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Review

A Review of Predictive and Prescriptive Offshore Wind Farm Operation and Maintenance

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Abstract: Offshore wind farms are a rapidly developing source of clean, low-carbon energy and as they continue to grow in scale and capacity, so does the requirement for their efficient and optimised operation and maintenance. Historically, approaches to maintenance have been purely reactive. However, there is a movement in offshore wind, and wider industry in general, towards more proactive, condition-based maintenance approaches which rely on operational data-driven decision making. This paper reviews the current efforts in proactive maintenance strategies, both predictive and prescriptive, of which the latter is an evolution of the former. Both use operational data to determine whether a turbine component will fail in order to provide sufficient warning to carry out necessary maintenance. Prescriptive strategies also provide optimised maintenance actions, incorporating predictions into a wider maintenance plan to address predicted failure modes. Beginning with a summary of common techniques used across both strategies, this review moves on to discuss their respective applications in offshore wind operation and maintenance. This review concludes with suggested areas for future work, underlining the need for models which can be simply incorporated by site operators and integrate live data whilst handling uncertainties. A need for further focus on medium-term planning strategies is also highlighted along with consideration of the question of how to quantify the impact of a proactive maintenance strategy.

Keywords: offshore wind; failure prediction; failure prognosis; operation and maintenance planning; prescriptive maintenance

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1. Introduction

Twenty years ago, the deployment of offshore wind farms began to accelerate. From making up just 1% of global installed wind capacity in 2009, this percentage had increased to 10% by 2019, the equivalent of 28.3 GW [1]. According to the Global Wind Energy Council, this figure is set to increase by another 30 GW in the next four years [2]. In Europe alone, the EU have set a target of 230 to 450 GW of offshore wind capacity by 2050 [3], an ambitious target from the installed capacity of 22.5 GW in 2019 as seen in Figure 1. On top of increasing installed capacity, offshore wind turbines are also increasing in size, with next-generation turbines expected to exceed 15 MW and 200 m in rotor diameter.

Operation and maintenance (O&M) of offshore wind turbines is inherently a more challenging and costly task compared to their onshore counterparts. A 2018 NREL report [4] found the average cost of onshore wind O&M is $12.1 per MWh. In contrast, a cost of $30.3 per MWh was given for an average offshore wind fixed-bottom project. The same report found O&M makes up 34% of total fixed-bottom offshore wind farm (OWF) lifetime

costs. The combination of increasing size, capacity and number of offshore wind turbines (WTs), alongside greater access difficulties, makes it critical for them to have increased reliability and availability. This in turn will require strategic O&M improvements.

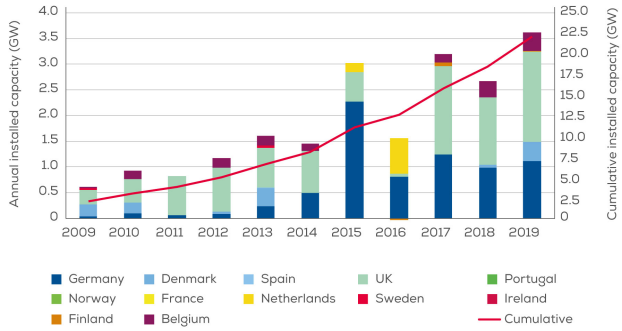

Figure 1. European offshore wind installed and cumulative capacity [5].

Maintenance strategies can be classified according to many different taxonomies. One decomposition can be seen in Figure 2, where strategies are separated into reactive and proactive, with opportunistic sitting between the two. Reactive strategies allow the turbine to run until a component fails, with technicians undertaking repairs only once a failure has occurred. Proactive strategies aim to prevent failures occurring by taking action before they have chance to fail [6], through periodic, predictive or prescriptive maintenance. Opportunistic maintenance aims to carry out preventive maintenance actions whenever the opportunity arises in order to reduce costs [7]. Within proactive maintenance, there are different strategies. Periodic maintenance is based on recommended maintenance intervals from the original equipment manufacturer (OEM). Components can be repaired either at regular time intervals (time-based) or after a prescribed number of cycles (use based). Condition-based maintenance (CBM) uses monitoring devices across various elements of operating assets to identify and prevent deterioration and failure. Maintenance can be triggered when measured parameters fall out of bounds, or the collected data can be combined with predictive and prescriptive analytics to try and predict and prevent failures in advance, as discussed in this review. An overview of the turbine condition development according to different maintenance strategies is shown in Figure 3.

Presently, offshore wind O&M strategies are dominated by reactive and periodic maintenance, with some predictive techniques being used [8]. Whilst a predominately corrective method maximises the useful life of components, it also leads to catastrophic failures which can incur increased downtime while the repair is carried out, and increased cost. Periodic maintenance may lead to wasted useful life of components with parts being replaced before necessary, and can also lead to failure if more wear occurs than anticipated. In order to combat the problems associated with current maintenance, industry across all sectors is moving towards an increasingly automated approach to O&M. Predictive maintenance uses real-time data and predictive analytics to try and predict failures before they occur. Prescriptive maintenance strategies aim to predict when impending failures will occur (failure prognosis), and go a step further then predictive maintenance by providing optimised O&M actions to address the predicted failure mode [9]. Combined with unmanned inspections and repairs, and improved weather modelling, prescriptive maintenance could play a major part in the industry vision of unmanned, autonomous wind farms [10].

Similar to offshore wind farms, onshore farms are also equipped with condition monitoring systems which monitor the state of the turbines. Research is being carried out into various areas of operation and maintenance for onshore wind, as summarised in a recent review by Costa et al. [11], including work on predictive approaches. However, given the location of onshore wind farms, there is less need to optimise maintenance planning based on turbine or farm accessibility. This means a prescriptive approach to maintenance, where a failure is predicted, an action recommended and an optimised maintenance plan

produced, is less beneficial for onshore farms where operators can deploy repair teams far more easily. This review focuses on prescriptive maintenance, and therefore restricts its attention and cited literature to offshore wind farms where more research is being carried out in this area.

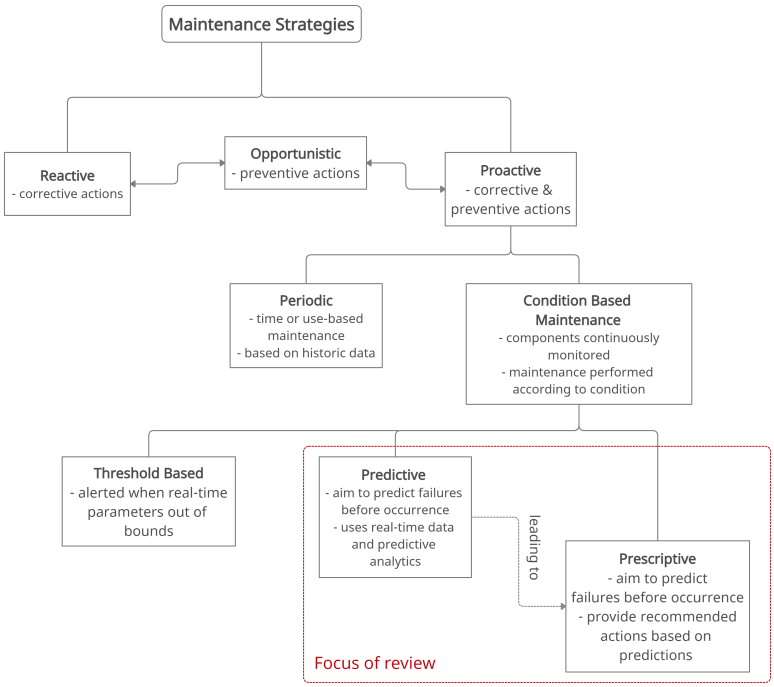

Figure 2. Categorisation of maintenance strategies.

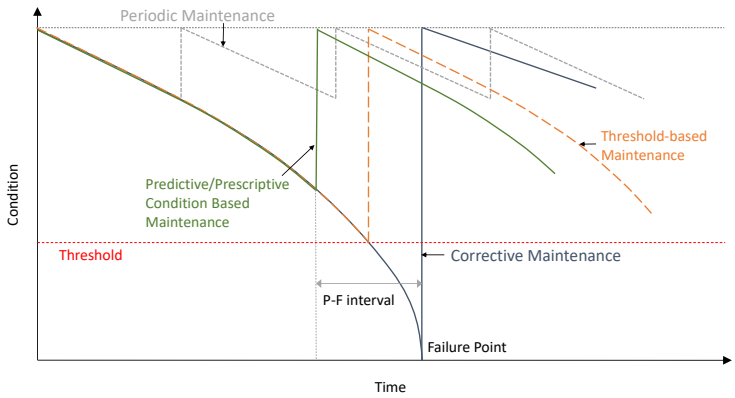

Figure 3. Turbine condition development for different types of maintenance strategies. Adapted from [12].

To the best of the authors' knowledge, there are a lack of review papers considering offshore wind prescriptive maintenance which incorporate both aspects of failure prognosis and O&M planning. This work aims to address this by bringing together a review of these two constituent elements and discussing the current state of existing prescriptive maintenance models. Section 2 provides an overview of the review methodology. Section 3 introduces some common modelling tools used in CBM, failure prediction and prognosis. Section 4 focuses on the application of these to predictive maintenance, highlighting how techniques have evolved from diagnostic to predictive to prognostic. Having covered failure prediction in Section 4, Section 5 covers the second half of a prescriptive maintenance model, O&M planning and Section 6 considers existing complete prescriptive models. Finally, in Section 7, recommendations are made for areas of key focus and future work.

2. Review Methodology

In order to carry out a review of the existing literature in the area of prescriptive maintenance, keywords are used to survey available research. The repositories searched are Google Scholar, Semantic Scholar and Scopus. Different keywords are used for individual sections and these are summarised in Table 1.

Table 1. Keyword Search Strings.

Section	Keywords
Section 4.3: Failure Diagnosis	offshore wind turbine; fault diagnosis; condition monitoring; vibration data; fault detection; fault tree
Section 4.4: Failure Prediction	offshore wind turbine; failure prediction; predictive maintenance; vibration data; SCADA data; condition monitoring
Section 4.5: Failure Prognosis	offshore wind turbine; failure prognosis; lifetime estimation; prescriptive maintenance; remaining useful life; vibration data; SCADA data; condition monitoring
Section 5.1: Strategic O&M Planning	maintenance optimisation; offshore wind farm; long-term operation; vessel fleet; strategic; maintenance planning; assets; decision support system
Section 5.2: Tactical O&M Planning	maintenance optimisation; offshore wind farm; spare parts; opportunistic maintenance; condition-based maintenance; decision support system; logistics; maintenance planning
Section 5.3: Operational O&M Planning	maintenance optimisation; offshore wind farm; maintenance scheduling; daily maintenance; vessel routing; short-term decision making; probabilistic operations; offshore maintenance forecasting

The division of sections arises from the definition of prescriptive maintenance. The first half of a prescriptive maintenance strategy requires failure prognosis (determining time to failure), which itself developed from failure prediction (binary predictions) and failure diagnosis (post-event failure cause). The literature is therefore searched separately for each of these three distinct topics in Section 4. After initial investigation of the available research, it is decided to record the summary of the literature in each section slightly differently. Section 4.3 is not the main focus of this paper, and therefore a brief summary of diagnostic tools grouped by component is considered sufficient. Sections 4.4 and 4.5 are more comprehensive and rather than grouping by component, after researching available literature, it is decided to group by the predictive technique applied (as discussed in Section 3) in the considered work. This enables this review to compare the different algorithms and approaches and summarise the advantages and disadvantages of each for the interested reader. Further searches for each approach are then carried out to ensure the most relevant literature is included. For Section 4.4, the majority of the literature uses data-driven or physics-based methods and these form the bulk of the discussion. For Section 4.5, data-driven, physics-based, stochastic and hybrid methods are commonly seen in theliterature, and thus they are grouped according to these categories.

The second half of a prescriptive maintenance technique, the O&M planning, is covered in Section 5. Here, an existing review by Shafiee et al. [13] is used to determine three categories of maintenance planning, and keywords are searched according to these categorisations, as shown in Table 1.

3. Common Techniques for Offshore Wind Condition-Based Maintenance Strategies

According to European standards, [14] CBM is a form of "preventive maintenance which includes assessment of physical conditions, analysis and the possible ensuing maintenance actions". CBM has been studied in the context of offshore wind for many years, developing from cost justification through to state-of-the-art in OWF maintenance, mod-

elling interactions between failures and maintenance actions across a farm [15–19]. At its simplest, CBM acts as a type of threshold-based maintenance, triggering maintenance when parameters reach a defined limit [20]. However, CBM has developed far beyond this and is now primarily used in the context of predictive and prescriptive maintenance [21]. This will be the main focus of this review.

This section introduces some common techniques used in predictive and prescriptive maintenance. A condition-based approach requires information on the current state of the turbine [18]. There are two main systems which provide data from a WT, the Supervisory Control and Data Acquisition (SCADA) system and condition monitoring systems (CMS). There are also other sources, such as daily operational reports, met-ocean data, stock levels and inspection reports which can be used to build an accurate picture of the turbine condition.

SCADA systems are typically installed on every turbine and provide information on a wide range of systems, including wind speed, rotational speeds, energy production, component temperatures and alarms. They usually sample at high frequency but report averaged data every 10 min. SCADA systems are also used to trigger alarms if any parameters fall outside predetermined operating zones.

CMS uses techniques such as vibration analysis, particle counting and strain measurements to monitor the health of components [22]. CMS typically samples at a higher frequency than SCADA, and comes at a higher cost, both financially and in terms of data transfer and storage. Monitoring is usually at key components, including the gearbox, generator, bearings and rotor.

In the case of failure prediction, normal behaviour models (NBM) [23] can be used to examine the difference between predicted variables and measured outcomes, using residuals to estimate whether an error is going to occur.

With failure prognosis, models can either measure cumulative damage (or an equivalent health indicator (HI) [24]) and extrapolate out to a damage threshold, or estimate the remaining useful life (RUL) directly from the data [25]. The RUL represents the remaining time that an item, component, or system is estimated to be able to operate effectively before requiring replacement. A similar concept is the P–F interval [26], which is the time difference between point P, potential failure, to point F, functional failure, as shown in Figure 4. The aim is to maximise the difference between these points.

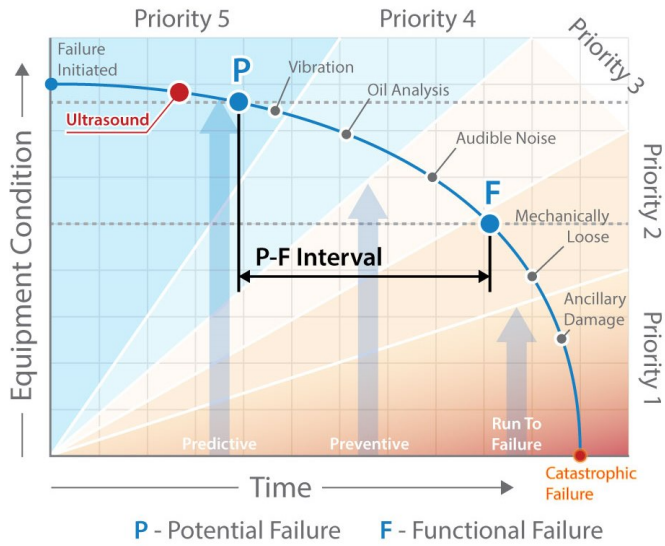

Figure 4. P–F curve [27] shows the interval between potential and functional failure, highlighting possible modes of detection along the curve.

In general, the tools used in predictive or prescriptive CBM can be split into data-driven, physics-based, stochastic or hybrid approaches.

3.1. Data-Driven Techniques

Data-driven approaches use a number of information sources from the turbine and surrounding systems to build up a picture of the O&M state of the turbine. They require no previous knowledge of the system which is investigated. They do, however, require a large amount of data for training and testing, along with a sufficient quantity of 'failures' in the data set so that the system can learn to detect them.

A range of data-driven approaches exist, including artificial intelligence (AI), statistical methods, time series analysis [28], rough sets [29] and grey system theory [30]. In offshore wind O&M, statistical methods and AI (which grew out of statistics originally) are most common and are considered separately in this review for the sake of readability. A brief overview of these techniques is given below.

3.1.1. Artificial Intelligence Models

AI approaches, widely known as Machine Learning (ML), have become prevalent with the increase in available data, along with data handling, storage and processing capabilities [31]. They are particularly relevant for continuously monitored systems and useful when a system is too complex to model physically. For this reason they are often cheaper to create than other approaches and can be deployed more quickly.

AI approaches can use either supervised, semi-supervised, unsupervised or reinforcement learning. In terms of wind turbine O&M [32], supervised approaches make use of labels indicating turbine state or dependent variable values in order to train a model to identify these. Semi-supervised techniques use a small amount of labelled data and large amounts of unlabelled data. Unsupervised models do not use labelled data, and the most common technique is cluster analysis which aims to find hidden patterns or groups within the data. Reinforcement learning learns optimal behaviours in order to maximise reward. It does not require labelled data, but learns through interactions with the environment and observations of results.

Under the umbrella of supervised learning, techniques can be further defined as classification or regression algorithms. At the simplest level, regression techniques return a numerical (continuous) variable, whereas classification techniques return categorical (discrete) outputs.

Some commonly used techniques for AI failure prediction include linear regression [33], support vector machines (SVMs) [34], decision trees/random forests [35], K-Nearest neighbours (KNNs) [36] and artificial neural networks (ANNs) [37], including adapative neuro-fuzzy inference systems (ANFIS) [38].

3.1.2. Statistical Models

Statistical models use existing monitoring data and previous knowledge of failures to estimate failure rates and degradation. They are usually used for short-term prediction due to their dynamic noise, sensitivity to initial conditions and potential for accumulation of systematic errors. The simplest technique uses previous failure data to model distributions such as exponential, lognormal, Gaussian and Weibull functions to provide information about when failures are expected to occur [39]. The Weibull function is commonly used to model component reliability as, in particular, the classical bathtub curve seen in Figure 5 can be made up of three Weibull distributions with different shape parameter, β, values which represent the different failure rate behaviours. During early life, components experience a decrease in failure rate as they 'wear in', $\beta < 1$. During the majority of their useful life, failure rates are constant, $\beta = 1$, and at the end of their life, failure rates increase, $\beta > 1$, as they 'wear out'.

One common statistical approach in failure prognosis is to apply an AutoRegressive Integrated Moving Average (ARIMA) model to time series data. ARIMA models combine autoregressive (AR) models with moving-average (MA) models and are a widely used approach to time series forecasting [40].

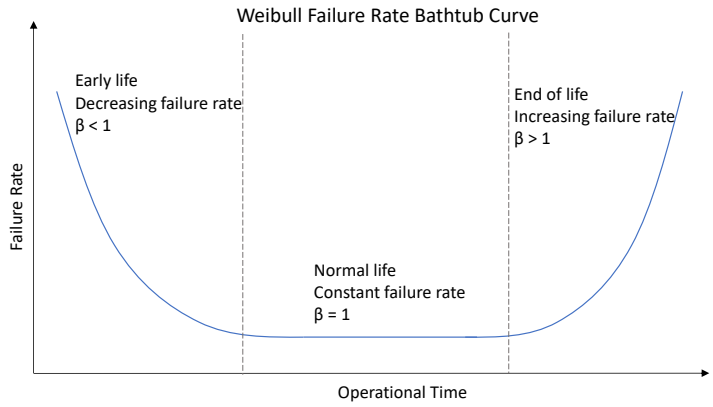

Figure 5. 'Bathtub' curve representing common reliability lifetime trend of components.

3.2. Physics-Based Techniques

The physics-based approach relies on a deep understanding of the physical system or process and uses scientifically established relationships to describe it. Residuals between measurements from the real system and the expected output of the physical model can be used to monitor the operational state [41].

Most models used for wind turbine maintenance are based on fatigue lifetime prediction, using Paris' law to study degradation or Palmgren–Miner's rule to predict failures, of which more information can be found in Dowling 2012 [42].

3.3. Stochastic Techniques

In this review, stochastic approaches are taken as those which possess and use inherent randomness in their modelling and usually provide a probability distribution of the variable of interest as an output. Data are usually collected and analysed in order to determine the necessary model parameters. In this way, there is some overlap with data-driven models; however, the inherent probabilistic nature of the models themselves means for classification purposes they are grouped under 'stochastic' here. A more in-depth analysis of stochastic methods used in industry can be found in Sikorska 2011 and Rafsanjani 2014 [43,44].

Markov processes are used to forecast variables whose predicted value is only influenced by its current state. They are used to model systems where the number of possible states is finite and the probabilities remain constant and the reader is referred to [45] for a general overview of the subject. In offshore wind O&M, Markov processes are applied in two main areas. Hidden Markov Models (HMMs) are used to model RUL of a system [46] and add an 'unobservable' state to the system which degrades according to a Markov process. An observable process depends on this hidden state and can be measured, allowing the hidden state to be inferred. For a WT, which produces huge amounts of data related to the state of the machine, but is unable to measure the degradation itself, this is a powerful tool. Maintenance decision support models often use Markov decision processes [47], which extend Markov models with the possibility of taking actions and receiving rewards. This enables the model to simulate a scenario where outcomes are partly random and partly controlled by a decision maker [48].

Another common approach is the use of particle filters (PFs). The objective of PFs is to update the posterior distribution of a Markov process, given noise, as new observations arrive sequentially in time [49]. It uses 'particles' or points to represent sampled values from an unknown state space and a set of associated weights which denote the discrete probability masses of these particles. In the case of offshore wind O&M, the posterior distribution of interest is usually the RUL.

3.4. Hybrid Techniques

In real-world failure prediction or prognostic processes, trends of the characteristic parameters are difficult to predict using a single method. It is often the case that two

methodologies can be combined to take advantage of the strengths of each model. Hybrid models often combine knowledge of a physical failure process with data which cannot easily be modelled in a physical model, for example, environmental or inspection data.

4. Offshore Wind Predictive Maintenance

This section focuses on the advances and latest work in offshore wind predictive CBM, briefly discussing available failure data, data cleaning and failure diagnosis before moving onto failure prediction and prognosis. These consecutive steps are displayed in Figure 6.

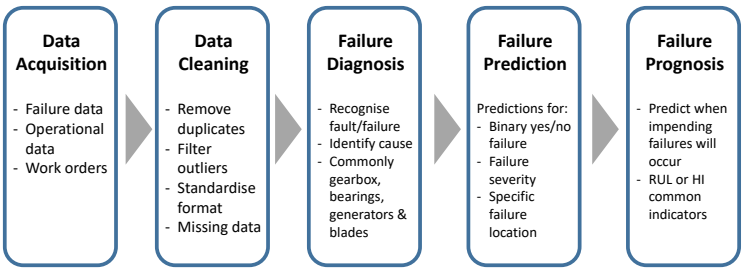

Figure 6. Process from failure data acquisition to failure prognosis.

4.1. Failure Data

In order to predict failures, it is first necessary to understand which components are most likely to fail. Turbine failure data are generally difficult to obtain. There are a small number of public databases available for onshore wind turbines. Of these, the most well known include WMEP [50], WindStats [51], CIRCE [52] and the Reliawind project (2008–2011) [53]. There are several recent reviews which compare and collate results from different databases, identifying key failure modes, trends and differences between the databases [54–56].

When investigating failures in offshore wind turbines, obtaining access to results is much more challenging; however, there have been some studies published on this topic. Particularly, in the last 5 years, work has been done by a group at Strathclyde University which uses data collected over a period of 5 years from a group of 350 turbines from the same manufacturer. This research has led to several publications [57–59] with more precise offshore failure rates, broken down in various ways according to sub-component, drive train configuration etc. These studies show the largest contributor to the overall failure rate for offshore wind turbines is the pitch and hydraulic systems which account for 13%. 'Other Components' (usually auxiliary components such as trap doors, ladders, door seals) is the second largest contributor with 12.2% of the overall failures. The generator, gearbox, and blades are the third, fourth and fifth most significant contributors respectively.

The main alternative to the Strathclyde offshore failure data comes from SPARTA [60]. This is a UK offshore wind performance data bench-marking platform, operated by ORE Catapult and the Crown Estate, and covering 93% of the UK's installed offshore wind capacity. Whilst it provides results from a broader range of turbines, these are published in graph form, making it difficult to extract numerical values. Failure definitions are also not provided.

The exact definition of failures and which components belong to which category differ between studies so it is difficult to compare them definitively. However, pitch, gearbox, generator and blades tend to appear most frequently and it will be seen in the rest of this review that these are the components where the most effort has been placed in terms of failure prediction and prognosis.

Another issue with failure data arises from the fact failures are events which by their nature are aimed to be avoided. This inherently makes it difficult to access sufficient failure events which can be used to train predictive and prognostic algorithms.

4.2. Data Cleaning

Data preprocessing is an important and potentially time-consuming step between data acquisition and failure predictions [61]. Before operational data can be used in models, it is first necessary to remove unnecessary or duplicate values, filter outliers, standardise data structures and handle missing data.

Some work focuses specifically on the preprocessing step for offshore wind data. Zhang et al. [62] demonstrate an automatic data cleaning and operating conditions classification approach on SCADA data from a wind farm in China and show the method can classify operating conditions for different wind turbines automatically. Other work investigates wind power curve data cleaning [63,64] and data imputation methods [65,66].

4.3. Failure Diagnosis

The ability to recognise and identify the cause of a fault is the first step in any predictive maintenance strategy. This began to develop in the offshore wind industry in the late 2000s and marked the precursor to failure prediction. As shown in reviews specific to condition monitoring (CM) and fault diagnosis [67,68], diagnostic methods have primarily focused on gearbox and bearings, generators, and blade systems. Some common techniques used in offshore wind for failure diagnosis of these components are discussed below.

As found in the failure rate studies above, the gearbox is prone to failure and is also well instrumented, making it an obvious choice for condition monitoring analysis. Common techniques include vibration [69], acoustic emission (AE) [70] and temperature [71] monitoring. Bearings, used throughout the wind turbine in components such as gearboxes, generator and pitch systems, have been shown to lead to catastrophic failures in these sub-systems [72,73]. They are diagnosed using similar techniques to the gearbox, including vibration and electrical signals [74,75] and lubricated bearings can be monitored using oil particle counting [76].

Blades are prone to corrosion and creep fatigue and are monitored in practice by visual inspection, but studies have also looked at using AE or strain monitoring techniques which detect abnormal vibrations of the blades [77,78]. There have been several studies on generator fault diagnosis, using vibration signal analysis [79,80] and stator electrical current signals [81]. Ruiz et al. [82] propose a method for detection and classification of wind turbine actuators and sensor faults, including pitch and generator faults.

These fault diagnosis methods offer the potential for a deeper understanding of failure mechanisms in turbines and are often accompanied with failure mode effect and criticality analysis (FMECA) [83]. This information can be used to improve engineering design, determine how a turbine failed, and lead to a reduction in the number of technicians having to go offshore.

4.4. Failure Prediction

As discussed in an early study by Kusiak and Li [84], there are various levels of fault prediction: fault and no-fault prediction, fault severity and finally the specific fault itself. As fault prediction has become more sophisticated, more models are able to predict specifically where the fault will occur. This section considers the application of data-driven and physics-based models discussed in Section 3 to WT failure prediction. Stochastic and hybrid models are not considered as they are less common in failure prediction, but are discussed in Section 4.5. A summary of the models discussed is displayed in Table 2.

4.4.1. Data-Driven Techniques

This section draws on existing reviews of the subject found in [85,86].

1. Linear Regression
   There have been several examples of regression models for offshore wind turbine failure prediction. Orozo et al. [87] built different models, including linear and multivariate polynomial regressive models, to evaluate temperature sensor data anomalies for gearbox components. In spite of the complex, non-linear behaviour of

a turbine, the linear model performed better than the more complex random forest and neural network (see below) models. Abdusamad et al. [88] investigated the use of multiple linear regression models to estimate the temperature of the generator. Regan et al. [89] used acoustic-based structural sensing with a logistic regression model to investigate blade damage detection, with feature classification possible with minimal overfitting.

These models have the benefit of being relatively simple to build and train, require comparatively less data than other options below and are easy to update and understand. However, non-linear relationships require higher order polynomial models which increase computational time and complexity of design. It is also necessary to determine which independent variables must be used in the model. Given the quantity of SCADA and CMS data features, this is often not a straight forward decision.

2. Support Vector Machine

   SVM is a common tool in failure predictions and is used for bearing faults [90,91] and more generally across the whole turbine [92]. The bearing fault studies use signal processing to investigate time and frequency domain features and use these spectra to train SVM classifiers. In [91], an accuracy of 67% is found for detection 1–2 months in advance. This highlights the difficulties of detecting in advance as will be discussed further in Section 4.5.

   SVM is a relatively simple algorithm to implement and works well with higher dimension data such as that produced by SCADA systems. However, as with any ML technique, it needs sufficient training and testing data and often it is difficult to find a suitable kernel function to fit the data. Additionally, SVM algorithms are suitable for datasets with many features but few instances; however, they do not scale well with many data points as memory to store the kernel matrix scales quadratically with the number of data points. They are also sensitive to noise in the data.

3. Decision Trees/Random Forests

   Several papers make use of this technique [93–96], in particular to build holistic fault detection and classification frameworks. An example of this is seen in work by Abdallah et al. [94], which reviews the use of different decision tree learning algorithms with big data to try and automatically link excessive vibrations to their root causes. Zhang et al. [95] also investigate the use of decision trees to create a data-driven fault detection framework, using decision tree-based models to rank the data features by importance and then training a classifier on the three top-ranking features. Compared to SVM, this proposed method has less tendency to over-fit, meaning it responds well to new information.

   Decision trees tend to be easy to implement and offer more transparency than other methods as the decision branches can be examined and understood. Decision trees should have certain limits placed on them, for example, the number of branches, in order to prevent from over-fitting.

4. K-Nearest Neighbours

   One recent study by Koukoura et al. [97] uses the KNN algorithm to classify vibration data collected from accelerometers installed on the gearbox surface in order to predict gearbox faults. The authors note this method seems to reveal fault signatures more clearly than a simple envelope analysis; however, other ML algorithms should be tested too.

   In another study, Lin et al. [98] use KNN to classify current signals for fault recognition of a gearbox oil leakage. In this work, a faulty gearbox is constructed and experimental results indicate the proposed method effectively recognises the fault; however, a quantitative comparison is required. KNN is also used in a study by Skrimpas et al. [99] to investigate the detection of icing on wind turbine blades. This uses nacelle acclerometers and power performance analysis, using KNN to group underperforming points below the power curve.

The KNN approach has the advantage of being good with large and noisy datasets; however, with higher dimension data, it is less successful and it is also dependent on choosing a good distance metric.

5. Artificial Neural Networks
   Helbing and Ritter [100] found most ANN studies use shallow multi-layer Perceptrons to build NBMs. Applications based on SCADA data usually estimate a residual from this NBM which is used to indicate whether the turbine is operating normally. Applications based on vibration data from CMS usually use spectral decomposition [101] and train ANNs to detect faults directly from this data.
   Carroll et al. [102] use large amounts of SCADA and vibrational data to examine gearbox failures. ANNs perform better than SVM and logistic regression approaches, predicting gear tooth failures up to a month in advance with 75% accuracy using SCADA data and 100% accuracy using vibrational data. Bangalore and Tjernberg [103] use an unsupervised approach to train an NBM to predict faults in gearbox bearings according to temperature measurements. Their algorithm is able to predict a bearing fault a week before it was indicated by the CMS. Tautz-Weinert and Watson [104] model bearing and generator temperatures using SCADA data from more than 100 turbines. Unsupervised ANN approaches were found to usually outperform other tested algorithms, with linear regression occasionally performing better.
   Results obtained using neural networks are highly dependent on the choice of architecture used and ANNs are characterised by high sensitivity to a number of tuning parameters. The training process requires effort and expertise to ensure appropriate tuning and thereby accurate outcomes. However, ANNs offer the potential to model complicated, non-linear processes using the large quantity of data which are produced by a turbine. As neural network capabilities continue to advance, they offer an important method of future failure prediction.

4.4.2. Physics-Based Techniques

Examples of these methods are less common than the above data-driven techniques due to the need for an in-depth physical understanding of the extremely complex physics of failure methodologies. However, there are a few examples. Gray and Watson [105] researched the potential modes of failure of a wind turbine and then demonstrated a physics of failure approach to modelling gearbox bearing failure. They used empirical equations to model force on a bearing, and then calculate the damage based on measured load history. A Weibull reliability model was then fitted to calculate reliability values for individual turbines.

Nejad et al. [106] use a multi-body dynamic simulation to model gearbox behaviour and calculate dynamic load responses in the gearbox. By using a general equation of motion and measuring gearbox angular velocity at the input shaft and output to generator, an error function is defined and compared in faulty and fault-free conditions. It is shown this procedure is accurate enough for early fault detection.

Physical models are challenging to create and require in-depth knowledge of the system being modelled along with high quality reliable data to validate the models. Physics-based models should be developed for specific failure modes in order to avoid computationally expensive models which are too complicated to understand in depth. This makes it difficult to create a general physical model for component failure prediction as the number of possible failure modes is large and some may not be well suited to physic-based modelling. However, once a good physical model has been created, it can be applied to all comparable problems and can be more reliable than data-driven alternatives.

4.5. Failure Prognosis

Failure prognosis is the ability of a model to predict when impending failures will occur. There are several useful reviews on failure prognosis which have provided a base for this discussion [21,107–109]. The papers discussed below are summarised in Table 3.

Table 2. Summary of references considered in Section 4.4 regarding failure prediction.

	Method	**Linear Reg**			**SVM**			**Decision Trees**			**KNN**			**ANN**			**Physics**	
	Reference	[87]	[88]	[89]	[90]	[91]	[92]	[93]	[94]	[95]	[96]	[97]	[98]	[99]	[102]	[103]	[104]	[105]	[106]
Component	Gearbox	✓			✓		✓				✓	✓	✓		✓	✓			✓
	Generator		✓			✓	✓				✓						✓		
	Blades			✓							✓			✓					
	Pitch						✓												
	Rotor						✓												
	Non-Specific							✓	✓	✓								✓	
Input Data	SCADA	✓	✓				✓	✓	✓	✓	✓				✓	✓	✓	✓	
	Vibration			✓	✓	✓						✓		✓	✓				
	Torque									✓									✓
	Alarm Data							✓							✓	✓			
	Current												✓						
Output	Binary Failure (Y/N)	✓			✓	✓	✓	✓	✓			✓	✓	✓	✓	✓	✓		✓
	Failure Severity																	✓	
	Failure Mode			✓	✓				✓	✓	✓								
	Time Before Failure				✓	✓						✓			✓				
	Model Metric	✓	✓	✓	✓	✓		✓		✓	✓				✓		✓		
Validated?			✓	✓		✓			✓		✓	✓		✓	✓	✓		✓	✓

Table 3. Summary of references considered in Section 4.5 regarding failure prognosis.

	Method	**Statistical**		**AI**				**Physics**			**Stochastic**			**Hybrid**	
	Reference	[110]	[111]	[112]	[113]	[114]	[115]	[116]	[117]	[118]	[119]	[120]	[121]	[122]	[25]
Component	Gearbox	✓						✓						✓	
	Generator														
	Blades								✓	✓					
	Pitch				✓	✓									
	Bearings			✓							✓	✓	✓		
	Non-Specific		✓				✓								✓
Input Data	SCADA	✓		✓	✓	✓	✓							✓	
	Vibration			✓								✓	✓		
	Torque							✓							
	Alarm Data				✓	✓									
	Failure Data									✓	✓				✓
	Met Ocean								✓						
Output	Failure Severity	✓	✓												
	Failure Mode						✓						✓		✓
	RUL	✓	✓	✓	✓	✓	✓			✓		✓	✓	✓	✓
	HI			✓											
	pdf/cdf									✓	✓		✓		
	Cycles to Failure						✓								
	Inspection Interval								✓						
Validated?				✓	✓	✓					✓	✓	✓		

4.5.1. Data-Driven Techniques

Statistical Models

Godwin and Matthews [110] use the Mahalanobis distance to determine outliers within SCADA data to detect impending gearbox failures. A prognostic horizon of over 146 days was achieved and due to the use of NBM, no gearbox fault data were required for training.

Asgarpour and Sørensen [111] use an exponential degradation model with a stochastic scale factor to predict RUL. Based on CMS data and using Bayes' rule, the parameters of the model are updated as new data are obtained. This approach combines statistical and stochastic approaches and could be extended further by using a data-driven model for degradation, rather than the standard exponential approach.

Artificial Intelligence Models

Guo et al. [112] use a recurrent neural network (RNN) to predict the HI level of bearings. A feature set is narrowed down using sensitivity metrics to create features to train the RNN with. The results of the network predict HI levels of the bearing which are then correlated to RUL. The results show the RNN-HI obtains fairly high monotonicity and correlation values.

Chen, Matthews and Tavner [113] investigate ANFIS to predict wind turbine pitch faults. SCADA data including six previous pitch faults are used to train the network and is tested in a new wind farm, comparing this result to a general alarm approach. It is found that the general alarm approach gives fewer warnings than the proposed ANFIS approach and predicts more '0' day warning times, i.e., no warning at all. This work is built upon by the same authors [114] where a method for automated on-line fault prognosis of pitch failures is proposed. This is demonstrated to detect pitch faults on two SCADA datasets with different pitch configurations and is able to give a warning up to 21 days in advance.

Zhou et al. [115] also use ANFIS after using a clustering algorithm to group abnormal data by considering the effects of wind speed. Domain knowledge is then used to adapt an ANFIS model to establish early fault warnings and diagnosis. With sparse training data, this method is shown to function better than the traditional threshold model; however, faults were only able to be detected up to approximately 7 h before failure, which does not provide enough time to incorporate this into a maintenance schedule.

Neural network approaches offer many benefits and are becoming more central to RUL predictions. They deal well with the large quantities of noisy data which are extracted from a wind farm and require no knowledge of the system beforehand. However, finding sufficient data for training is problematic and if transparent models are required, they are not suitable.

4.5.2. Physics-Based Techniques

Grujicic et al. [116] model a WT gearbox using finite element methods (FEM) to investigate the root cause of tooth-bending fatigue. Fatigue crack growth is analysed and used to estimate RUL. In particular, the paper studies the effect of gear misalignment on the number of years of service and finds a 3 degree misalignment could reduce the years of service from 100 to 10. Florian and Sørensen [117] present an approach based on Paris' law. They create a fracture mechanics-based model for estimating the RUL of a WT blade, focusing on the crack propagation in the blades adhesive joints which could be used in a risk-based maintenance decision system to plan for the blades lifetime.

Similar to fault prediction, physics-based prognostics offers the advantage of precise modelling for a specific failure type; however, these models can oversimplify the real-life failure process.

4.5.3. Stochastic Techniques

In the domain of failure prognosis, there are two common stochastic modelling methods: HMM and PF.

Nielsen and Sørensen [118] propose a method for calibration of a Markov deterioration model based on past data for a range of blades. Using historic data, they apply the maximum likelihood method for estimation of state transition probabilities and then model this using HMM. This is then applied to predict RUL, and the model can be updated using either inspection or CM data. Li, Zhang et al. [119] use HMM to assess reliability of a wind turbine bearing. The performance degradation rule of the bearing is derived using CM data and a HMM model adapted to create a new time-correlated state transition probability matrix with degradation features. The reliability curve of a known faulty bearing is calculated and compared to real degradation data. It is shown the degradation HMM model is more accurate than the traditional HMM model.

HMMs have found use in WT RUL prediction as they are easy to realise in software and well suited to the information which can be determined about the state of a turbine. They provide confidence limits as part of their RUL prediction, can model different stages of degradation and do not require specific knowledge of the failure mechanism.

However, a large volume of data (although not as large as data-driven methods) is required for training. Another issue is the Markovian assumption that the state at $t + 1$ only depends on the state at t. This is addressed with a hidden semi-Markov model (HSMM) where the hidden state transition probabilities are no longer determined by a steady state Markov process and instead depend on the amount of time which has elapsed.

Cheng et al. [120] apply a modified PF to predict the RUL of a bearing in the gearbox where it performs better than the standard algorithms it is compared to, predicting failure 12 days before the fault indicator exceeds the threshold with an error margin of 2 days. Wang et al. [121] use PF to predict degradation status with uncertainty quantification. This approach is experimentally validated using vibration signals from a wind turbine gearbox run-to-failure test. The defect status of the gearbox is determined and from this, RUL can be predicted. At 50 h after the training period ends and the prediction phase begins, it was found the RUL was within the inter-quartile range of the true RUL, predicting an RUL of roughly 180 h.

PF is a useful technique for nonlinear processes with non-Gaussian error, such as are found in WTs. Moreover, this method requires fewer samples than data-driven methods to approximate trends with acceptable accuracy and requires shorter computational time.

Stochastic approaches to failure prognosis are particularly useful for medium (several months to years)—to long-term (5+ years) modelling of the RUL distribution. These models return not only predictions for mean RUL, but also uncertainty parameters such as variance and confidence intervals, which can then be used as input into O&M modelling tools.

4.5.4. Hybrid Techniques

Cheng, Qu and Qiao [122] combine ANFIS with PF to predict RUL of wind turbine gearboxes. The fault feature is taken as the generator stator current. The model is tested on a gearbox and is able to predict the failure time of the gearbox when the RUL is still 33% of its lifetime.

Djeziri et al. [25] use a physical model to generate a database covering features under normal and failure operating condition and model the degradation process using the principle of geolocation. This involves estimating time to travel between two points, knowing the start and end point (i.e., healthy and failed), and the evolution of speed of movement (i.e., degradation rate).

Hybrid methods are able to function without high-fidelity models or large volumes of data by bringing data-driven, stochastic and physical models together. At the same time, the fact they require both a physical model and access to data can add complexity to the approach, and practical implementation can be difficult.

4.6. Best Practice in Predictive Maintenance

As discussed, there are many different approaches associated with predictive maintenance for OWF. Prognosis represents the state of the art in predictive maintenance as it not

only predicts a failure is impending, but also RUL. Compared to diagnostic or predictive methods, prognosis gives higher levels of automation and should lead to reduced downtime as maintenance can be more accurately scheduled according to failure time predictions. However, it requires more time and data to achieve prognostic predictions and there can be larger uncertainty associated with the results as it attempts to return a more specific metric than binary yes/no failure predictions.

Regarding techniques across predictive maintenance, data-driven approaches offer the best method for increasing automation across a system and are able to transform the high-dimensional noisy data from a wind farm into useful information to inform decisions. However, if failure data are scare, this method may not be suitable. Data-driven approaches are useful for short-term predictions after indications of failure begin to materialise in operating data and are used in failure prediction and prognosis.

Physical models do not appear as frequently in OWF O&M literature as they cannot fully capture the complexity of a wind turbine or farm. They are therefore limited to use in certain specific situations, for example, where only one component failure mode is of interest.

Stochastic models are often used in failure prognosis as they output a distribution of the metric of interest, such as RUL, which is useful for input to a maintenance optimisation model. They can be used for short- or long-term predictions.

5. O&M Planning Models

To achieve prescriptive maintenance, two components are required: the ability of a model to predict impending failures; and the ability to suggest outcome focused recommendations for O&M planning, for example, an optimised O&M schedule. Section 4 has discussed the existing literature around the first requirement of failure prediction or prognosis. This section covers the second requirement of a prescriptive strategy and gives an overview of various O&M planning tools which can be used for maintenance strategy recommendations.

A review by Hofmann in 2011 [123] covered a comprehensive list of decision support models for OWF, which was updated recently by Anaya-Lara et al. [124]. Shafiee and Sørensen also provide a recent review of maintenance optimisation and inspection planning literature [125]. This section will review existing models described in the literature, grouping them according to [13] as:

- Strategic—Long-Term (5+ years) Strategies;
- Tactical—Medium-Term (∼months to several years) O&M Organisation;
- Operational—Short-Term (∼days to several months) Planning.

It should be noted, these models can stand alone, with no required input from failure predictions and used in this way, they do not form part of a prescriptive maintenance strategy.

5.1. Strategic

These models represent long-term decisions, from roughly 5 years to the end of life of the farm. In terms of O&M this normally means decisions surrounding the overarching maintenance strategy, identification of the annual number of required technicians, and the required chartered vessels for operations. Shafiee [13] found strategic models were the most researched of the three above.

One of the most common problems in the area of strategic O&M planning is the determination of the vessel fleet size and mix [126–130]. For example, Halvorsen-Weare et al. [126] look at a metaheuristic solution method to determine the most cost-efficient vessel fleets to support maintenance tasks at OWFs under uncertainty. The solution considers weather conditions and failures leading to corrective maintenance tasks as stochastic parameters, and incorporates solutions into a decision support system (DSS). Stalhåne et al. [127] present a stochastic programming model to find the optimal fleet of vessels to minimise the total O&M costs at an offshore wind farm. They use a maintenance strategy

based on a combination of preventive and corrective maintenance tasks. Rinaldi et al. [128] use genetic algorithms to optimise the O&M assets of an OWF, considering turbine reliability statistics and maintenance fleet composition. The objective is to minimise operating costs whilst also maximising reliability and availability.

Sperstad et al. [130] investigate six decision support tools to determine optimal vessel fleets for OWFs. The results show the tools usually agree on the optimal fleet, but the relative rankings of different vessel combinations is different. The ranking is particularly sensitive to the vessel's wave height limits but also to turbine failure rates and vessel day rates. This highlights again the problem that access to open-source reliability data for OWFs is difficult. A significant proportion of failure rates used in O&M modelling studies are taken from onshore wind farm data, with or without scaling factors and ignoring environmental factors such as OWF site location. Modelling with fixed failure rates can lead to inaccurate results as shown in Carroll et al. [131]

In work outside fleet composition, NOWIcob, a tool produced by the NOWITECH project [132], was developed to simulate the operational phase of an offshore wind farm and allows both controllable, such as vessel mix, and uncontrollable external factors, such as market rates, to be varied in order to evaluate their impact on performance. It uses a Monte Carlo (MC) simulation model to estimate long-term availability and predicted costs and can be used to support decisions around logistics and profitability.

Li et al. [133] created both deterministic and stochastic optimisation models which consider several strategic decisions such as personnel optimisation, vessel numbers, and breakdown of O&M costs. The deterministic model is used when the failure rate is known, for example, for developers with direct access to site failure data, whilst the stochastic model is used in the case where generic failure data have to be used. These models were then implemented into a DSS designed to assist decision makers in determining the most cost effective maintenance strategy.

5.2. Tactical

Tactical strategies are usually medium term, in terms of months to several years and could include choices such as staff resource planning, vessel lease/purchase decisions and spare parts inventory planning.

Spare parts planning is a common problem, not only for OWFs but for many operations which require both maintenance and spare parts [134–137].

Zhang et al. [136] developed an opportunistic maintenance strategy for WTs combining stochastic weather conditions and spare parts management. The optimal maintenance and inventory strategy is obtained and the effects of different applied parameters are described. Tracht et al. [137] describe an approach for spare parts planning by considering restrictions that exist offshore which may not be considered onshore. The model demonstrates how factors such as limited availability of vessels, meteorological conditions and necessity of maintenance can influence O&M costs and how spare parts supply processes can be adapted to these restrictions.

Maintenance support activities such as the provision of helicopters, crane ships and jack-up boats are required for certain operations. The optimisation of transport methods and technician numbers can help to avoid excessive rental charges or long downtimes. Dalgic et al. [138] considered a range of planning activities including cost of jack-up vessels, technician requirements and helicopter use, and how each impacts cost. This was implemented using a MC approach to investigate the most cost effective approach to allocate O&M resources. There have also been separate studies done on the impact of individual resources, such as Domínguez et al.'s [139] work on the use of helicopters for operations and Zhang et al.'s [140] paper on stochastic network modelling of service vessels.

Linked to maintenance support activities, there has been work done in the area of lease or charter vessel decisions and the sharing of these resources between wind farms. Uit het Broek et al. [141] looked at jack-up vessel costs and found collaboratively purchasing and sharing a jack-up vessel outperforms individually leasing it. Schrotenboer et al. [142]

aim to find the cost-minimising distribution of maintenance tasks between vessels from the viewpoint of a maintenance provider responsible for multiple wind farms, for different contractual obligations.

5.3. Operational

This category covers short-term planning, taking into account factors such as weather and staff availability, routine maintenance tasks and routing of vessels.

The most common areas of research have focused on scheduling of day-to-day maintenance tasks [143–146] and the routing of maintenance vehicles [138,147,148]. In particular, the uncertainty of weather forecasts make scheduling maintenance for more than a few days ahead difficult.

A recent review of the literature covering the problem of daily maintenance scheduling in offshore wind can be found in Stock-Williams and Swamy [143]. They also present an automatic scheduling optimisation model and a valuation methodology which considers short- and long-term effects of the scheduling decisions. Pinciroli, Zio et al. [149] use reinforcement learning to use information from CMS systems to optimise O&M planning in terms of number of trips to turbines. They compare this with common policies such as predictive and scheduled and find higher average profit using the reinforcement learning approach. Schrotenboer et al. [146] solve a variant of the resource-constrained shortest-path problem to optimise maintenance task scheduling taking into account the relative scarcity of service personnel available.

A group from Strathclyde University have also recently published several papers around the subject of access forecasting, which focuses on the prediction of weather conditions during vessel transfer windows [150–152].

The problem of vessel routing is a variation on the travelling salesman problem. Many studies have considered various aspects of this, including Dalgic et al. [138] who consider four different transportation systems and how best they can be used considering access restrictions, shift lengths, travel time and usage costs. Vessel routing is also examined in Schrotenboar et al. [147] where existing maintenance routing problems are generalised and technician sharing between wind farms is used to reduce costs, whilst also reducing the number of vessel trips and the mean time to maintenance. Dawid, McMillan and Revie [148] have created a decision tool which recommends an on-the-day vessel routing strategy which minimises costs whilst maximising number of turbines repaired and includes a case study based on an existing UK wind farm. The same authors also present a methodology to incorporate uncertainties such as maintenance duration into the vessel routing process [153].

The combined problem of maintenance routing and scheduling was first introduced by Dai, Stålhane and Utne [154] for one farm and base. Irawan, Ouelhadj et al. [8] develop this further, proposing a model which deals with multiple farms and bases and finds the optimal schedule for maintaining the turbines and the optimal routes for the crew transfer vessels to service the turbines along with the number of technicians required for each vessel. Raknes et al. [155] and Stålahne, Hvattuma and Skåra [156] also consider the problem of combined scheduling and vessel routing.

6. Prescriptive Maintenance Tools

Having considered failure prognosis and O&M models, this section will summarise existing prescriptive maintenance tools which combine both these components.

Seminal work was done in this area by Byon, Ding and Ntaimo [157]. This work aims to use CMS data to create an optimal preventive maintenance policy which minimises costs. They use a partially observed Markov decision process to represent the degradation process and given the state of the system, three options are available (no action, preventive maintenance, observation). The work considers factors such as weather conditions, long lead times and production losses which are specific to offshore wind. Byon and Ding [16] develop the previous work further, incorporating more realistic aspects from a real OWF.

This includes time-varying, season-dependent weather conditions, partial and perfect repairs and stochastic revenue losses.

Other early examples include work done by Tamilselvan et al. [158] which creates a framework for prognostic maintenance based on three modules: performance degradation, O&M performance analysis and failure prognostics. Sinha, Steel and Andrawus [159] propose the use of a dedicated tool to examine turbine failure and maintenance planning. The suggested tool contains reference to a wide range of variables, including staff details and their skill sets, service history, regulatory provisions, as well as assisting with financial calculations and inventory control. This is evaluated in [160] using some case studies to show this model could bring financial benefits to OWF operators.

More recently, Yildirim, Sun and Gebraeel [161,162] published a two-paper study detailing a CBM prescriptive approach for generators. They incorporate dynamic information on the generator's heath from Bayesian prognostic models to create an optimised maintenance schedule. They also consider the effects of maintenance on network operation. The same authors [163] propose an integrated framework for OWF maintenance which incorporates a predictive analytics tool using real-time sensor data with an optimisation model. This tool focuses on decision making at a whole fleet level, describing an optimal fleet-level maintenance schedule and considering economic and maintenance interdependencies between turbines.

Prescriptive techniques can also be combined with other maintenance strategies. For example, Bangalore and Patriksson [164] suggest a framework which combines age-based and condition-based maintenance scheduling. Fault prediction capability is included using ANN-based condition monitoring and a mathematical maintenance optimisation model is modified for this hybrid maintenance scheduling. Zhou and Yin [18] develop an opportunistic CBM (OCBM) strategy which is based on condition maintenance and opportunistic maintenance thresholds and provides an optimal schedule for components with different degradation states across an OWF. Bakir, Yildirim and Ursavas [19] also consider OCBM and integrate component-level prognosis with farm level O&M. Opportunistic maintenance is incorporated across components, turbines and multiple farms with real-time component RUL impacting multiple wind farm O&M decisions and vessel routes.

Prescriptive approaches can be applied to many aspects of an O&M strategy. For example, Schuh et al. [165] proposed a prescriptive approach towards the spare parts inventory. This uses CMS data to predict the RUL of certain components and determines the most economic stock quantity. Comparison of the spare part inventory prediction to wind farm's failure data proves the model's accuracy.

Recent work has started to consider jointly optimising wind turbine production with maintenance decisions. Uit het Broek et al. [166] begin by considering a system for which the next maintenance action is fixed (such as in many real-life systems where maintenance planning is not flexible). Condition data are used to optimise the production rate, which directly impacts the deterioration rate, rather than the maintenance schedule. This method can reduce failure risk and increase total output. This work is developed further in uit het Broek et al. [167] where condition-based maintenance is jointly optimised with production. The cost effectiveness depends on characteristics such as planning time, corrective maintenance cost and rate of deterioration but overall this strategy reduces failure risk and leads to fewer maintenance actions. Uit het Broek et al. [168] take this approach further again and investigate the impact of altering production rates to redistribute loads across units (or turbines in the case of OWF) based on condition data. Results show significant cost savings can be achieved compared to CBM with equal load-sharing.

As prescriptive maintenance as a strategy has developed, it can be seen that more aspects of maintenance are included and the models begin to replicate real-life more closely. Similar trends are being seen industry wide, where holistic prescriptive maintenance frameworks are offering end-to-end maintenance solutions [169]. On top of failure prognosis and actionable insights, some solutions are now incorporating feedback loops and knowledge management processes which promote continuous learning and improvement. Given its

remote location, wealth of operating data, and specific maintenance requirements, offshore wind is in a prime position to develop the capabilities of prescriptive maintenance further and lead the way across industry.

7. Scope for Future Work in Predictive and Prescriptive Maintenance

In many industries, it is becoming clear that predictive maintenance can improve reliability, availability and safety, helping to reduce overall O&M costs [170]. In offshore wind, predictive and prescriptive strategies could reduce WT downtime, improve safety by minimising the number of trips to sea, maximise the working life of components and help avoid catastrophic damage.

There are also some limitations to these approaches, such as the lack of access to failure data and the inherent issue that a wind farm should not have many failures in its data set, making training models difficult. In addition, predictive algorithms have a probability of returning false positives (predicting a failure when the machine is healthy) or false negatives (predicting the machine is healthy when actually it is going to fail). Whilst the former could lead to additional costs by repairing an actually healthy turbine, the latter has potentially more serious consequences as the turbine is assumed to be healthy when a failure is imminent.

Another limitation to the deployment of predictive or prognostic strategies is the cost of fitting monitoring systems and model development. However, Onyx Insight found that by adopting data-driven strategies, maintenance budgets could be cut by 30% [171], a worthwhile saving given maintenance can account for 70% of the O&M costs [172].

The present review has identified the following areas as important to consider going forward in predictive and prescriptive maintenance:

1. The models above mainly focus on single component predictions and prognosis. Bringing these together into a holistic turbine model which could predict failures across key components and display results at both component and turbine level would create a more practical tool for operators. The HOME Offshore project also identified this area as important and dedicated one of its work packages to developing ideas around this theme [173,174]. Similarly, the models are often designed for use at one site, based on unique site-specific parameters. If models could be built which are adaptable across sites or scalable across turbines this would greatly increase their applicability and utility;
2. Incorporation of live data into a model and the automation of failure prediction/prognosis is a requirement for a functional prescriptive maintenance strategy. Linked to this is the ability of the model to update itself as new data are gathered and learn from this information. This real-time capability is something which has received little focus to date, as most work reviewed uses historic data for training and testing;
3. The models reviewed here focus on structured SCADA and CMS data; however, the usefulness of unstructured data (if access is possible) such as O&M inspection reports and daily planning minutes should not be ignored. These can provide detailed information regarding the condition of a site and exact maintenance activities carried out; however, the data processing and cleaning costs will be higher than those for structured data, and open-source access may be difficult;
4. There is still significant uncertainty in most failure and RUL predictions. There is a balance between the usefulness of an uncertain, early prediction and a more certain, but shorter warning. The optimal warning will depend on the size and type of the component predicted to fail, availability of replacements and will also have a seasonal dependence due to access conditions. Minimum RUL prediction is an area which has not been explored; however, as failure prognosis models mature, it would be useful to differentiate between RUL requirements for different components and sites;
5. Considering O&M models to date, more attention has been paid to strategic long-term maintenance planning and operational day-to-day scheduling. Medium-term

planning covers the timescale of a few months and the possibility of incorporating RUL predictions in these models has not been fully explored and;

6. Finally, there is also a question of how to quantify the impact of a prescriptive maintenance strategy in order to ensure it is a worthwhile investment for an OWF. Predictive maintenance strategies have been included in cost modelling work; however, given the novelty of prescriptive strategies, there is not much literature on their cost–benefit analysis. Other criteria could also be used to measure the success of a prescriptive strategy such as the percentage of the maintenance work flow generated by predictive models, or percentage of maintenance suggestions implemented by operators.

It should be highlighted that an aspect missing, or not fully explored, in most of the literature reviewed here is the link to the current position of the OWF industry. This again relates to the problem discussed in Section 4.1 regarding the lack of publicly available information for wind farm O&M, and a disparity between academic research and tools available commercially. Industrially, tools are being made available which deal with data management, analytics, O&M modelling, and predictive and prescriptive maintenance for offshore wind farms. Companies offer tools which claim to provide a whole range of resources, ranging from failure diagnosis through to applying prognostics models to predict RUL.

It is important for academic and industrial efforts in the offshore wind farm industry to remain aligned. Therefore, it is important to consider currently commercially available tools and how further academic research could build and improve on these in order to develop more effective predictive and prescriptive maintenance strategies.

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