control designs capable of mitigating a wide range of faults amongst various components are still scarce.
- Most of the existing solutions have been developed for a given operational region of the WT. Considering adaptive and real-time methodologies capable of working for the

whole operational region of the WT have the potential to provide better performance and meet the requirements of Industry 4.0.

- Most of the FTC approaches were designed with the assumption of the availability of accurate information from the FDD unit. Studies that look into the robust integration of FDD and FTC schemes are very limited and conservative.
- Most of the proposed approaches were validated using either a simulation study or a WT benchmark and only considered limited fault scenarios. More research efforts should be done towards validation using hardware in the loop high fidelity simulators and considering realistic fault scenarios.
- None of the existing literature has considered the performance assessment of FTC designs in experimental-scale WTs.
- Compared to FDD techniques, existing literature for WT FTC design is still scarce, and only a few research papers have covered this issue.

4. Conclusions

Wind turbine's fault diagnosis and fault tolerant control schemes are crucial to their reliability, availability and cost-effectiveness. This paper provided an overview of some of the existing strategies for fault detection and diagnosis along with a thorough review of fault tolerant control designs for wind turbines. Both model-based, signal-based and data-based fault diagnosis approaches were briefly reviewed. It is worth noting that signal and data-based approaches are condition-specific techniques and rely on the accuracy and high resolution of available signals either emanating from sensors or SCADA systems. Model-based techniques, on the other hand, rely on mathematical models and the input-output information that could be retrieved from the wind turbine. Various data analysis and signal processing techniques are used to enable to extract useful information about the fault features and detect their occurrence.

In terms of fault tolerant control designs, passive and active fault tolerant control approaches were discussed and some examples from the literature were reviewed. Whereas passive approaches are simpler and easier to implement, they mostly rely on robust control techniques, they are very conservative and cannot account for a large number of faults nor deal with unforeseen faults that were not considered at the design stage. This is the main reason that its application in wind turbines is limited. Indeed, the conservatism is clearly against the adoption of fault tolerant control on wind turbines, which requires a focus on optimizing and maximizing power generation. Active fault tolerant control designs on the other hand are more complex to implement but capable of dealing with a large number of fault scenarios and can deal with unforeseen faults. Control reconfiguration, observer-based control, switching between controllers, adaptive control, or the use of software (virtual sensors/actuators)/hardware redundancies are among the techniques considered in fault-tolerant control design.

Some open research problems still exist, however. For instance, most of the studies have focused on fault detection and diagnosis, rather than fault tolerant control design. Also, the available controllers are mostly dedicated to a given operational region of wind turbines. Accordingly, the need is to further investigate fault tolerant control designs, especially, with a focus on adaptive schemes, as the newest innovative active/passive fault-tolerant concept, for the whole operational region. The performance analysis of the fault detection and diagnosis and fault tolerant control techniques in the presence of multiple and simultaneous faults is also another area of future research. Moreover, by the adoption of expert's knowledge into the design, using soft computing approaches, e.g., fuzzy if-then rules, neural networks or Bayesian frameworks, we can take the nonlinear and disturbed wind turbine model into consideration for more accurate fault diagnosis. Some faults are better dealt with at the wind farm control level, e.g., blade debris build-up, erosion and slowly developing faults, however, the literature on this concept is still scarce. So, it is beneficial to investigate new schemes for detection, isolation and accommodation of faults at the wind farm level. Optimal selection, placement, calibration, implementation and installation of sensors and devices are worth considering.

Research into artificial intelligence-enabled and advanced machine learning techniques for wind turbines' diagnostic and prognostic is still in its infancy and can benefit from additional investigations [185]. The future development tendency of fault diagnosis and fault tolerant control of wind turbines is towards considering cyber-resilient approaches to reduce wind turbines vulnerability to cyber-attacks. Another future tendency is the use of Internet of Things technologies to both create a vast amount of data and enable the remote condition monitoring of wind turbines from any location. In addition, one can use the smart sensor technology with the Internet of Things for remote real-time data acquisition and transmission throughout large wind farms. Furthermore, the big data concept can be used for the extraction of useful features, and the quality and completeness of data. Within the Industry 4.0 framework, the generation of digital twins to cover useful features of wind turbines is significantly beneficial in fault detection, diagnosis and monitoring.

Author Contributions: Conceptualization, investigation, and writing—original draft preparation, A.F., H.H.; writing—review, editing, A.F., H.H. and S.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare that they have no conflict of interest.

References

1. World Wind Energy Association. Available online: https://gwec.net/gwec-forecasts-817-gw-of-wind-power-in-2021 (accessed on 2 June 2022).
2. Richard, C. Solar PV to Overtake Wind by 2023, Wind Power Monthly. 2019. Available online: https://www.windpowermonthly.com/article/1525730/solar-pv-overtake-wind-2023 (accessed on 12 July 2022).
3. Verbruggen, T. Wind turbine operation & maintenance based on condition monitoring. In *ECN Wind Energy*; Technical Report ECN-C-03-047; ECN: Petten, The Netherlands, 2003.
4. McMillan, D.; Ault, G. Quantification of condition monitoring benefit for offshore wind turbines. *Wind. Energy* **2007**, *31*, 267–285. [CrossRef]
5. Walford, C. *Wind Turbine Reliability: Understanding and Minimizing Wind Turbine Operation and Maintenance Costs*; Sandia Report Sandia; Sandia National Laboratories (SNL): Albuquerque, NM, USA; Livermore, CA, USA, 2006; pp. 2006–2110.
6. Echivarria, E.; Van Bussel, G.; Hahn, B.; Tomiyama, T. Reliability of Wind Turbine Technology Through Time. *J. Sol. Eng.* **2008**, *130*, 031005. [CrossRef]
7. Vidal, Y.; Tutivén, C.; Rodellar, J.; Acho, L. Fault diagnosis and fault-tolerant control of wind turbines via a discrete time controller with a disturbance compensator. *Energies* **2015**, *8*, 4300–4316. [CrossRef]
8. Badihi, H.; Zhang, Y.; Jiang, B.; Pillay, P.; Rakheja, S. A comprehensive review on signal-based and model-based condition monitoring of wind turbines: Fault diagnosis and life prognosis. *Proc. IEEE* **2022**, *110*, 754–806. [CrossRef]
9. Habibi, H.; Howard, I.; Simani, S. Reliability improvement of wind turbine power generation using model-based fault detection and fault tolerant control: A review. *Renew. Energy* **2019**, *135*, 877–896. [CrossRef]
10. Blanke, M.; Kinnaert, M.; Lunze, J.; Staroswiecki, M. *Diagnosis and Fault Tolerant Control*, 3rd ed.; Springer: Berlin/Heidelberg, Germany, 2016.
11. Odgaard, P.F.; Stoustrup, J.; Kinnaert, M. Fault Tolerant Control of Wind Turbines Benchmark Model. In Proceedings of the IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes, Barcelona, Spain, 30 June–3 July 2009; pp. 155–160.
12. Odgaard, P.F.; Stoustrup, J.; Kinnaert, M. Fault Tolerant Control of Wind Turbines: A Benchmark Model. *IEEE Trans. Control Syst. Technol.* **2013**, *21*, 1168–1182. [CrossRef]
13. Dobrila, C.; Stefansen, R. Fault Tolerant Wind Turbine Control. Master's Thesis, Technical University of Denmark, Kongens Lyngby, Denmark, 2007.
14. Karimi, S.; Gaillard, A.; Poure, P.; Saadate, S. Current sensor fault-tolerant control for WECS with DFIG. *IEEE Trans. Ind. Electron.* **2009**, *56*, 4660–4670. [CrossRef]
15. Parker, M.A.; Ng, C.; Ran, L. Fault-tolerant control for a modular generator–converter scheme for direct-drive wind turbines. *IEEE Trans. Ind. Electron.* **2011**, *58*, 305–315. [CrossRef]
16. Sloth, C.; Esbensen, T.; Stoustrup, J. Active and passive fault-tolerant LPV control of wind turbines. In Proceedings of the American Control Conference, Marriott Waterfront, Baltimore, MD, USA, 30 June–2 July 2010; pp. 4640–4646.
17. Sloth, C.; Esbensen, T.; Stoustrup, J. Robust and fault-tolerant linear parameter-varying control of wind turbines. *Mechatronics* **2011**, *21*, 645–659. [CrossRef]

18. Gao, Z.; Liu, X. An Overview on Fault Diagnosis, Prognosis and Resilient Control for Wind Turbine Systems. *Processes* **2021**, *9*, 300. [CrossRef]
19. Ghane, M.; Rasekhi Nejad, A.; Blanke, M.; Gao, Z.; Moan, T. Diagnostic monitoring of drivetrain in a 5 MW spar-type floating wind turbine using Hilbert spectral analysis. *Energy Procedia* **2017**, *137*, 204–213. [CrossRef]
20. Laouti, N.; Sheibat-Othman, N.; Othman, S. Support vector machines for fault detection in wind turbines. In Proceedings of the IFAC World Congress, Milano, Italy, 28 August–2 September 2011; pp. 7067–7707.
21. Odgaard, P.F.; Stoustrup, J. Gear-box fault detection using time frequency-based methods. *Annu. Rev. Control* **2015**, *40*, 50–58. [CrossRef]
22. Barszcz, T. *Vibration-Based Condition Monitoring of Wind Turbines*; Springer: Berlin/Heidelberg, Germany, 2019.
23. Guo, P.; Infield, D.; Yang, X. Wind turbine generator condition monitoring using temperature trend analysis. *IEEE Trans. Sustain. Energy* **2012**, *3*, 124–133. [CrossRef]
24. Santos, P.; Villa, L.F.; Renones, A.; Bustillo, A.; Maudes, J. Wind turbines fault diagnosis using ensemble classifiers. In Proceedings of the 12th Industrial Conference on Advances in Data Mining: Applications and Theoretical Aspects, Berlin, Germany, 13–20 July 2012; pp. 67–76.
25. Qiao, W.; Lu, D. A survey on wind turbine condition monitoring and fault diagnosis—Part I: Components and systems. *IEEE Trans. Ind. Electron.* **2015**, *62*, 6536–6545. [CrossRef]
26. Qiao, W.; Lu, D. A survey on wind turbine condition monitoring and fault diagnosis—Part II: Signals and signal processing methods. *IEEE Trans. Ind. Electron.* **2015**, *62*, 6546–6557. [CrossRef]
27. Chaari, M.; Fekih, A.; Seibi, A. Current state of wind turbine's health monitoring. In Proceedings of the IEEE Green Technology Conference, Lafayette, LA, USA, 3–6 April 2019; pp. 1–6.
28. Márquez, F.P.G.; Tobias, M.; Perez, J.M.P.; Papaelias, M. Condition monitoring of wind turbines: Techniques and methods. *Renew. Energy* **2012**, *46*, 169–178. [CrossRef]
29. Li, W.; Zhang, S.; Rakheja, S. Feature denoising and nearest-farthest distance preserving projection for machine fault diagnosis. *IEEE Trans. Ind. Inform.* **2016**, *12*, 393–404. [CrossRef]
30. Adams, D.; White, J.; Rumsey, M.; Farrar, C. Structural health monitoring of wind turbines: Method and application to a HAWT. *Wind Energy* **2011**, *14*, 603–623. [CrossRef]
31. Gangsar, P.; Tiwari, R. Signal based condition monitoring techniques for fault detection and diagnosis of induction motors: A state-of-the art review. *Mech. Syst. Signal Process.* **2020**, *144*, 106908. [CrossRef]
32. Zhang, C.; Mousavi, A.; Masri, S.; Gholipour, G.; Yan, K.; Li, X. Vibration feature extraction using signal processing techniques for structural health monitoring: A review. *Mech. Syst. Signal Process.* **2022**, *177*, 109175. [CrossRef]
33. Ding, S. *Model-Based Fault Diagnosis Techniques. Design Schemes, Algorithms and Tools*; Springer: Berlin/Heidelberg, Germany, 2013.
34. Noshirvani, G.; Askari, J.; Fekih, A. A Robust Fault Detection and Isolation Filter for the Pitch System of a Variable Speed Wind Turbine. *Int. J. Electr. Eng. Syst.* **2018**, *28*, e2625. [CrossRef]
35. Ziyabari, S.; Shoorehdeli, A.; Karimirad, M. Robust fault estimation of a blade pitch and drivetrain system in wind turbine model. *J. Vib. Control* **2021**, *27*, 277–294. [CrossRef]
36. Habibi, H.; Howard, I.; Simani, S.; Fekih, A. Decoupling adaptive sliding mode observer design for wind turbines subject to simultaneous faults in sensors and actuators. *IEEE/CCA Autom. Sin.* **2021**, *8*, 837–847. [CrossRef]
37. Blesa, J.; Puig, V.; Saludes, J.; Fernández-Cantí, R.M. Set-membership parity space approach for fault detection in linear uncertain dynamic systems. *Int. J. Adapt. Control Signal Process.* **2016**, *30*, 186–205. [CrossRef]
38. Idrissi, I.; Bachtiri, R.; Chafouk, H. A Bank of Kalman Filters for Current Sensors Faults Detection and Isolation of DFIG for Wind Turbine. In Proceedings of the International Renewable and Sustainable Energy Conference, Tangier, Morocco, 4–7 December 2017; pp. 1–6.
39. Cho, S.; Cho, M.; Gao, Z.; Moan, T. Fault detection and diagnosis of a blade pitch system in a floating wind turbine based on Kalman filters and artificial neural networks. *Renew. Energy* **2021**, *169*, 1–13. [CrossRef]
40. Sanchez, H.; Escobet, T.; Puig, V.; Odgaard, P. Fault diagnosis of an advanced wind turbine benchmark using interval-based ARRs and observers. *IEEE Trans. Ind. Electron.* **2015**, *62*, 3783–3793. [CrossRef]
41. Zhang, Y.; Zheng, H.; Liu, J.; Zhao, J.; Sun, P. An anomaly identification model for wind turbine state parameters. *J. Clean. Prod.* **2018**, *195*, 1214–1227. [CrossRef]
42. Odgaard, P.; Stroustrup, J. Unknown input observer based detection of sensor faults in a wind turbine. In Proceedings of the IEEE International Conference on Control Applications, Yokohama, Japan, 8–10 September 2010; pp. 310–315.
43. Odgaard, P.; Stoustrup, J.; Nielsen, R.; Damgaard, C. Observer based detection of sensor faults in wind turbines. In Proceedings of the European Wind Energy Conference, Marseille, France, 16–19 March 2009.
44. Odgaard, P.; Stoustrup, J. Unknown input observer based scheme for detecting faults in a wind turbine converter. In Proceedings of the 7th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes, Barcelona, Spain, 30 June–3 July 2009; pp. 161–166.
45. Ouyssaad, H.; Chafouk, H.; Lefevre, D. Doubly fed induction generator fault diagnosis using unknown input Takagi-Sugeno observer. In Proceedings of the International Conference on Control, Decision and Information Technologies, Hammamet, Tunisia, 6–8 May 2013; pp. 530–535.

46. Abdelmalek, S.; Brazane, L.; Larabi, A.; Bettayed, M. A novel scheme for current sensor faults diagnosis in the stator of a DFIG described by a T-S fuzzy model. *Measurement* **2016**, *91*, 680–691. [CrossRef]
47. Georg, S.; Schulte, H. Actuator fault diagnosis and fault-tolerant control of wind turbines using a Takagi-Sugeno sliding mode observer. In Proceedings of the International Conference on Control and Fault-Tolerant Systems, Nice, France, 9–11 October 2013; pp. 516–522.
48. Blesa, J.; Jimneze, P.; Rotondo, D.; Nejjari, F.; Puig, V. Fault Diagnosis of a Wind Farm using Interval Parity Equations. *IFAC Proc.* **2014**, *47*, 4322–4327. [CrossRef]
49. Simani, S.; Farsoni, S.; Castaldi, P. Wind turbine simulator fault diagnosis via fuzzy modeling and identification techniques. *Sustain. Energy Grids Netw.* **2015**, *1*, 45–52. [CrossRef]
50. Puig, V. Fault diagnosis and fault tolerant control using set-membership approaches: Application to real case studies. *Int. J. Appl. Math. Comput. Sci.* **2010**, *20*, 619–635. [CrossRef]
51. Tabatabaeipour, S.M.; Odgaard, P.F.; Bak, T.; Stoustrup, J. Fault detection of wind turbines with uncertain parameters: A set-membership approach. *Energies* **2012**, *5*, 2424–2448. [CrossRef]
52. Díaz, H.; Guedes Soares, C. Review of the current status, technology and future trends of offshore wind farms. *Ocean Eng.* **2020**, *209*, 107381. [CrossRef]
53. Li, H.; Huang, C.G.; Guedes Soares, C. A real-time inspection and opportunistic maintenance strategies for floating offshore wind turbines. *Ocean Eng.* **2022**, *256*, 111433. [CrossRef]
54. Castro-Santos, L.; Martins, E.; Guedes Soares, C. Cost assessment methodology for combined wind and wave floating offshore renewable energy systems. *Renew. Energy* **2016**, *97*, 866–880. [CrossRef]
55. Castro-Santos, L.; Silva, D.; Bento, A.R.; Salvacao, N.; Guedes Soares, C. Economic feasibility of floating offshore wind farms in Portugal. *Ocean Eng.* **2020**, *207*, 107393. [CrossRef]
56. Yeter, B.; Garbatov, Y.; Guedes Soares, C. Risk-based maintenance planning of offshore wind turbine farms. *Reliab. Eng. Syst. Saf.* **2020**, *202*, 107062. [CrossRef]
57. Li, H.; Díaz, H.; Guedes Soares, C. A Developed Failure Mode and Effect Analysis for Floating Offshore Wind Turbine Support Structures. *Renew. Energy* **2020**, *164*, 133–145. [CrossRef]
58. Li, H.; Teixeira, A.P.; Guedes Soares, C. A Two-Stage Failure Mode and Effect Analysis of an Offshore Wind Turbine. *Renew. Energy* **2020**, *162*, 1438–1461. [CrossRef]
59. Li, H.; Díaz, H.; Guedes Soares, C. A Failure Analysis of Floating Offshore Wind Turbines using AHP-FMEA Methodology. *Ocean Eng.* **2021**, *234*, 109261. [CrossRef]
60. Bhardwaj, U.; Teixeira, A.P.; Guedes Soares, C. Reliability prediction of an offshore wind turbine gearbox. *Renew. Energy* **2019**, *141*, 693–706. [CrossRef]
61. Kang, J.; Sun, L.; Guedes Soares, C. Fault Tree Analysis of floating offshore wind turbines. *Renew. Energy* **2019**, *133*, 1455–1467. [CrossRef]
62. Sinha, Y.; Steel, J.A. A progressive study into offshore wind farm maintenance optimisation using risk based failure analysis. *Renew. Sustain. Energy Rev.* **2015**, *42*, 735–742. [CrossRef]
63. Reder, M.; Yürüşen, N.Y.; Melero, J.J. Data-driven learning framework for associating weather conditions and wind turbine failures. *Reliab. Eng. Syst. Saf.* **2018**, *169*, 554–569. [CrossRef]
64. Alkaff, A.; Qomarudin, M.N.; Bilfaqih, Y. Network reliability analysis: Matrixexponential approach. *Reliab. Eng. Syst. Saf.* **2020**, *204*, 107192. [CrossRef]
65. Eryilmaz, S.; Kan, C. Reliability based modelling and analysis for a wind power system integrated by two wind farms considering wind speed dependence. *Reliab. Eng. Syst. Saf.* **2020**, *203*, 107077. [CrossRef]
66. Langseth, H.; Portinale, L. Bayesian networks in reliability. *Reliab. Eng. Syst. Saf.* **2007**, *92*, 92–108. [CrossRef]
67. Bobbio, A.; Portinale, L.; Minichino, M.; Ciancamerla, E. Improving the analysis of dependable systems by mapping fault trees into Bayesian networks. *Reliab. Eng. Syst. Saf.* **2001**, *71*, 249–260. [CrossRef]
68. Li, H.; Guedes Soares, C.; Huang, H.Z. Reliability analysis of floating offshore wind turbine using Bayesian Networks. *Ocean Eng.* **2020**, *217*, 107827. [CrossRef]
69. Isermann, R. Model-based Fault Detection and Diagnosis-Status and Applications. *Annu. Rev. Control* **2005**, *29*, 71–85. [CrossRef]
70. Dong, J.; Verhaegen, M. Data driven fault detection and isolation of a wind turbine benchmark. In Proceedings of the International Federation of Automatic Control (IFAC) World Congress, Milano, Italy, 28 August–2 September 2011; Volume 2, pp. 7086–7091.
71. Simani, S.; Castaldi, P.; Tilli, A. Data-driven approach for wind turbine actuator and sensor fault detection and isolation. In Proceedings of the International Federation of Automatic Control (IFAC) World Congress, Milano, Italy, 28 August–2 September 2011; pp. 8301–8306.
72. Stoican, F.; Raduinea, C.F.; Olaru, S. Adaptation of set theoretic methods to the fault detection of wind turbine benchmark. In Proceedings of the IFAC World Congress, Milano, Italy, 28 August–2 September 2011; pp. 8322–8327.
73. Nazir, M.; Khan, A.Q.; Mustafa, G.; Abid, M. Robust fault detection for wind turbines using reference model-based approach. *J. King Saud Univ. Eng. Sci.* **2017**, *29*, 244–252. [CrossRef]
74. El Sayed, W.; Abd El Geliel, M.; Lotfy, A. Fault Diagnosis of PMSG Stator Inter-Turn Fault Using Extended Kalman Filter and Unscented Kalman Filter. *Energies* **2020**, *13*, 2972. [CrossRef]

75. Wu, D.; Gao, C.; Zhai, Y.; Shen, Y.; Ji, Z. Fault diagnosis of pitch sensor bias for wind turbine based on the multi-innovation Kalman filter. In Proceedings of the Chinese Control Conference, Chengdu, China, 27–29 July 2016; pp. 6403–6407.
76. Mengnan, C.; Yingning, Q.; Yanhui, F.; Hao, W.; Infield, D. Wind Turbine Fault Diagnosis Based on Unscented Kalman Filter. In Proceedings of the International Conference on Renewable Power Generation, Beijing, China, 17–18 October 2015; pp. 1–5.
77. An, L.; Sepehri, N. Hydraulic actuator leakage fault detection using extended Kalman filter. *Int. J. Fluid Power* **2005**, *6*, 41–51. [CrossRef]
78. Ghareveran, M.; Yazdizadeh, A. Estimation of V47/660kW Wind Turbine State and Fault Detection with Extended Kalman Filter. In Proceedings of the International Conference on Control, Instrumentation, and Automation, Sanandaj, Iran, 30–31 October 2019; pp. 1–7.
79. Negre, P.; Puig, V.; Pinda, I. Fault detection and isolation of a real wind turbine using LPV observers. In Proceedings of the IFAC World Congress, Milano, Italy, 8 August–2 September 2011; pp. 12372–12379.
80. Negre, P.; Puig, V.; Pinda, I. Interval LPV Identification and Fault Diagnosis of a Real Wind Turbine. In Proceedings of the IFAC Symposium on System Identification, Brussels, Belgium, 11–13 July 2012; pp. 1689–1694.
81. Tutiven, C.; Vidal, Y.; Acho, L.; Rodellar, J. Fault detection and isolation of pitch actuator faults in a floating wind turbine. *IFAC PapersOnLine* **2018**, *51*, 480–487. [CrossRef]
82. Borja-Jaimes, V.; Adam-Medina, M.; López-Zapata, B.Y.; Vela Valdés, L.G.; Claudio Pachecano, L.; Sánchez Coronado, E.M. Sliding Mode Observer-Based Fault Detection and Isolation Approach for a Wind Turbine Benchmark. *Processes* **2022**, *10*, 54. [CrossRef]
83. Haghani, A.; Krueger, M.; Jeinsch, T.; Ding, S.; Engel, P. Data-Driven Multimode Fault Detection for Wind Energy Conversion Systems. *IFAC PapersOnLine* **2015**, *48*, 633–638. [CrossRef]
84. Jihong, L.; Daping, X.; Xiyun, Y. Sensor fault detection in variable speed wind turbine system using $H\_/H\infty$ method. In Proceedings of the 7th World Congress on Intelligent Control and Automation, Chongqing, China, 25–27 June 2008.
85. Wei, X.; Verhaegen, M.; Van Engelen, T. Sensor fault detection and isolation for wind turbines based on subspace identification and Kalman filter techniques. *Int. J. Adapt. Control* **2010**, *24*, 687–707. [CrossRef]
86. Chen, W.; Ding, S.X.; Sari, A.; Naik, A.; Khan, A.Q.; Yin, S. Observer-based FDI schemes for wind turbine benchmark. In Proceedings of the IFAC World Congress, Milano, Italy, 28 August–2 September 2011; pp. 7073–7078.
87. Bangalore, P.; Tjernberg, L.B. An artificial neural network approach for early fault detection of gearbox bearings. *IEEE Trans. Smart Grid* **2015**, *6*, 980–987. [CrossRef]
88. Jiang, G.; He, H.; Yan, J.; Xie, P. Multiscale convolutional neural networks for fault diagnosis of wind turbine gearbox. *IEEE Trans. Ind. Electron.* **2019**, *4*, 3196–3207. [CrossRef]
89. Liu, X.; Cai, Y.; Song, Y.; Tan, L. Bearing Fault Diagnosis Based on Multi-scale Neural Networks. In Proceedings of the IEEE International Conference on Electro Information Technology (eIT), Mankato, MN, USA, 19–21 May 2022; pp. 80–85.
90. Mansouri, M.; Dhibi, K.; Hajji, M.; Bouzara, K.; Nounou, H.; Nounou, M. Interval-Valued Reduced RNN for Fault Detection and Diagnosis for Wind Energy Conversion Systems. *IEEE Sens. J.* **2022**, *22*, 13581–13588. [CrossRef]
91. Zhu, H.; Liu, J.; Lu, D.; Wang, Z. A Novel Wind Turbine Fault Detection Method Based on Fuzzy Logic System Using Neural Network Construction Method. *IFAC PapersOnLine* **2020**, *53*, 664–668. [CrossRef]
92. Farsoni, S.; Simani, S.; Castaldi, P. Fuzzy and Neural Network Approaches to Wind Turbine Fault Diagnosis. *Appl. Sci.* **2021**, *11*, 5035. [CrossRef]
93. Wang, L.; Zhang, Z.; Long, H.; Xu, J.; Liu, R. Wind turbine gearbox failure identification with deep neural networks. *IEEE Trans. Ind. Inform.* **2017**, *3*, 1360–1368. [CrossRef]
94. Chen, L.; Xu, G.; Zhang, Q.; Zhang, X. Learning deep representation of imbalanced SCADA data for fault detection of wind turbines. *Measurement* **2019**, *139*, 370–379. [CrossRef]
95. Chen, B.; Matthews, P.C.; Tavner, P.J. Wind turbine pitch faults prognosis using a-priori knowledge-based ANFIS. *Expert Syst. Appl.* **2013**, *40*, 6863–6876. [CrossRef]
96. Schlechtingen, M.; Santos, I.F. Wind turbine condition monitoring based on SCADA data using normal behavior models. Part 2: Application examples. *Appl. Soft Comput.* **2014**, *14*, 447–460. [CrossRef]
97. Carroll, J.; Koukoura, S.; McDonald, A.; Charalambous, A.; Weiss, S.; McArthur, S. Wind turbine gearbox failure and remaining useful life prediction using machine learning techniques. *Wind Energy* **2019**, *22*, 360–375. [CrossRef]
98. Papatheou, E.; Dervilis, N.; Maguire, A.E.; Antoniadou, I.; Worden, K. A performance monitoring approach for the novel lillgrund offshore wind farm. *IEEE Trans. Ind. Electron.* **2015**, *62*, 6636–6644. [CrossRef]
99. Kong, Z.; Tang, B.; Deng, L.; Liu, W.; Han, Y. Condition monitoring of wind turbines based on spatio-temporal fusion of SCADA data by convolutional neural networks and gated recurrent units. *Renew. Energy* **2020**, *146*, 760–776. [CrossRef]
100. Xiang, L.; Wang, P.; Yang, X.; Hu, A.; Su, H. Fault detection of wind turbine based on SCADA data analysis using CNN and LSTM with attention mechanism. *Measurement* **2021**, *175*, 109094. [CrossRef]
101. Guo, P.; Fu, J.; Yang, X. Condition Monitoring and Fault Diagnosis of Wind Turbines Gearbox Bearing Temperature Based on Kolmogorov-Smirnov Test and Convolutional Neural Network Model. *Energies* **2018**, *11*, 2248. [CrossRef]
102. Sun, J.; Wen, J.; Yuan, C.; Liu, Z.; Xiao, Q. Bearing Fault Diagnosis Based on Multiple Transformation Domain Fusion and Improved Residual Dense Networks. *IEEE Sens. J.* **2022**, *22*, 1541–1551. [CrossRef]

103. Toma, R.N.; Piltan, F.; Im, K.; Shon, D.; Yoon, T.H.; Yoo, D.-S.; Kim, J.-M. A Bearing Fault Classification Framework Based on Image Encoding Techniques and a Convolutional Neural Network under Different Operating Conditions. *Sensors* **2022**, *22*, 4881. [CrossRef] [PubMed]
104. Guo, P.; Infield, D. Wind turbine power curve modeling and monitoring with Gaussian process and SPRT. *IEEE Trans. Sustain. Energy* **2020**, *11*, 107–115. [CrossRef]
105. Ghane, M.; Rasekhi Nejad, A.; Blanke, M.; Gao, Z.; Moan, T. Statistical fault diagnosis of wind turbine drivetrain applied to a 5MW floating wind turbine. *J. Phys. Conf. Ser.* **2017**, *753*, 052017. [CrossRef]
106. Ghane, M.; Rasekhi Nejad, A.; Blanke, M.; Gao, Z.; Moan, T. Condition monitoring of spar-type floating wind turbine drivetrain using statistical fault diagnosis. *Wind Energy* **2018**, *21*, 575–589. [CrossRef]
107. Heydari, A.; Garcia, D.; Fekih, A.; Keynia, F.; Tjernberg, L.; Santoli, L. A hybrid intelligent model for the condition monitoring and diagnostics of wind turbines gearbox. *IEEE Access* **2021**, *9*, 89878–89890. [CrossRef]
108. Wang, L.; Jia, S.; Yan, X.; Ma, L.; Fang, J. A SCADA-Data-Driven Condition Monitoring Method of Wind Turbine Generators. *IEEE Access* **2022**, *10*, 67532–67540. [CrossRef]
109. Jiang, G.; Xie, P.; He, H.; Yan, J. Wind Turbine Fault Detection Using a Denoising Autoencoder with Temporal Information. *IEEE/ASME Trans. Mechatron.* **2018**, *23*, 89–100. [CrossRef]
110. Zimroz, R.; Bartelmus, W.; Barszcz, T.; Urbanek, J. Diagnostics of bearings in presence of strong operating conditions non-stationarity—A procedure of load-dependent features processing with application to wind turbine bearings. *Mech. Syst. Signal Process.* **2014**, *46*, 16–27. [CrossRef]
111. Nguyen, C.; Huynh, T.; Kim, J. Vibration-based damage detection in wind turbine towers using artificial neural networks. *Struct. Monit. Maint.* **2018**, *5*, 507–519.
112. Teng, W.; Ding, X.; Cheng, H.; Han, C.; Liu, Y.; Mu, H. Compound faults diagnosis and analysis for a wind turbine gearbox via a novel vibration model and empirical wavelet transform. *Renew. Energy* **2019**, *136*, 393–402. [CrossRef]
113. Toma, R.N.; Kim, J.M. Article bearing fault classification of induction motors using discrete wavelet transform and ensemble machine learning algorithms. *Appl. Sci.* **2020**, *10*, 5251. [CrossRef]
114. Mauricio, A.; Qi, J.; Gryllias, K. Vibration-based condition monitoring of wind turbine gearboxes based on cyclostationary analysis. *J. Eng. Gas Turbines Power* **2019**, *141*, 031026. [CrossRef]
115. Elasha, F.; Shanbr, S.; Li, X.; Mba, D. Prognosis of a wind turbine gearbox bearing using supervised machine learning. *Sensors* **2019**, *19*, 3092. [CrossRef]
116. Kim, H.-C.; Kim, M.-H.; Choe, D.-E. Structural health monitoring of towers and blades for floating offshore wind turbines using operational modal analysis and modal properties with numerical-sensor signals. *Ocean Eng.* **2019**, *188*, 106226. [CrossRef]
117. Abouhnik, A.; Albarbar, A. Wind turbine blades condition assessment based on vibration measurements and the level of an empirically decomposed feature. *Energy Convers. Manag.* **2012**, *64*, 606–613. [CrossRef]
118. Pozo, F.; Vidal, Y. Wind turbine fault detection through principal component analysis and statistical hypothesis testing. *Energies* **2016**, *9*, 3. [CrossRef]
119. Yoon, J.; He, D.; Van Hecke, B. On the use of a single piezoelectric strain sensor for wind turbine planetary gearbox fault diagnosis. *IEEE Trans. Ind. Electron.* **2015**, *62*, 6585–6593. [CrossRef]
120. Wen, B.; Tian, X.; Jiang, Z.; Li, Z.; Dong, X.; Peng, Z. Monitoring blade loads for a floating wind turbine in wave basin model tests using fiber Bragg grating sensors: A feasibility study. *Mar. Struct.* **2020**, *71*, 102729. [CrossRef]
121. Rotondo, D.; Nejjari, F.; Puig, V.; Blesa, J. Fault tolerant control of the wind turbine benchmark using virtual sensors/actuators. *IFAC Proc.* **2012**, *45*, 114–119. [CrossRef]
122. Simani, S.; Castaldi, P. Adaptive fault-tolerant control design approach for a wind turbine benchmark. In Proceedings of the Fault Detection, Supervision and Safety of Technical Processes Conference, Mexico City, Mexico, 29–31 August 2012; pp. 319–324.
123. Shaker, M.; Patton, R. Fault tolerant adaptive sliding mode controller for wind turbine power maximization. *IFAC Proc.* **2012**, *45*, 499–504.
124. Odgaard, P.F.; Stoustrup, J. Fault tolerant control of wind turbines using unknown input observers. *IFAC Proc. Vol.* **2012**, *45*, 313–318. [CrossRef]
125. Odgaard, P.F.; Stoustrup, J. A benchmark evaluation of fault tolerant wind turbine control concepts. *IEEE Trans. Control Syst. Technol.* **2015**, *23*, 1221–1228. [CrossRef]
126. Simani, S.; Castaldi, P. Data–Driven Design of Fuzzy Logic Fault Tolerant Control for a Wind Turbine Benchmark. In Proceedings of the Fault Detection, Supervision and Safety of Technical Processes, Mexico City, Mexico, 29–31 August 2012.
127. Simani, S.; Castaldi, P. Active actuator fault-tolerant control of a wind turbine benchmark model. *Int. J. Robust Nonlinear Cont.* **2014**, *24*, 1283–1303. [CrossRef]
128. Lan, J.; Patton, R.; Zhu, X. Fault tolerant wind turbine pitch control using adaptive sliding mode estimation. *Renew. Energy* **2018**, *116*, 219–231. [CrossRef]
129. Kamal, E.; Aitouche, A.; Ghorbani, R.; Bayart, M. Robust fuzzy fault tolerant control of wind energy conversion systems subject to sensor faults. *IEEE Trans. Sustain. Energy* **2012**, *3*, 231–241. [CrossRef]
130. Shaker, M.; Patton, R. Active sensor fault tolerant output feedback tracking control for wind turbine systems via T–S model. *Eng. Appl. Artif. Intell.* **2014**, *34*, 1–12. [CrossRef]

131. Li, S.; Wang, H.; Aitouche, A.; Christov, N. Active fault tolerant control of wind turbine systems based on DFIG with actuator fault and disturbance using Takagi–Sugeno fuzzy model. *J. Frankl. Inst.* **2018**, *355*, 8194–8212. [CrossRef]
132. Azizi, A.; Nourisola, H.; Shoja-Majidabad, S. Fault tolerant control of wind turbines with an adaptive output feedback sliding mode controller. *Renew. Energy* **2019**, *135*, 55–65. [CrossRef]
133. Badihi, H.; Zhang, Y.; Hong, H. Fuzzy gain-scheduled active fault tolerant control of a wind turbine. *J. Frankl. Inst.* **2014**, *351*, 3677–3706. [CrossRef]
134. Mazare, M.; Taghizadeh, M.; Ghaf-Ghanbari, P. Pitch actuator fault-tolerant control of wind turbines based on time delay control and disturbance observer. *Ocean Eng.* **2021**, *238*, 109724. [CrossRef]
135. Noshirvani, G.; Askari, J.; Fekih, A. Fractional-order fault-tolerant pitch control design for a 2.5 MW wind turbine subject to actuator faults. *Struct. Control Health Monit.* **2019**, *26*, e2411.
136. Musarrat, M.N.; Fekih, A. A fractional order sliding mode control-based topology to improve the transient stability of wind energy systems. *Int. J. Electr. Power Energy Syst.* **2021**, *133*, 107306. [CrossRef]
137. Mousavi, Y.; Bevan, G.; Kucukdemiral, I.; Fekih, A. Maximum Power Extraction from Wind Turbines using a Fault-Tolerant Fractional-order Nonsingular Terminal Sliding Mode Control. *Energies* **2022**, *18*, 5887.
138. Mousavi, Y.; Bevan, G.; Kucukdemiral, I.; Fekih, A. Active Fault-tolerant Fractional-order Terminal Sliding Mode Control for DFIG-based Wind Turbines Subjected to Sensor Faults. In Proceedings of the IEEE IAS GLOBCONET Conference, Arad, Romania, 20–22 May 2022; pp. 1–6.
139. Morshed, M.J.; Fekih, A. A Sliding mode approach to enhance the power quality of wind turbines under unbalanced grid conditions. *IEEE/CAA J. Autom. Sin.* **2019**, *6*, 566–574. [CrossRef]
140. Yang, B.; Yu, T.; Shu, H.C.; Zhang, Y.M.; Chen, J.; Sang, Y.Y.; Jiang, L. Passivity-based sliding-mode control design for optimal power extraction of a PMSG based variable speed wind turbine. *Renew. Energy* **2018**, *119*, 577–589. [CrossRef]
141. Shaker, M.S.; Kraidi, A. Robust fault-tolerant control of wind turbine systems against actuator and sensor faults. *Arab. J. Sci. Eng.* **2017**, *42*, 3055–3063. [CrossRef]
142. Fekih, A. Effective Fault Tolerant Control Design for a Class of Nonlinear Systems: Application to a Class of Motor Control. *IET Control Theory Appl.* **2008**, *2*, 762–772. [CrossRef]
143. Morshed, M.J.; Fekih, A. Design of a Chattering-free integral terminal sliding mode approach for DFIG-based wind energy systems. *Optim. Control Appl. Methods* **2020**, *41*, 1718–1734. [CrossRef]
144. Morshed, M.J.; Fekih, A. Second Order Integral Terminal Sliding Mode Control for Voltage Sag Mitigation in DFIG-based Wind Turbines. In Proceedings of the IEEE Conference on Control Technology and Applications, Maui, HI, USA, 27–30 August 2017; pp. 614–619.
145. Fekih, A.; Mobayen, S.; Chen, C.C. Adaptive robust fault-tolerant control design for wind turbines subject to pitch actuator faults. *Energies* **2021**, *14*, 1791. [CrossRef]
146. Kim, J.; Yang, I.; Lee, D. Control allocation based compensation for faulty blade actuator of wind turbine. *IFAC Proc.* **2012**, *45*, 355–360. [CrossRef]
147. Sloth, C.; Esbensen, T.; Niss, M.; Stoustrup, J.; Odgaard, P.F. Robust LMI-Based Control of Wind Turbines with Parametric Uncertainties. In Proceedings of the 3rd IEEE Multi-Conference on Systems and Control, Saint Petersburg, Russia, 8–10 July 2009.
148. Badihi, H.; Zhang, Y.; Rakheja, S.; Pillay, P. Model-Based Fault-Tolerant Pitch Control of an Offshore Wind Turbine. *IFAC PapersOnLine* **2019**, *51*, 221–226. [CrossRef]
149. Odgaard, P.F.; Johnson, K.E. Wind turbine fault detection and fault tolerant control-an enhanced benchmark challenge. In Proceedings of the 2013 American Control Conference (ACC), Washington, DC, USA, 17–19 June 2013; IEEE: Piscataway, NJ, USA, 2013; pp. 4447–4452.
150. Pao, L.Y.; Johnson, K.E. Control of Wind Turbines. *IEEE Control Syst.* **2011**, *31*, 44–62. [CrossRef]
151. Freeman, J.; Balas, M. An investigation of variable speed horizontal-axis wind turbines using direct model-reference adaptive control. In Proceedings of the 37th Aerospace Sciences Meeting and Exhibit, American Institute of Aeronautics and Astronautics, Reno, NV, USA, 11–14 January 1999.
152. Frost, S.A.; Balas, M.J.; Wright, A.D. Direct adaptive control of a utility-scale wind turbine for speed regulation. *Int. J. Robust Nonlinear Control* **2009**, *19*, 59–71. [CrossRef]
153. Díaz-Guerra, L.; Adegas, F.D.; Stoustrup, J.; Monros, M. Adaptive control algorithm for improving power capture of wind turbines in turbulent winds. In Proceedings of the American Control Conference, Montreal, QC, Canada, 27–29 June 2012; pp. 5807–5812.
154. Kumar, A.; Stol, K. Scheduled Model Predictive Control of a wind Turbine. In Proceedings of the AIAA Sciences Meeting, Orlando, FL, USA, 5–8 January 2009.
155. Bianchi, F.D.; De Battista, H.; Mantz, R.J. *Wind Turbine Control Systems: Principles, Modelling and Gain Scheduling Design, Advances in Industrial Control*; Springer: London, UK, 2007.
156. Yang, X.; Maciejowski, J.M. Fault-tolerant model predictive control of a wind turbine benchmark. *IFAC Proc.* **2012**, *45*, 337–342. [CrossRef]
157. Benlahrache, M.A.; Othman, S.; Sheibat-Othman, N. Faults tolerant control of wind turbine based on Laguerre model predictive compensator. In Proceedings of the European Control Conference, Linz, Austria, 15–17 July 2015; pp. 3653–3658.

158. Soliman, M.; Malik, O.P.; Westwick, D.T. Multiple model MIMO predictive control for variable speed variable pitch wind turbines. In Proceedings of the American Control Conference, Baltimore, MD, USA, 30 June–2 July 2010; pp. 2778–2784.
159. Novak, J.; Chalupa, P. Wind Turbine Control with Multiple Model Predictive Control. In Proceedings of the 14th International Conference on Automation & Information, Valencia, Spain, 6–8 August 2013; pp. 97–102.
160. Hovgaard, T.G.; Boyd, S.; Jørgensen, J.B. Model predictive control for wind power gradients. *Wind Energy* **2015**, *18*, 991–1006. [CrossRef]
161. Benlahrache, M.A.; Laib, K.; Othman, S.; Sheibat-Othman, N. Fault Tolerant Control of Wind Turbine Using Robust Model Predictive Min-Max approach. *IFAC-PapersOnLine* **2017**, *50*, 9902–9907. [CrossRef]
162. Evans, M.A.; Cannon, M.; Kouvaritakis, B. Robust MPC Tower Damping for Variable Speed Wind Turbines. *IEEE Trans. Control Syst. Technol.* **2015**, *23*, 290–296. [CrossRef]
163. Mirzaei, M.; Poulsen, N.K.; Niemann, H.H. Robust model predictive control of a wind turbine. In Proceedings of the American Control Conference, Montreal, QC, Canada, 27–29 June 2012; pp. 4393–4398.
164. Mousavi, Y.; Bevan, G.; Kucukdemiral, I.; Fekih, A. Sliding Mode Control of Wind Energy Conversion Systems: Trends and Applications. *Renew. Sustain. Energy Rev.* **2022**, *167*, 112734. [CrossRef]
165. Maati, Y.; Bahir, L. Optimal fault tolerant control of large-scale wind turbines in the case of the pitch actuator partial faults. *Complexity* **2020**, *2020*, 6210407. [CrossRef]
166. Li., S.; Aitouche, A.; Nicolai, C. Fault-Tolerant Control of Wind Turbine System Using Linear Parameter-Varying Model. *Math. Probl. Eng.* **2022**, *2022*, 1290639.
167. Badihi, H.; Jadid, S.; Zhang, Y.; Pillay, P.; Rakheja, S. Fault-Tolerant Cooperative Control in a Wind Farm Using Adaptive Control Reconfiguration and Control Reallocation. *IEEE Trans. Sustain. Energy* **2020**, *11*, 2119–2129. [CrossRef]
168. Badihi, H.; Zhang, Y.; Hong, H. Wind Turbine Fault Diagnosis and Fault-Tolerant Torque Load Control Against Actuator Faults. *IEEE Trans. Control Syst. Technol.* **2015**, *23*, 1351–1372. [CrossRef]
169. Yi, Y.; Bai, X.; Zhang, J.; Chen, C.; Wang, L.; Li, M. Second-order fast non-singular terminal sliding mode fault tolerant control for wind-turbine system. In Proceedings of the International Conference on Control Science and Electric Power Systems, Shanghai, China, 28–30 May 2021.
170. Shi, F.; Patton, R. An active fault tolerant control approach to an offshore wind turbine model. *Renew. Energy* **2015**, *75*, 788–798. [CrossRef]
171. Casau, P.; Rosa, P.; Tabatabaeipour, S.M.; Silvestre, C. Fault detection and isolation and fault tolerant control of wind turbines using set-valued observers. *IFAC Proc.* **2012**, *45*, 120–125. [CrossRef]
172. Cheng, M.; Jiang, Y.; Han, P.; Wang, W. Fault tolerant control for power side current sensor in wind energy conversion system with cascaded brushless DFIG. In Proceedings of the 2017 IEEE International Electric Machines and Drives Conference (IEMDC), Miami, FL, USA, 21–24 May 2017.
173. Chen, J.; Yao, W.; Ren, Y.; Duan, W.; Kan, J.; Jiang, L. Adaptive active fault-tolerant MPPT control of variable speed wind turbine considering generator actuator failure. *Int. J. Electr. Power Energy Syst.* **2022**, *143*, 108443. [CrossRef]
174. Kamal., E.; Aitouche, A.; Ghorbani, R.; Bayart, M. Unknown Input Observer with Fuzzy Fault Tolerant Control for Wind Energy System. *IFAC Proc.* **2012**, *45*, 946–951. [CrossRef]
175. Schulte, H.; Gauterin, E. Fault-tolerant control of wind turbines with hydro-static transmission using Takagie Sugeno and sliding mode techniques. *Annu. Rev. Control* **2015**, *40*, 82–92. [CrossRef]
176. Musarrat, M.N.; Fekih, A. A fault tolerant control paradigm for DFIG-based wind energy conversion systems in a Wind/PV hybrid microgrid. *IEEE J. Emerg. Sel. Top. Power Electron.* **2021**, *9*, 7237–7252. [CrossRef]
177. Vidal, Y.; Rodellar, J.; Acho, L.; Tutivén, C. Active Fault Tolerant Control for Pitch Actuators Failures Tested in a Hardware-in-the Loop Simulation for Wind Turbine Controllers. In Proceedings of the 23rd Mediterranean Conference on Control and Automation (MED), Torremolinos, Spain, 16–19 June 2015.
178. Niss, M.; Esbensen, T.; Sloth, C.; Stoustrup, J.; Odgaard, P.F. A Youla-Kucera approach to Gain-Scheduling with Application to Wind Turbine Control. In Proceedings of the IEEE Multi-Conference on Systems and Control, Saint Petersburg, Russia, 8–10 July 2009.
179. Acho, L.; Rodellar, J.; Tutiven, C.; Vidal, Y. Passive Fault Tolerant Control Strategy in Controlled Wind Turbines. In Proceedings of the 3rd Conference on Control and Fault-Tolerant Systems (SysTol), Barcelona, Spain, 7–9 September 2016; pp. 636–641.
180. Fan, L.; Song, Y. Neuro-adaptive model-reference fault-tolerant control with application to wind turbines. *IET Control Theory Appl.* **2012**, *6*, 475–486. [CrossRef]
181. Han, B.; Zhou, L.; Yang, F.; Xiang, Z. Individual pitch controller based on fuzzy logic control for wind turbine load mitigation. *IET Renew. Power Gener.* **2016**, *10*, 687–693. [CrossRef]
182. Meisami-Azad, M.; Grigoriadis, K.M. Anti-windup linear parameter-varying control of pitch actuators in wind turbines. *Wind Energy* **2015**, *18*, 187–200. [CrossRef]
183. Habibi, H.; Nohooji, H.R.; Howard, I. Adaptive PID control of wind turbines for power regulation with unknown control direction and actuator faults. *IEEE Access* **2018**, *6*, 37464–37479. [CrossRef]
184. Wu, A.H.; Zhao, B.H.; Mao, J.F.; Wu, B.W.; Yu, F. Adaptive active fault-tolerant MPPT control for wind power generation systems under partial loss of actuator effectiveness. *Int. J. Electr. Power Energy Syst.* **2019**, *105*, 660–670. [CrossRef]
185. Zhao, Z.; Wu, J.; Li, T.; Sun, C.; Yan, R.; Chen, X. Challenges and Opportunities of AI-Enabled Monitoring, Diagnosis & Prognosis: A Review. *Chin. J. Mech. Eng.* **2021**, *34*, 56.