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Review

A Review of Predictive Techniques Used to Support Decision Making for Maintenance Operations of Wind Turbines

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Abstract: The analysis of reliable studies helps to identify the credibility, scope, and limitations of various techniques for condition monitoring of a wind turbine (WT) system's design and development to reduce the operation and maintenance (O&M) costs of the WT. In this study, recent advancements in data-driven models for condition monitoring and predictive maintenance of wind turbines' critical components (e.g., bearing, gearbox, generator, blade pitch) are reviewed. We categorize these models according to data-driven procedures, such as data descriptions, data pre-processing, feature extraction and selection, model selection (classification, regression), validation, and decision making. Our findings after reviewing extensive relevant articles suggest that (a) SCADA (supervisory control and data acquisition) data are widely used as they are available at low cost and are extremely practical (due to the 10 min averaging time), but their use is in some sense nonspecific. (b) Unstructured data and pre-processing remain a significant challenge and consume a significant time of whole machine learning model development. (c) The trade-off between the complexity of the vibration analysis and the applicability of the results deserves further development, especially with regards to drivetrain faults. (d) Most of the proposed techniques focus on gearbox and bearings, and there is a need to apply these models to other wind turbine components. We explain these findings in detail and conclude with a discussion of the main areas for future work in this domain.

Keywords: wind turbine; predictive maintenance; big data computation; condition monitoring; data-driven models

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1. Introduction

Wind power is one of the most sustainable and eco-friendly energy sources. With the rapid development of wind turbines (WTs), there is an increasing need to lower the Cost of Energy (COE) of wind power. The United Kingdom (UK) aims to double its renewable energy capacity by 2026. Propelled by green funding initiatives, the UK aims to double wind power investments. The total installed capacity of solar and wind power plants will climb to 64 GW in 2026. The installed offshore WT capacity is set to rise, from 10.5 GW in 2020, to 27.5 GW by 2026. The rapid deployment of offshore wind will require a substantial increase in the size of turbines [1].

Wind turbines experience extreme and varying loads and are designed to operate remotely for long periods of time without interventions in limited-access wind farms [2]. In recent years, an effort has been made to deploy advanced condition monitoring and maintenance optimization techniques to improve the availability of wind turbines. Rotating machine parts, such as yaw drives, shafts, bearings, and gears, are prone to performance deterioration, which, if ignored, might result in system failure or breakdown [3,4]. The identification of critical components of a wind turbine is vital so they can be monitored more cost effectively and efficiently with minimum downtime. Larger WTs have SCADA systems, but these systems also have issues with prediction, reliability, and accuracy [5,6].

It has long been difficult to operate offshore wind power installations with high operational availability, and as of today, a figure of 95% is considered the industry standard [7].

Availability is one of the metrics most frequently used to quantify operating performance in the wind sector. It is described as the percentage of time a wind turbine produces energy over a specific time interval or the amount of power produced over the theoretically produced amount of time. Since profits can only be realised when power is produced and transmitted to a system, maximizing availability is the foremost aim for offshore wind operators.

Condition monitoring (CM) methods depend on the examinations of certain measures and operational elements (e.g., vibration analysis, strain measurement, thermography, and acoustic emissions). Recent advancements in big data management, machine learning (ML), sensor and signal processing systems, and computational capabilities have created opportunities for integrated and in-depth CM analytics, where various data types can support well-informed, dependable, economical, and robust decision making in CM [8]. Additionally, the likelihood of material flaws occurring at a key location is higher with larger bearings, which raises the likelihood of failure. In wind turbine gearbox bearings (WTGBs), axial cracking of the bearing raceways and white structure flaking (WSF), also known as irregular white etching area (IrWEA) development, have both been documented as mechanisms of premature failure. White etching cracks (WECs), a known damage feature observed in rolling element bearings, may form at so-called butterfly cracks, which are assumed to be related to both failure types. WECs are found in material directly under bearing raceway contact surfaces (REBs). Despite significant research efforts, it is still unclear how WECs cause WTGB failure; hence, there is no practical way to determine how long a bearing will still be viable in WTG applications.

Motivations and Structure of the Work

Based on the above premise, the objective of the present review paper is a critical analysis of the techniques employed for wind turbine condition monitoring, with a particular focus on data-driven approaches. Therefore, Section 2 contains a brief general introduction to how wind turbine condition monitoring is typically intended. There are substantially three types of approaches, i.e., predetermined (or periodical) maintenance, corrective maintenance (which is applied upon the onset of a fault), and condition-based maintenance, whose general objective is minimizing the producible energy losses and maximizing the lifetime of the wind turbines' fleet. The latter approach, which is typically intended as the smartest one, requires the online evaluation of the condition of the components. This is far from a trivial task because wind turbines are complex machines operating under non-stationary conditions that are of course site dependent. For this reason, condition monitoring is mainly formulated as the problem of establishing a normal behavior model from which the deviations are monitored. This motivates the fact that the selected techniques depend heavily on the type of data at disposal and on the component that is to be monitored.

The above line of reasoning therefore motivates the structure of this work. In Section 3, we briefly recall the types of data that are employed for wind turbine condition monitoring and we summarize their main characteristics, as well as the general approaches for extracting features from them. Section 4 is structured with several subsections, each of which is devoted to the condition monitoring of a particular component. Selected studies are discussed and grouped depending mainly on the type of employed data and on their sampling-averaging time (ten minutes for SCADA data, up to KHz for accelerometer data). The studies are selected based on the authors' discretion for the objectives of the paper. In general, the majority of the selected studies have been published recently. In Section 5, the conclusions arising from the long review of Section 4 are outlined. These can be summarized as follows:

- The literature about gears and bearing condition monitoring is largely dominant;
- Performance monitoring of wind turbines is an overlooked topic that should be addressed more systematically because non-negligible portions of producible energy could be recovered;

- The above objective would require a deeper investigation of the health status of components (such as the hydraulic blade pitch) to which few studies have been devoted, but the attention on this topic has been recently growing;
- The use of SCADA data for wind turbine condition monitoring is somehow lacking specificity in the fault location and in the prognosis, but recent developments in the literature are promising;
- The analysis of vibrations collected at gears and bearings is complicated and demanding (e.g., the geometry of the gear should be known in detail), but it is much more powerful for condition monitoring;
- The co-integration of multiple time scales analysis is an interesting research direction, which could help leverage the pros and circumvent the cons of the various types of employed data.

2. Need for Wind Turbine Condition Monitoring

The failure behavior, or physics of failure, of a component, must be known in order to deploy a CM approach; however, typically, a CM strategy is most effective if a developing failure can be identified well in advance. To assess this, the P–F intervals (potential failure and functional failure) method is popularly used in industries [7]. Since the failure can be detected once the functional period has begun, the P–F interval is smaller than the lead time to failure (TTF) in the case of wind turbines [7]. Furthermore, due to the limitations imposed by the offshore environment and the growing number of machines in a typical wind farm, maintenance is changing from being planned or reactive to becoming more proactive and predictive. An important component of this change has been the more sophisticated condition monitoring of the wind turbine (WT) state of health (CM) [5,6].

Condition monitoring (CM) provides accurate information about the component's health. CM is often defined as the process of monitoring a parameter of condition in machinery (for example, vibration or temperature) such that a significant change is indicative of a developing failure. Maximizing electricity production from wind requires an improvement in wind turbine reliability. Component failures force turbines to undergo unplanned or reactive maintenance, which raises production costs and causes substantial downtime. This eventually limits the competitiveness of renewable energy sources. Thus, the use of condition monitoring to find flaws early is a crucial duty, see Figure 1. Compared to wind turbines' regular maintenance, this can save maintenance expenses by up to 20–25%. It is possible to learn more about the dynamic performance of a certain system and, in turn, spot any potential problems or errors by detecting vibrations throughout the nacelle. Predictive maintenance techniques that leverage past failures to learn from and forecast failure and the remaining usable life of various wind turbines can significantly reduce O&M expenses [9]. It is crucial to take into account the failure rates and downtimes per failure of various sub-components when choosing which components to monitor. Components that are more likely to malfunction or cause prolonged downtime should receive priority attention because of the potential severity of their effects [8].

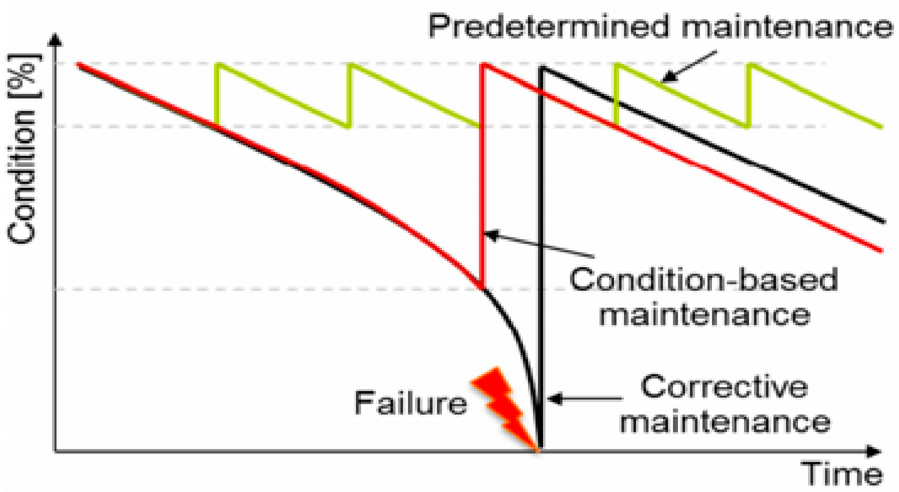

Figure 1. Influence of the maintenance strategy on the asset condition [10].

Three maintenance strategies are commonly implemented [11]: time-based (TBM, which is preventive), failure-based (FBM, corrective), and condition-based (CM, predictive). Preventive and corrective maintenance operations comprise the majority of traditional onshore O&M activities, although this strategy may be improved and is risky offshore. From TBM and FBM, the new trends are shifting to CM [12]. In the latter strategy, CM determines the optimum point between preventive and corrective maintenance, which reduces unnecessary repair actions and saves unplanned downtime [13]. In this framework, condition monitoring has been identified as the key to achieving higher availabilities while reducing O&M costs. Nevertheless, the secrecy present in the wind energy sector makes it difficult to understand which components are critical for condition monitoring [14]. In [7], the author highlights how changing the maintenance strategy by turning unforeseen activities into planned interventions that can be carried out during a suitable weather window prior to a component failure can result in lower O&M costs and also quantifies the benefits of a longer warning time of potential-to-functional failure (P–F interval) for availability.

The asset offers more predictable and dependable power with a preventative maintenance plan, delivering an optimized financial return. When compared to other types of power plants, the system's operational and maintenance expenses are a clear indicator of how efficient it is at producing energy [15]. To make wind turbines more dependable, operators and researchers are emphasizing the improvement of problem detection tools. In order to identify and isolate the many types of failures, condition monitoring systems use fault detection and diagnosis (FDD). There are three types of FDD approaches: model-based approaches, data-driven methods, and knowledge-based methods, listed in that order [16].

3. Data-Driven Approach Overview

3.1. Data Descriptions

The condition monitoring systems (CMS) monitor several key parameters including drive train vibration, oil quality, and temperatures in some of the main subassemblies. These systems are often deployed in addition to the basic WT setup as "add-ons." However, a standard SCADA system is included in every large utility-scale WT and is mostly utilized for performance monitoring. Within the typical 10 min average period, such systems provide a plethora of information; however, the range and type of signals captured can differ greatly from one turbine type to another. A variety of methods employing these data for early failure detection have been developed recently since CM using SCADA data is a potentially low-cost option that does not call for any new sensors. This paper presents a thorough examination of the potential applications of SCADA data for monitoring various subassemblies [5].

A database is presented in [17] that contains differences in the test bench's environmental characteristics. The suggested method enables the use of actual data with all of its complexity as a foundation for the simulation framework and, at the same time, offers the capability to precisely manage the simulation process in order to obtain a thorough evaluation of the fault detection performance. A controlled simulation framework is first needed to analyze how environmental changes affect the detection capacities of various condition-monitoring systems. A modelling framework is necessary because it is often difficult to identify several, similar fault signatures on geographically distant wind farms, making it challenging to distinguish between the effects of failures and other local causes. Therefore, a controlled yet accurate simulation setup is required for the comparison of standardized performance under various test circumstances.

Data typically available in a wind turbine pose "big data" challenges [8]:

1. Volume: A typical wind farm can create between 60 to 100 SCADA signals, which, when sampled every second, would result in around 0.2 GB of raw data per turbine. Each wind turbine would have 20 to 30 sensors.
2. Velocity is the frequency at which modern wireless and acoustic sensors create and send data.
3. Variety: CM systems must include sensor data with pictures, video (perhaps shot by drones), free-text action reports, and other types of data.
4. Reliability: Ideally, data should not contain missing values, impossible values, or inconsistent values; in this case, automatic or semi-automatic data cleaning (scrubbing) operations are usually required. This demand grows when there are more data sources, especially if they are heterogeneous.

Model-free models, commonly referred to as data-driven approaches, simply require past system data to build problem diagnostic systems [16]. Numerous conventional diagnosis techniques, such as those that analyze the vibration signal, the acoustic signal, the temperature, and the lubricating oil parameter, have been employed in wind turbine systems to find bearing defects [13]. All of these diagnostic techniques, however, need signal-acquisition tools with high sample rates. Additionally, while signals are being transmitted between faulty components and sensors, they may be muted or interfered with. As a result of their non-intrusiveness and affordability, electrical signal-based analysis techniques have gained increased attention in recent years [18].

3.2. Feature Operations (Covering Selection and Extraction)

One of the crucial tasks while building a machine learning model is outlier identification. Careful consideration should be given to the correlation of the variables while filtering the outliers. Because many of the outliers automatically identified were genuine failure states of the turbine, it was observed that the outlier filtering methods can reduce the error on the training data set but increase the error in the test data set. In order to pre-define the variable's absolute and relative ranges, expert input is advised [8]. Features that are related to the outcome we want to analyze, comprehend, or forecast should be selected—in this case, time series signals. Under the supervision of an expert, this can be accomplished mechanically or semi-automatically. In the existing literature, there are two general feature selection methods: filter-based and wrapper methods. The wrapper technique seeks to choose a small number of features as a study set and search for the best or worse features among all characteristics by selecting all possible feature combinations. However, because of the repeated learning phases, the wrapper is frequently computationally expensive. The filter-based approach uses a metric to choose the best suitable feature according to that metric. Finally, it chooses the traits with the highest rankings. In filter-based categories, correlation coefficient analysis is a method that is frequently employed [16,19].

With feature extraction, the primary properties of high-dimensional time series (such sensor signals) are preserved while noise and correlations are eliminated. By doing this, model training should go more quickly and result in better results than when using the original, raw data [8]. The unnecessary data must be deleted from the many variables that modern SCADA data contain. This procedure is aided by neighborhood component analysis for regression, which computes feature weights. Regression analysis takes into account features of greater importance and tests SVR, neural networks, decision trees, and logistic regression. In the experiment by [20], an accuracy of up to 99% was noted. According to [9], it is possible to successfully anticipate failure 1–2 months in advance with an accuracy of 67% by analyzing high-frequency vibration data and extracting critical features for training support vector machine algorithms.

4. Review of Methodologies Used for Wind Turbines O&M Tasks

Despite the same kind of data being employed for the condition monitoring of various wind turbine components for different reasons (for example, low-frequency SCADA data or, on the other hand, high-frequency vibration measurements), there are techniques that are specific for the monitored components. It is therefore meaningful to discuss the latest developments in wind turbine condition monitoring by dividing per component, as is done in the following.

4.1. Bearing Failure

An important factor in unexpected maintenance, repairs, and replacement downtime in energy generation is bearing failures in wind turbines. This primary cost failure type increases the O&M costs for the energy operator as well as the customer's electricity bills. According to the Gearbox Reliability Database (GRD) of the National Renewable Energy Laboratory (NREL), 76% of gearbox failures were attributable to bearing failures, while 17% were attributable to gear failures. This demonstrates the value of dependable bearings and gearboxes for the functioning of wind turbines to the economy and society [21].

Common causes for bearing failure are excessive load, fatigue, contamination, misalignments, overheating etc. The latter phenomenon is addressed in several papers, as for example, in [22]. As the approach considered is fault estimation, it can be categorized as model-based and data-driven. In that method, the aim was to determine the bearing fault at least 33 days prior using statistical features of residuals evaluating Bayesian state prediction. An artificial neural network (ANN) was chosen for modelling the temperatures of the main bearing component. Prediction of the event bearing over-temperature was possible, but over a limited set of time series, it could give confidence one month prior to the failure of the bearing. Further analysis is necessary for the accuracy of other event failures for different time series.

Jian et al. introduced deep learning for WT condition monitoring in [23]. An adaptive elastic network, a convolutional neural network (CNN), and an LSTM (Long Short-Term Memory) were coupled to perform feature extraction, dimension reduction, and classification. The gradient explosion and overfitting problems were resolved by this technique, lowering the prediction error. Before the data gathered by SCADA are analyzed, the suitable variables associated with the transmission-bearing temperature must be selected as the research object. Gearbox-bearing temperatures are impacted differently by variables with various relationships [23]. In [24], LSTM is used to solve the problem of the exploding gradient and vanishing gradient when the layer of the network increases and the subsequent node perceptions for the previous nodes become weak. In [25], a prognosis indicator for the health status of the main bearing of wind turbines is formulated based on the number of times the residual between the measured component temperature and the model-based estimate exceeds a certain threshold. SCADA data are employed for this aim through artificial neural network modelling. In [26], a physics-domain method for high-speed shaft axial crack prognosis is formulated and validated by using SCADA data with an averaging time of ten minutes. The frictional energy and the electrical power are employed as damage metrics, and it is shown that the advantage of physics-domain models is not only the capability of estimating damage probabilities but also a deeper insight into the failure mechanism. In [27], a mixture of physics-domain and data-driven modelling is employed and applied to two test cases: a planetary and a high-speed bearing fault. It is shown that the combined approach is superior to a purely data-driven method for fault prognosis.

The huge data problem in WT can be resolved by using sparse representation techniques to greatly compress the observed signal into a few nonzero coefficients as a signal projection on dictionaries. Typically, measured current/vibration signals are used to extract the defect characteristics of wind turbine bearings. It is crucial to keep in mind that this approach will fall short if the model cannot accurately capture the mathematical operation of the dictionary. Although the K-singular value decomposition (K-SVD) and general principal component analysis (GPCA) are more adaptable to describe signal data, the learning procedure is difficult and time consuming. To determine the failure of high-speed shaft bearing (HSSB), a vibration-based diagnosis methodology for wind turbine high-speed bearing is proposed using principal component analysis (PCA) [28]. Though this method fails to predict the exact date of failure in advance, it showed good accuracy in monitoring the health of the component. In [29], vibrations collected with a frequency of the order of 16,000 Hz by eight acceleration transducers placed in the drivetrain are processed through an artificial neural network in order to estimate the remaining useful life of high-speed shaft bearings. M. Kordestani et al. [16] proposed a fault detection and diagnosis (FDD) method consisting of feature extraction/feature selection and an adaptive neuro-fuzzy inference system (ANFIS) method. The feature extraction and selection phase identified proper features to capture the nonlinear dynamics of the failure. Then, the ANFIS classifier was used to diagnose the failure type using the extracted features.

To identify wind turbine bearing issues, Ref. [30] provide a feature selection and learning vector quantization (LVQ) neural network technique combination. The right features are extracted using Empirical Mode Decomposition (EMD). The LVQ neural network is then utilized to categorize different failures. The results of the experimental tests show that the suggested fault diagnosis approach is highly accurate. According to [18], the modulation signal bispectrum (MSB) detector is used to identify bearing problems in DFIGs of WT. Overlapping segmentation is suggested as a way to increase computational accuracy with sparse data. The MSB algorithm was discovered to be an efficient, space-saving method to retrieve modulation information from data, while traditional methods based on a single spectrum were concerned only with the amplitude. Quadratic phase coupling (QPC) and amplitude modulation (AM) were caused by vibration caused by bearing faults.

The work in [31] deals with the estimation of the remaining useful lifetime of wind turbine bearings through the analysis of vibration data collected with a frequency of 97,000 kHz. The building blocks of the algorithm are wavelet transform pre-processing, Bayesian state-space modelling, and particle filter. In [32], the remaining useful lifetime of a high-speed shaft wind turbine bearing is estimated based on processing the statistical features of vibration signals collected with a frequency in the order of 100 Hz. Vibration data from a real-world wind turbine are analyzed, and the prognostic capability of several signal processing techniques is compared. Data are collected at nominal speed and are sampled at 97,656 Hz for 6 s. It is shown that spectral kurtosis followed by envelope analysis provides early fault detection compared to the other techniques employed. In [33], the angular velocity error at the various stages of the gearbox is selected as a target to monitor for individuating bearing faults. In [34], the proposed approach is based on the co-integration of multiple industrial data types, with different sampling times. Using SCADA data averaged on a 10-minute basis, the main bearing fault is identified by monitoring the residuals between measured and model-estimated bearing temperatures. The individuation of the precise location of the damage is corroborated by the analysis of vibration signals collected by the industrial Turbine Condition Monitoring (TCM) system: the statistical novelty between healthy and faulty wind turbines is identified through Principal Component Analysis (PCA) of a set of features.

The above study indeed solves by integration of multiple data sources an issue that is quite common in SCADA-based wind turbine condition monitoring. Actually, the main bearing temperature is often selected as the target temperature to monitor, typically based on data-driven considerations. Yet, there is a physical reason why the temperature of this component is quite responsive to incoming faults: the main bearing is a large component, which rotates relatively slowly, and it is, therefore, reasonable that it releases much heat in a way that can be easily captured (together with its anomalies) by data-driven algorithms. In fact, in [35], it is shown that by monitoring the temperature of the main bearing, it is possible to diagnose a stator fault. Finally, it is worth noting that a few studies [36] approach the diagnosis of bearing faults through the analysis of tower sound and vibration, without knowing the transfer function between the bearings and the tower. Statistical analysis techniques are used for distinguishing features of faulty and healthy vibration signals.

4.2. Gearbox Failure

In [37], the testing is based on Condition Monitoring System (CMS) data from 10 WTs to detect the common failures in the gearbox HS module. The signal correlation with RMS values was found to be good for detecting progressive failures such as HS bearing pitting or shaft cracks at least one month in advance but was not suitable for detecting gear tooth fracture. Using correlation and an extreme vibration model, the peak value did a better job detecting gear tooth fracture. As the extreme vibration model does not rely on historical data, it can be used for new WTs or WTs with missing CMS history. The "delta RMS" plot gives insight into the severity of the failure. One of the limitations of this model is that changes in RMS vibrations are sensitive only to high shaft revolutions and therefore can only be used for high-speed modules of the gearbox, with higher shaft revolutions than other modules.

Compared to the traditional gradient-based training algorithm widely used in the single-hidden layer feed-forward neural network, Extreme Learning Methods (ELMs) can randomly choose the input weights and hidden biases and need not be tuned in the training process. Therefore, the ELM algorithm can dramatically reduce the learning time. The drawbacks of the traditional gradient-based training algorithms, such as overtraining, high computational time, and trapping at local minima, can all be overcome by the ELM algorithm, as it randomly chooses the input weights and hidden biases and needs not to be tuned in the training process [38].

In [39], a Deep Belief Network (DBN) is used to merge in a purely data-driven way the measurements collected by four vibration sensors attached on the casing of the gearbox from low-speed to high-speed stages of a wind turbine gearbox, for which accelerated lifetime tests are conducted in the laboratory. The Wiener model is employed to describe the process of gearbox degradation and to predict the remaining useful lifetime. In [40], accelerated lifetime tests are performed as well. A method for signal de-noising is proposed, which is based on complete ensemble empirical mode decomposition with adaptive noise and kernel principal component analysis. Multi-sensor fusion is performed using kernel principal component analysis and Hotelling statistics, and the estimation of the remaining useful lifetime is optimized through the fruit fly algorithm.

In [41], real-world data sets from three Suzlon wind turbines (two healthy and one faulty) are analyzed. Vibrations are measured at the pinion gears with a sampling rate of 97.656 (kHz) and a recording time of 6 s. The Signal Intensity Estimator (SIE) method and the principal component analysis of the statistical features of the vibration signals are employed for estimating the remaining useful lifetime. This work indicates that it is possible to extract meaningful prognosis information from highly modulated real-world data, such as those originating from wind turbine gears. The SIE method is also employed in [42].

In [24], the LSTM prediction model is implemented to indicate abnormal behavior in the gearbox by monitoring the gearbox bearing rise in temperature. It should be noticed that SCADA data are much more used for bearing condition monitoring, i.e., as opposed to gearbox data. This occurs because the heat released by bearings is easier to use as a target to monitor, while the precise location of the gearbox fault requires specific measurements, which are collected through accelerometers that are placed ad hoc. SCADA data are employed in [43] for a long-term fatigue life assessment based on a three-stage gearbox multibody dynamic model. The main result is that the most vulnerable part of the gearbox is the sun gears, which are mostly stressed at wind speeds higher than 10 m/s. In [44], a method for prognosis based on SCADA data is formulated, which employs Gaussian process and principal component analysis. A fleet of 24 faulty wind turbines is selected for validating the model. The detection rate is 79% and 76% component-wise, where the most important involved components are the gearbox and the generator. In [45], the health status of wind turbine main components (gearbox and generator, mainly) is assessed through a regression model based on an Extreme Learning Machine (ELM) strategy. Internal temperatures are simulated by using as input variables other internal temperatures, environmental variables, and working parameters of the machine. The health status of the component is assessed by performing a linear regression between simulated and measured target variables once per day and analyzing how much the slope deviates from the unity. The prognosis is formulated by analyzing the time evolution of such estimated slopes. High-frequency SCADA data are employed in [46], where a normal-behavior model for the gearbox oil temperature is set up and a one-class Support Vector Machine (SVM) classifier is employed for setting a threshold for anomaly detection. A sensitivity study on the data averaging time is performed, and it is shown that the trade-off is non-trivial, in the sense that, the higher the frequency, and the higher the information but at the same time the higher the noise. In [47], the measured one-phase stator current of a wind turbine is processed in order to extract information on the health status of the gearbox through the adaptive neuro-fuzzy inference system (ANFIS) and particle filtering (PF) approaches.

4.3. Generator Failure

Condition monitoring of wind turbine generators is a fundamental task given that this component ranks in the top three regarding failure rates and downtime [48,49]. The diagnosis of generator faults has more or less the same balance between pros and cons as the other rotating elements. On the one hand, TCM systems recording vibrations at the sub-component are costly, and inspections based on voltages and current analysis are even more costly [50,51]. On the other hand, SCADA data have a much lower cost but their diagnostic and prognostic capabilities are questionable, especially regarding electrical faults. Nevertheless, some interesting attempts at using SCADA data for generator diagnosis and prognosis are being developed. The method described in [52] does not require any additional hardware beyond the SCADA system for determining WT generator failure. The authors propose a method to predict the remaining useful life (RUL) of generators using the Anomaly Operation Index (AOI), which determines performance degradation in runtime. SCADA monitors the run-time operation condition of the wind turbine, such as temperature, speed, and power. Such information may be leveraged to support the generator's prognosis. This method proposes an autoregressive integrated moving average (ARIMA)-based statistical model to conduct online prognostics and a time series analysis-based RUL estimation method to provide accurate RUL prediction.

The SCADA system is the only new hardware needed for the method proposed in [51] to determine WT generator failure. The Anomaly Operation Index (AOI), which measures performance degradation in runtime, is used by the authors to offer a method for estimating the remaining usable life (RUL) of generators. SCADA keeps track of the wind turbine's operational parameters during operation, including temperature, speed, and power. The generator's prediction may be strengthened with the use of such information. This approach suggests using a time series analysis-based RUL estimation method in combination with an autoregressive integrated moving average (ARIMA)-based statistical model to undertake online prognostication. In order to forecast performance, AOI is analyzed using historical failure data from the past. The normal and anomaly can be determined at runtime with the use of sophisticated data mining techniques such as DBScan and the SVM algorithm. This makes this experiment a more effective and cost-effective technique of failure detection. In [53], a series of phenomena related to generator incoming faults is individuated through SCADA data analysis. These include miscorrelation between the rotational speed and active or reactive power, anomalous heating, and anomalies related to the shaft torque.

In [54], the Mahalanobis distance between appropriately selected features is employed to diagnose generator bearing

The peculiarity of the study in [19] is the attempt at diagnosing an electrical generator fault using SCADA data. A normal behavior model for the power and for the voltage and current of each phase is constructed through a support vector regression, where the input variables are working parameters (such as the blade pitch and rotational speed) and generator temperatures. The features are pre-processed through PCA, and a threshold for alarm raising is identified from the statistical properties of the residuals between measurements and model estimates. In that work, it is shown that the alarm raising occurs two weeks before a real-world electrical fault of a wind turbine generator, and this anticipates the alarm log book collected by the SCADA control system.

Similarly, in [51,54], an anomaly operation index is formulated based on the number of anomalous points in the feature space with respect to normal behavior. A one-class support vector machine is employed for anomaly identification, and the AOI is de-trended by employing a moving average. An Autoregressive Integrated Moving Average (ARIMA) method allows forecasting the remaining useful life, and the results show that the model successfully forecasts failures of the generator while providing a 21-day lead time for the operators to plan the necessary maintenance action.

4.4. Blade Pitch System Failure

Attention has been growing in the literature regarding the assessment of the health status of the blade pitch systems because evidence is being collected about the decisive role of blade pitch degradation on wind turbine performance worsening. In [55], an a priori knowledge-based adaptive neuro-fuzzy inference system is employed with the aim to achieve automated detection of significant pitch faults. The method is tested on variable speed, variable pitch wind turbines, and on variable pitch, fixed-speed wind turbines; 49 GB of SCADA data from several companies are analyzed by the authors. Furthermore, in [55], an interesting discussion is conducted on the pros and cons of the two methods for controlling the blade pitch of a wind turbine, which are hydraulic and electrical. While each blade is controlled by an electric servo-motor connected to a gearbox that lowers the motor speed to apply torque to the blades, in the case of hydraulic pitch control, actuators in the rotor hubs provide torque directly or via mechanical linkages. The advantages of the former type are the simplicity and the high torque that can be exerted. This is fundamental if one takes into account that such a mechanism is also responsible for stopping the wind turbine in the case of gusts. The diffusion of electrical pitch control is growing, but at present, the majority of wind turbines have hydraulic blade pitch control.

Several studies have recently been devoted to the investigation of the long-term health state of hydraulic vs. electrical blade pitch, based on SCADA data analysis. In [56], it is shown that the aging of electrical blade pitch motors leads to performance worsening over time, which is quite limited. In [57,58], through comparative test case analysis, it is shown that the aging of hydraulic blade pitch actuators likely leads to performance worsening over time, which can also be severe. This is due to pressure losses, which lead to the fact that the wind turbine operates at a non-optimal working point and, in turn, also in the full aerodynamic load regime where less power can be extracted for a given rotational speed. Intelligent predictive maintenance strategies should therefore be developed for optimal management of the blade pitch health, which is an overlooked topic in wind energy practice and literature.

The aging of the blade pitch systems and their health state prognosis are also addressed in the recent study [59], where several indicators are formulated: the behavior of the power coefficient, the power fluctuations above the rated speed (the higher the fluctuations, the more degraded the blade pitch system), overheating, and failure rates. The diagnosis of electrical blade pitch faults through SCADA data analysis is pursued, for example, in [60], where an optimized relevance vector machine regression is set up for the blade pitch motor power upon feature selection through the random forest algorithm. In total, 38 pitch system fault cases are analyzed, which provides an interesting overview: nine encoder failures, seven pitch controller failures, seven electric motor failures, eight slip ring failures, three limit switch failures, two backup battery failures, and two stud failures.

4.5. Yaw Failure

The yaw mechanism of wind turbines is quite delicate because the yaw motion needs to counteract the large inertia of the rotor in order to achieve the best possible orientation with respect to incoming wind that has rapid fluctuations. The yaw movement is typically achieved through yaw motors that undergo alternating stress and might suffer from mechanical damages, such as tooth face abrasion, gearbox failure, yaw bearing failure, and brake actuator failure.

Vibration analysis techniques have been employed for detecting slewing bearing damages, for example, in [61,62]. In [63], a method based on circular domain resampling and piecewise aggregate approximation is formulated and validated through a highly accelerated life test. It is shown that the incoming fault can be identified through the statistical features of the processed signal. In [18], acoustical damage detection of a wind turbine yaw system is proposed. A real-world experiment is proposed: a microphone is mounted inside the nacelle of a 1.5 MW WT sited in China. The collected measurements have a frequency of 64,000 Hz. The sound pressure levels are extracted from the raw signals, and a data discretization method based on a self-organizing map and information gain rate are employed. Finally, a Bayesian Network diagnostic model is used to detect the incoming fault. In [64], several types of faults are simulated and diagnosed using a data-driven method based on a benchmark model of wind turbine component's functioning. It follows the construction of robust residual generators using the observer-based residual generation technique, and one of the diagnosed faults regards the yaw actuator.

The yaw system of a wind turbine might be affected by systematic error (also known as zero-point shift), which can be relevantly non-vanishing if the wind vane sensor is incorrectly aligned with the rotor shaft due to wind vane defects, incorrect installation or maintenance, or the aging of the machine. Numerous research papers have been devoted to the individuation of such a type of fault through SCADA data analysis, despite it being non-trivial to formulate reliable and general algorithms. In [65], (Jing, 2020), the power curve is analyzed, which is the relationship between the wind speed measured by the nacelle anemometer and the extracted power. The rationale for analyzing the power curve for individuating a systematic yaw error is the expectation that an underperformance should be visible. However, this task is challenging due to the multivariate dependence of the wind turbine power on environmental conditions and working parameters, and adequate data-mining methods are required. Furthermore, in [65], for example, the power curve is studied per interval of yaw error. In [66], a similar approach is employed, but the power curve is analyzed through a different model, which is a least-square B-spline approximation. In [67], a multivariate data-driven power curve model is employed, in the form of Gaussian process regression that takes as input the rotational speed and the blade pitch. The systematic yaw error is individuated from the mismatch between the measured power and model estimate. In a yaw error case study performed in [68], two methodologies—Gaussian process and IEC binned power curve—are used to predict the anomaly. In [69], the power curve is also analyzed with a non-trivial data rejection algorithm. The idea of diagnosing the systematic yaw error by observing under-performance is shown in [70]. The peculiarity of that study is that the data are labelled, in the sense that a utility-scale wind turbine installed at a research facility was controllable by the authors, who imposed yaw offsets and therefore had at their disposal ground truth associated with the observed behavior.

The limitations of the above-cited studies about the systematic yaw error are the lack of validation, in the sense that it is unclear if one or more data-driven algorithms work accurately for most wind turbine models available on the market. It is desirable to formulate a comprehensive approach, similar to what has been done in [59] for the blade pitch health status, based on the observation of several manifestations, such as under-performance, augmented tower vibrations, heating, and anomalous blade loads.

4.6. Underperformance and Power Coefficient

How effectively a WT turns wind energy into electricity is shown by the power coefficient (Cp). Researchers attempted to create an adaptive neuro-fuzzy inference system (ANFIS) in Table 1 to calculate the power coefficient of the WT. Applications for ANFIS include forecasting, managing, diagnosing, and classifying. This method combines a neural network with the Takagi–Sugeno fuzzy inference system.

Table 1. Statistical properties of wind turbine data [71].

Wind Turbine Parameters	Average Value	Max. Value	Min. Value
TSR	0.6640	30.758	0.4119
Pitch angle (degree)	0	5	−5
Power coefficient	0.1707	0.4868	−5.4984

In an ideal situation, it would be anticipated that all wind energy would be transformed into power (electricity); however, in reality, this is not feasible for a variety of clear reasons: 53% of the wind energy input is the maximum amount of energy a wind turbine can output. In the experiment described in [71], the optimal result was observed when the input was a 6-bell-shaped membership function. The Gaussian method also provides a close approximation of the optimal solution. The neuro-fuzzy system using a hybrid learning algorithm develops a fuzzy rule to obtain a minimum error. The model's accuracy is dependent upon the training and test dataset provided to the algorithm. Hence, close attention should be given to the input values. High errors may lead to overfitting of the model. ANFIS is an adaptive and fast-speed operation. Other hybrid learning systems should also be adapted for a comparative study.

The decrease of the power coefficient with respect to the normal behavior, which is typically established through data-driven analyses, can be employed for individuating faults that have the peculiarity of resulting in noticeable underperformance. Mechanical damage to rotating elements is typically characterized by negligible under-performance, but this is not the case, for example, of systematic errors affecting wind turbine operation, such as the systematic yaw error. Actually, the decrease of the observed power coefficient is targeted for the diagnosis of the faults in [57,72].

4.7. Anomaly Detection

SCADA data comprise measures such as active and reactive power, generator current and voltages, wind speed, generator shaft speed, generator, gearbox, and nacelle temperatures, among others. The data are normally recorded at 10-minute intervals to reduce the sent data bandwidth and storage. The performing of statistical analysis on various trends within the data can determine when the turbine enters a time of sub-optimal performance or if there is a fault in the component of the system. Lily Hu et al. proposed in the paper [73] a way to derive features from SCADA data based on domain knowledge. These extra features are based on three factors: (1) knowledge of the physical quantities the SCADA sensors measure; (2) time series behavior of the sensor measurements; and (3) statistical features, see Table 2.

Table 2. Example Features from knowledge of WTs [73].

Average of	Front and Rear Bearing temp Rotor temp Stator temp
Difference Between	Max. and min. wind speed Max. and average wind speed Min. and average wind speed Front and rear bearing temperatures Nacelle ambient temperature Generator temperature and nacelle temperature
Ratio of	Average power to available power (from wind, technical reasons, force, external reasons)

This enables higher classification scores and improved detection of faults while using fewer features—an improvement in the F1 score of almost 20% while using a similar number of features. This method allows the freedom to decide the number of features to select for the machine learning algorithm best suited for the selected parameters. It is a very smart and efficient manner of analyzing the data [73]. The blade pitch angle curve describes the nonlinear relationship between the pitch angle and hub height wind speed and can be used for the detection of faults. An SVM is an improved version of an artificial neural network (ANN) and is widely used for classification- and regression-related problems. The binning method is a benchmark data reduction approach for the wind industries, but its application is generally limited to the power curve; its use is seen in [74] to calculate the blade pitch curve. In [75], the performance of wind turbines is monitored through data-driven models for power, rotor speed, and blade pitch curves, having the wind speed as input. A multivariate outlier detection approach based on k-means clustering and the Mahalanobis distance is applied. In [76,77], a similar approach is formulated for operation curves that do not employ the wind speed as input: namely, the rotor speed-power and the blade pitch-power curves, which are modelled through a support vector regression with Gaussian kernel.

5. Conclusions

This paper reviews different approaches used for the condition monitoring of wind turbines using different types of data that can be available from industrial systems. Particular attention has been devoted to the application for wind turbine predictive maintenance, which means not only fault diagnosis but also prognosis.

The main conclusion from the review conducted in this work is that wind turbine fault diagnosis has reached a high level of accuracy, using techniques and data sources that are particular to the monitored component. In particular, SCADA data are vastly helpful because they are available at low cost and are extremely practical (due to the 10 min averaging time), but their use is in some sense nonspecific. As regards drivetrain faults, very high accuracy is on average achievable using state-of-the-art methods for modelling the normal behavior of component temperatures, but there are critical points regarding the alarm raising (prognosis) and the fault location (specificity). These critical points can be overcome by using complex signal processing techniques on vibration measurements collected in the various drivetrain subcomponents. The trade-off between the complexity of the vibration analysis and the applicability of the results deserves further development. Attempts at establishing a compromise are being pursued by co-integrating data with multiple time scales in a simplified form, for example, SCADA data and pre-processed vibration signals collected by turbine condition monitoring systems. This point of view is promising because, to compute a holistic assessment of the component health of WTs, it is advisable to consider an approach that incorporates the strengths of multiple techniques.

Another observation that arises from the present review work is that most efforts regarding fault prognosis are devoted to gears and bearings, and there is a need for further developments regarding several components. For example, the generator scores in the top three wind turbine components regarding the failure rates and downtime, but the literature devoted to generator fault prognosis is in its early stages. Similarly, the contribution of the health status of the blade pitch system to the wind turbine energy conversion efficiency is vastly overlooked in predictive maintenance frameworks. In fact, the degradation of the hydraulic blade pitch pistons affects the control of the rotational speed and in general that of the torque, and this affects the production from cut-in to rated speed, possibly up to several percent of the annual energy production. This makes it advisable for wind turbine predictive maintenance to advance to include the optimization of energy conversion efficiency in addition to the production time, especially given the large number of wind turbines approaching the end of their planned lifetime.

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References

1. Rystad Energy. Energy Voice. 2020. Available online: https://www.energyvoice.com/renewables-energy-transition/wind/uk-wind/274960/uk-renewable-energy-capacity-double-2026/ (accessed on 1 October 2022).
2. Shafiee, M.; Sørensen, J.D. Maintenance Optimization and Inspection Planning of Wind Energy Assets: Models, Methods and Strategies. *Reliab. Eng. Syst. Saf.* **2017**, *192*, 105993. [CrossRef]
3. Satymov, R.; Bogdanov, D.; Breyer, C. Global-local analysis of cost-optimal onshore wind turbine configurations considering wind classes and hub heights. *Energy* **2022**, *256*, 124629. [CrossRef]
4. Pandit, R.; Infield, D.; Santos, M. Accounting for Environmental Conditions in Data-Driven Wind Turbine Power Models. *IEEE Trans. Sustain. Energy* **2023**, *14*, 168–177. [CrossRef]
5. Tautz-Weinert, J.; Watson, S.J. Using SCADA data for wind turbine condition monitoring—A review. *IET Renew. Power Gener.* **2017**, *11*, 382–394. [CrossRef]
6. Pandit, R.; Astolfi, D.; Hong, J.; Infield, D.; Santos, M. SCADA data for wind turbine data-driven condition/performance monitoring: A review on state-of-art, challenges and future trends. *Wind. Eng.* **2022**, 0309524X221124031. [CrossRef]
7. Koukoura, S.; Scheu, M.N.; Kolios, A. Influence of extended potential-to-functional failure intervals through condition monitoring systems on offshore wind turbine availability. *Reliab. Eng. Syst. Saf.* **2021**, *208*, 107404. [CrossRef]
8. Stetco, A.; Dinmohammadi, F.; Zhao, X.; Robu, V.; Flynn, D.; Barnes, M.; Keane, J.; Nenadic, G. Machine learning methods for wind turbine condition monitoring: A review. *Renew. Energy* **2019**, *133*, 620–635. [CrossRef]
9. Turnbull, A.; Carroll, J.; Koukoura, S.; McDonald, A. Prediction of wind turbine generator bearing failure through analysis of high frequency vibration data and the application of support vector machine algorithms. In Proceedings of the 7th International Conference on Renewable Power Generation, DTU, Lyngby, Denmark, 26 August–27 September 2018.
10. Fischer, K.; Coronado, D. *Condition Monitoring of wind Turbines: State of the Art, User Experience and Recommendations*; FraunhoferI-WES: Bremerhaven, Germany, 2015.
11. Sinha, Y.; Steel, J. A progressive study into offshore wind farm maintenance optimisation using risk based failure analysis. *Renew. Sustain. Energy Rev.* **2015**, *42*, 735–742. [CrossRef]
12. Reder, M.; Gonzalez, E.; Melero, J. Wind turbine failures—Tackling current problems in failure data analysis. The science of making torque from wind (TORQUE 2016). In *Journal of Physics: Conference Series*; IOP Publishing: Bristol, UK, 2016; Volume 753, p. 072027.
13. Qiao, W.; Lu, D. A survey on wind turbine condition monitoring and fault diagnosis-part I: Components and subsystems. *IEEE Trans. Industr. Electron.* **2015**, *62*, 6536–6545.
14. Artigao, E.; Martín-Martínez, S.; Honrubia-Escribano, A.; Gómez-Lázaro, E. Wind turbine reliability: A comprehensive review towards effective condition monitoring development. *Appl. Energy* **2018**, *228*, 1569–1583. [CrossRef]
15. Salameh, J.; Cauet, S.; Etien, E.; Sakout, A.; Rambault, L. Gearbox condition monitoring in wind turbines: A review. *Mech. Syst. Signal Process.* **2018**, *111*, 251–264. [CrossRef]

16. Kordestani, M.; Rezamand, M.; Carriveau, R.; Ting, D.S.K.; Saif, M. Failure Diagnosis of Wind Turbine Bearing Using Feature Extraction and a Neuro-Fuzzy Inference System (ANFIS). In *Advances in Computational Intelligence IWANN 2019*; Lecture Notes in Computer Science; Rojas, I., Joya, G., Catala, A., Eds.; Springer: Cham, Switzerland, 2019; Volume 11506. [CrossRef]
17. Aziz, U.; Charbonnier, S.; Bérenguer, C.; Lebranchu, A.; Prevost, F. SCADA data based realistic simulation framework to evaluate environmental impact on performance of wind turbine condition monitoring systems. In Proceedings of the 2019 4th Conference on Control and Fault Tolerant Systems (SysTol), Casablanca, Morocco, 18–20 September 2019; pp. 360–365. [CrossRef]
18. Chen, X.; Xu, W.; Liu, Y.; Islam, M.R. Bearing Corrosion Failure Diagnosis of Doubly Fed Induction Generator in Wind Turbines Based on Stator Current Analysis. *IEEE Trans. Ind. Electron.* **2020**, *67*, 3419–3430. [CrossRef]
19. Castellani, F.; Astolfi, D.; Natili, F. SCADA Data Analysis Methods for Diagnosis of Electrical Faults to Wind Turbine Generators. *Appl. Sci.* **2021**, *11*, 3307. [CrossRef]
20. Dhiman, H.S.; Deb, D.; Carroll, J.; Muresan, V.; Unguresan, M.-L. Wind Turbine Gearbox Condition Monitoring Based on Class of Support Vector Regression Models and Residual Analysis. *Sensors* **2020**, *20*, 6742. [CrossRef]
21. Bearing Damage and Failure Analysis. Available online: https://www.skf.com/binaries/pub12/Images/0901d1968064c148-Bearing-failures---14219_2-EN_tcm_12-297619.pdf (accessed on 20 January 2023).
22. Herp, J.; Ramezani, M.H.; Bach-Andersen, M.; Pedersen, N.L.; Nadimi, E.S. Bayesian state prediction of wind turbine bearing failure. *Renew. Energy* **2018**, *116*, 164–172. [CrossRef]
23. Fu, J.; Chu, J.; Guo, P.; Chen, Z. Condition Monitoring of Wind Turbine Gearbox Bearing Based on Deep Learning Model. *IEEE Access* **2019**, *7*, 57078–57087. [CrossRef]
24. Feng, B.; Zhang, D.; Si, Y.; Tian, X.; Qian, P. A condition monitoring method of wind turbines based on Long Short-Term Memory neural network. In Proceedings of the 2019 25th International Conference on Automation and Computing (ICAC), Lancaster, UK, 5–7 September 2019; pp. 1–4. [CrossRef]
25. Encalada-Dávila, Á.; Puruncajas, B.; Tutivén, C.; Vidal, Y. Wind Turbine Main Bearing Fault Prognosis Based Solely on SCADA Data. *Sensors* **2021**, *21*, 2228. [CrossRef]
26. Guo, Y.; Sheng, S.; Phillips, C.; Keller, J.; Veers, P.; Williams, L. A methodology for reliability assessment and prognosis of bearing axial cracking in wind turbine gearboxes. *Renew. Sustain. Energy Rev.* **2020**, *127*, 109888. [CrossRef]
27. Corley, B.; Koukoura, S.; Carroll, J.; McDonald, A. Combination of Thermal Modelling and Machine Learning Approaches for Fault Detection in Wind Turbine Gearboxes. *Energies* **2021**, *14*, 1375. [CrossRef]
28. Maatallah, H.; Fuente, M.J.; Ouni, K. Condition monitoring of wind turbine bearings progressive degradation using principal component analysis. In Proceedings of the 2020 Fifteenth International Conference on Ecological Vehicles and Renewable Energies (EVER), Monte Carlo, Monaco, 10–12 September 2020; pp. 1–6. [CrossRef]
29. Teng, W.; Zhang, X.; Liu, Y.; Kusiak, A.; Ma, Z. Prognosis of the Remaining Useful Life of Bearings in a Wind Turbine Gearbox. *Energies* **2017**, *10*, 32. [CrossRef]
30. Shi, X.; Li, W.; Gao, Q.; Guo, H. Research on Fault Classification of Wind Turbine Based on IMF Kurtosis and PSO-SOM-LVQ. In Proceedings of the 2017 IEEE 2nd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC), Chengdu, China, 15–17 December 2017; pp. 191–196. [CrossRef]
31. Wang, J.; Liang, Y.; Zheng, Y.; Gao, R.X.; Zhang, F. An integrated fault diagnosis and prognosis approach for predictive maintenance of wind turbine bearing with limited samples. *Renew. Energy* **2020**, *145*, 642–650. [CrossRef]
32. Elasha, F.; Shanbr, S.; Li, X.; Mba, D. Prognosis of a Wind Turbine Gearbox Bearing Using Supervised Machine Learning. *Sensors* **2019**, *19*, 3092. [CrossRef] [PubMed]
33. Nejad, A.R.; Odgaard, P.F.; Gao, Z.; Moan, T. A prognostic method for fault detection in wind turbine drivetrains. *Eng. Fail. Anal.* **2014**, *42*, 324–336. [CrossRef]
34. Natili, F.; Daga, A.P.; Castellani, F.; Garibaldi, L. Multi-Scale Wind Turbine Bearings Supervision Techniques Using Industrial SCADA and Vibration Data. *Appl. Sci.* **2021**, *11*, 6785. [CrossRef]
35. Xiao, X.; Liu, J.; Liu, D.; Tang, Y.; Zhang, F. Condition Monitoring of Wind Turbine Main Bearing Based on Multivariate Time Series Forecasting. *Energies* **2022**, *15*, 1951. [CrossRef]
36. Mollasalehi, E.; Wood, D.; Sun, Q. Indicative Fault Diagnosis of Wind Turbine Generator Bearings Using Tower Sound and Vibration. *Energies* **2017**, *10*, 1853. [CrossRef]
37. Igba, J.; Alemzadeh, K.; Durugbo, C.; Eiriksson, E.T. Analysing RMS and peak values of vibration signals for condition monitoring of wind turbine gearboxes. *Renew. Energy* **2016**, *91*, 90–106. [CrossRef]
38. Qian, P.; Ma, X.; Wang, Y. Condition monitoring of wind turbines based on extreme learning machine. In Proceedings of the 21st International Conference on Automation and Computing, Glasgow, UK, 11–12 September 2015; pp. 1–6.
39. Pan, Y.; Hong, R.; Chen, J.; Wu, W. A hybrid DBN-SOM-PF-based prognostic approach of remaining useful life for wind turbine gearbox. *Renew. Energy* **2020**, *152*, 138–154. [CrossRef]
40. Pan, Y.; Hong, R.; Chen, J.; Singh, J.; Jia, X. Performance degradation assessment of a wind turbine gearbox based on multi-sensor data fusion. *Mech. Mach. Theory* **2019**, *137*, 509–526. [CrossRef]
41. Elforjani, M. Diagnosis and prognosis of real world wind turbine gears. *Renew. Energy* **2020**, *147*, 1676–1693. [CrossRef]
42. Elforjani, M.; Shanbr, S.; Bechhoefer, E. Detection of faulty high speed wind turbine bearing using signal intensity estimator technique. *Wind Energy* **2018**, *21*, 53–69. [CrossRef]

43. Qiu, Y.; Chen, L.; Feng, Y.; Xu, Y. An Approach of Quantifying Gear Fatigue Life for Wind Turbine Gearboxes Using Supervisory Control and Data Acquisition Data. *Energies* **2017**, *10*, 1084. [CrossRef]
44. Chen, N.; Yu, R.; Chen, Y.; Xie, H. Hierarchical method for wind turbine prognosis using SCADA data. *IET Renew. Power Gener.* **2017**, *11*, 403–410. [CrossRef]
45. Marti-Puig, P.; Blanco, M.A.; Serra-Serra, M.; Solé-Casals, J. Wind Turbine Prognosis Models Based on SCADA Data and Extreme Learning Machines. *Appl. Sci.* **2021**, *11*, 590. [CrossRef]
46. Verma, A.; Zappalá, D.; Sheng, S.; Watson, S.J. Wind turbine gearbox fault prognosis using high-frequency SCADA data. In *Journal of Physics: Conference Series*; IOP Publishing: Bristol, UK, 2022; Volume 2265, p. 032067.
47. Cheng, F.; Qu, L.; Qiao, W. Fault prognosis and remaining useful life prediction of wind turbine gearboxes using current signal analysis. *IEEE Trans. Sustain. Energy* **2017**, *9*, 157–167.
48. Carroll, J.; McDonald, A.; McMillan, D. Failure rate, repair time and unscheduled O&M cost analysis of offshore wind turbines. *Wind Energy* **2016**, *19*, 1107–1119.
49. Castellani, F.; Pandit, R.; Natili, F.; Belcastro, F.; Astolfi, D. Advanced Methods for Wind Turbine Performance Analysis Based on SCADA Data and CFD Simulations. *Energies* **2023**, *16*, 1081. [CrossRef]
50. Artigao, E.; Honrubia-Escribano, A.; Gómez-Lázaro, E. In-service wind turbine DFIG diagnosis using current signature analysis. *IEEE Trans. Ind. Electron.* **2019**, *67*, 2262–2271. [CrossRef]
51. Artigao, E.; Sapena-Bano, A.; Honrubia-Escribano, A.; Martinez-Roman, J.; Puche-Panadero, R.; Gómez-Lázaro, E. Long-term operational data analysis of an in-service wind turbine DFIG. *IEEE Access* **2019**, *7*, 17896–17906. [CrossRef]
52. Zhao, Y.; Li, D.; Dong, A.; Lin, J.; Kang, D.; Shang, L. Fault prognosis of wind turbine generator using SCADA data. In Proceedings of the 2016 North American Power Symposium (NAPS), Denver, CO, USA, 18–20 September 2016; pp. 1–6. [CrossRef]
53. Zhao, Y.; Li, D.; Dong, A.; Kang, D.; Lv, Q.; Shang, L. Fault prediction and diagnosis of wind turbine generators using SCADA data. *Energies* **2017**, *10*, 1210. [CrossRef]
54. Jin, X.; Xu, Z.; Qiao, W. Condition monitoring of wind turbine generators using SCADA data analysis. *IEEE Trans. Sustain. Energy* **2020**, *12*, 202–210. [CrossRef]
55. Chen, B.; Matthews, P.C.; Tavner, P.J. Automated on-line fault prognosis for wind turbine pitch systems using supervisory control and data acquisition. *IET Renew. Power Gener.* **2015**, *9*, 503–513. [CrossRef]
56. Astolfi, D.; Castellani, F.; Lombardi, A.; Terzi, L. Data-driven wind turbine aging models. *Electr. Power Syst. Res.* **2021**, *201*, 107495. [CrossRef]
57. Astolfi, D.; Castellani, F.; Terzi, L. An operation data-based method for the diagnosis of zero-point shift of wind turbines yaw angle. *J. Sol. Energy Eng.* **2020**, *142*, 024501. [CrossRef]
58. Astolfi, D.; Pandit, R.; Celesti, L.; Vedovelli, M.; Lombardi, A.; Terzi, L. Data-Driven Assessment of Wind Turbine Performance Decline with Age and Interpretation Based on Comparative Test Case Analysis. *Sensors* **2022**, *22*, 3180. [CrossRef]
59. Wei, L.; Qian, Z.; Zareipour, H.; Zhang, F. Comprehensive aging assessment of pitch systems combining SCADA and failure data. *IET Renew. Power Gener.* **2022**, *16*, 198–210. [CrossRef]
60. Wei, L.; Qian, Z.; Zareipour, H. Wind turbine pitch system condition monitoring and fault detection based on optimized relevance vector machine regression. *IEEE Trans. Sustain. Energy* **2019**, *11*, 2326–2336. [CrossRef]
61. Niu, M.Z.; Chen, J.; Feng, Y.; Wang, H. Fault diagnosis of wind power yawing slewing bearing based on support vector machine. *J. Nanjing Univ. Technol.* **2014**, *36*, 117–122.
62. Žvokelj, M.; Zupan, S.; Prebil, I. EEMD-based multiscale ICA method for slewing bearing fault detection and diagnosis. *J. Sound Vib.* **2016**, *370*, 394–423. [CrossRef]
63. Pan, Y.; Hong, R.; Chen, J.; Qin, Z.; Feng, Y. Incipient fault detection of wind turbine large-size slewing bearing based on circular domain. *Measurement* **2019**, *137*, 130–142. [CrossRef]
64. Yin, S.; Wang, G.; Karimi, H.R. Data-driven design of robust fault detection system for wind turbines. *Mechatronics* **2014**, *24*, 298–306. [CrossRef]
65. Jing, B.; Qian, Z.; Pei, Y.; Zhang, L.; Yang, T. Improving wind turbine efficiency through detection and calibration of yaw misalignment. *Renew. Energy* **2020**, *160*, 1217–1227. [CrossRef]
66. Bao, Y.; Yang, Q. A data-mining compensation approach for yaw misalignment on wind turbine. *IEEE Trans. Ind. Inform.* **2021**, *17*, 8154–8164. [CrossRef]
67. Pandit, R.; Infield, D.; Dodwell, T. Operational variables for improving industrial wind turbine yaw misalignment early fault detection capabilities using data-driven techniques. *IEEE Trans. Instrum. Meas.* **2021**, *70*, 1–8. [CrossRef]
68. Pandit, R.K.; Infield, D. SCADA-based wind turbine anomaly detection using Gaussian process models for wind turbine condition monitoring purposes. *IET Renew. Power Gener.* **2018**, *12*, 1249–1255. [CrossRef]
69. Qu, C.; Lin, Z.; Chen, P.; Liu, J.; Chen, Z.; Xie, Z. An improved data-driven methodology and field-test verification of yaw misalignment calibration on wind turbines. *Energy Convers. Manag.* **2022**, *266*, 115786. [CrossRef]
70. Gao, L.; Hong, J. Data-driven yaw misalignment correction for utility-scale wind turbines. *J. Renew. Sustain. Energy* **2021**, *13*, 063302. [CrossRef]
71. Asghar, A.; Liu, X. Estimation of wind turbine power coefficient by adaptive neuro-fuzzy methodology. *Neurocomputing* **2017**, *238*, 227–233. [CrossRef]

72. Yang, J.; Wang, L.; Song, D.; Huang, C.; Huang, L.; Wang, J. Incorporating environmental impacts into zero-point shifting diagnosis of wind turbines yaw angle. *Energy* **2022**, *238*, 121762. [CrossRef]
73. Hu, R.L.; Leahy, K.; Konstantakopoulos, I.C.; Auslander, D.M.; Spanos, C.J.; Agogino, A.M. Using Domain Knowledge Features for Wind Turbine Diagnostics. In Proceedings of the 2016 15th IEEE International Conference on Machine Learning and Applications (ICMLA), Anaheim, CA, USA, 18–20 December 2016; pp. 300–307. [CrossRef]
74. Pandit, R.K.; Infield, D. Comparative assessments of binned and support vector regression-based blade pitch curve of a wind turbine for the purpose of condition monitoring. *Int. J. Energy Environ. Eng.* **2019**, *10*, 181–188. [CrossRef]
75. Kusiak, A.; Verma, A. Monitoring Wind Farms With Performance Curves. *IEEE Trans. Sustain. Energy* **2013**, *4*, 192–199. [CrossRef]
76. Pandit, R.; Infield, D. Comparative Analysis of Binning and Support Vector Regression for Wind Turbine Rotor Speed Based Power Curve Use in Condition Monitoring. In Proceedings of the IEEE 53rd International Universities Power Engineering Conference (UPEC), Glasgow, UK, 4–7 September 2018; pp. 1–6. [CrossRef]
77. Pandit, R.; Infield, D. Comparative study of binning and gaussian process based rotor curves of a wind turbine for the purpose of condition monitoring. In Proceedings of the 3rd International Conference on Offshore Renewable Energy, Glasgow, UK, 28–29 August 2018.

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