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REVIEW

A review on data-centric decision tools for offshore wind operation and maintenance activities: Challenges and opportunities

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Abstract

This paper reviews state-of-the-art numerical tools for the operation and maintenance (O&M) of offshore wind farms, focusing on decision support models for maintenance scheduling and the consideration of human and environmental uncertainty. In this review, various factors that can influence the successful conduct of maintenance operations will be examined and special attention will be paid to the most significant ones. Data-driven technologies for improved offshore asset management are also examined and the most used data-driven methods for modeling and optimizing turbine operation and maintenance are presented. A focus will be placed on the choice of maintenance strategy, which is the basis for the planning of operations and thus the optimization problem discussed. As offshore maintenance is a complex operation whose efficiency and safety depend on human and environmental factors, special attention will be paid to the planning strategy that minimizes the risks involved while maximizing efficiency by considering these factors. The choice of planning technique for turbine maintenance and better consideration of uncertainties are crucial areas of improvement as they can lead to better overall efficiency, higher profit margins, better safety, and improved sustainability of offshore wind farms. The paper covers the application of digital technologies for offshore wind O&M planning and the associated challenges. The paper also highlights the various environmental and human factors to be considered for the operation and maintenance of wind turbines.

KEYWORDS

decision making, operation and maintenance, route planning, routing, wind turbine

1 | INTRODUCTION

Today, major environmental problems are being brought on by the unsustainable exploitation of natural resources worldwide. Many authorities have presented plans for lowering greenhouse gas emissions and developing renewable energy sources to combat the deterioration of the environment. Objectives ask for a 27% increase in energy efficiency, a 40% decrease in CO_2 emissions, and a binding objective of 27% for renewable energy by 2030.[1] The necessity of investing in renewable and clean energy resources is evident given the growing environmental and ecological issues. In recent years, renewable energy has become a key step in the development of natural energy goals. In many countries around the globe, energies from natural gas, coal, and fuel oil are being replaced by renewable energy sources including wind, solar, and geothermal energy.[2] Offshore wind energy is essential to the transformation of the world's energy system because it is a sustainable energy source. In comparison to equivalent and type onshore wind power, offshore wind farms (OWFs) produce 50% more electricity at higher speeds and with less turbulence.[3] Investment decision-makers around the world are extremely interested in the offshore wind because of its enormous potential, high average power generation, no land occupation, high level of cleanliness, and availability.[4] The current offshore wind potential is expected to multiply in the coming years, resulting in a monumental implementation state.[5] Due to supportive policies and increased energy production, offshore wind power projects have been proposed quickly. However, to compete with fossil fuels, both offshore and onshore wind turbines need to be as cost-effective and reliable as possible. This requires optimizing wind turbine maintenance work to avoid unnecessary costs. Operation and maintenance (O&M) work begins with OWF commissioning and continues through the final decommissioning phase. Costs in O&M phase are generally not as high as in the construction phase but are still significant due to the long operational duration during the lifecycle. Operating and maintenance costs for a typical 500 MW OWF range from £25 to £40 m.[6]

O&M activities are, therefore, paramount for lifetime power generation from OWFs. Failure of any element of the park can reduce or even stop power generation, resulting in significant economic loss. It is important to adopt a maintenance strategy that can reduce the number of failures through a series of planned O&M activities such as inspection, repair, and replacement.[7] Both long-term and short-term scenarios must be considered to create a reliable tool for OWF operations and maintenance planning. Long-term plans, generally developed at the design stage, are those in which the intervention is planned 1 year before or more. Short-term planning is for operational situations when already planned tasks need to be done the next day, or when an unexpected failure occurs, and repair needs to be done in the shortest possible time. To limit operating and maintenance costs, which typically represent 25%–30% of the total lifetime cost of an OWF, the effectiveness and efficiency of operating and maintenance plans should be maximized. With the growth of the offshore wind industry, the researcher has developed several numerical models that enable optimized planning of his O&M tasks.[8] The growth of OWFs depends significantly on how well offshore wind turbines (OWTs) are operated and maintained. Given the practical restrictions placed by offshore operations and the comparatively high expenses, maintenance, as opposed to operations, is a crucial component of the levelized cost of energy. An OWF's lifecycle is particularly variable and complex as a result of maintenance.

This study focused on how uncertainties such as weather conditions were considered as factors affecting the O&M plans. In fact, O&M planning relies heavily on the evaluation of weather conditions (especially wave height, wave period, current speed, and wind speed) and time windows during which the O&M operator can carry out work. Evaluation of weather windows typically consists of a simplified analysis of sea area data of interest using thresholds chosen for a particular task. A weather window is a period of time during which weather conditions do not exceed a set threshold for a sufficient period of time to accomplish this task. The choice of thresholds in weather window evaluation is primarily determined by the health, safety, and environmental requirements and considerations of the O&M operator as well as the economic factors of the wind farm operator. Met ocean conditions considered suitable for a particular task must be such that the O&M operator can safely perform that task. However, these thresholds should ensure that sufficient man-hours are available to carry out all planned O&M activities, thereby mitigating the risk of power generation downtime. Redesigning long-term planning and operations of charter vessels to withstand more severe conditions is also an important part of the optimization. Improving the reliability and suitability of weather window analysis will lead to more efficient and effective O&M planning. This means reducing the O&M costs for the offshore wind industry and making working conditions for O&M operators safer. This is especially true in short-term operational situations where the decision-making process about performing tasks becomes more important. In reality, there is a risk that the task will be scheduled for a particular day, but when the crew and technicians meet in port in the morning, they discover that bad weather makes sailing impractical or they may set sail and arrive at the OWF only to find that the weather conditions make it impossible to carry out the mission safely, or they may get seasick on the way to the OWF. In all of these situations, the scheduled task may not run and run on another day that was incorrectly determined to be inappropriate for its scope. This will eventually lead to more outages and longer periods when turbines are not generating power.

Uncertainty is also in the selection of threshold parameters and values that determine the feasibility of a set of weather conditions. In fact, thresholds such as maximum allowable significant wave height and peak wave period are indirect parameters rather than direct measures of the actual feasibility of the task. This overview presents tools that OWF are currently using to solve their O&M operations plan. For this purpose, numerical tools to assess the existence of weather windows for O&M tasks and maintenance planning are considered. The main feature of this paper is the investigation of decision-making tools in wind turbine maintenance planning, including uncertainties such as weather-related vessel movement, to determine operability.

The rest of the paper is organized as follows. In Section 2, we explain the overview of the wind turbine (onshore/offshore) asset management (AM) and decision support system. What parameters cause uncertainty to the offshore O&M will be covered in Section 3. Section 4 discusses the data used to construct techniques for optimizing the turbine's O&M activities, improving uncertainty, and minimizing maintenance costs. Different digital technologies used for wind turbine O&M are investigated in Section 5; this includes methods currently used in decision support models for OWF maintenance scheduling covering regression and classification models. Section 6 explores the challenges associated with Offshore decision management and concludes the paper in Section 7.

2 | OVERVIEW OF AM AND DECISION SUPPORT SYSTEM

In the financial sector, the term AM refers to the management of various financial tangible and intangible assets. However, the term is being used more and more frequently in the infrastructure industry as well, where it has been realized that having a well-thought-out management strategy in place is essential, particularly when it comes to the management of numerous, significant, and frequently diverse infrastructure assets.

Asset managers are under increasing pressure to accurately understand the condition of the power assets in their network so they can choose the most cost-effective plan of action for operation, maintenance, and replacement. But how can you tell which assets require care while ensuring that risks are kept to a minimum and when is the best time? Are you convinced that the rating for your asset is based on the most recent data? Making choices on these matters is very challenging because the system has such a large number of valued goods.

The Institute of Asset Management, in part in collaboration with the British Standards Institute, issued a number of publications on AM in response to the growing demand for a standardized framework. The AM frameworks were released in 2006. The Publicly Accessible Standard for Asset Management, or PAS 55, was released in 2008. ISO 55000, 55001, and 55002 were developed by the International Organization for Standardization based on PAS 55:2008 and released in 2014. The “Asset Management—An Anatomy,” evaluation of the ISO 55000 series was released by the IAM in 2015. It considers all previously published texts and provides an explanation of AM, including why and practical applications. Assets are complex, interdependent, dynamic in behavior, subject to rapid change, varying in a lifetime, have to be monitored, analyzed, and diagnosed to understand them and require technical knowledge, according to “Asset Management—An Anatomy,” which challenges this claim. Assets also have to be monitored, analyzed, and diagnosed to understand them and require technical knowledge Based on the following six principles, the ISO 55000 approaches this challenge:

- The organization's core value, which needs to be identified
- There must be a direct link between the company plan and the AM services provided by the team.
- To ensure that AM is nicely carried out, the organization's objectives are met and AM thinking, and practices overcome traditional boundaries, leadership must bear direct responsibility for its execution. As a result, it must be exhibited by all organizational authorities.
- Monitoring and auditing to ensure that assets and linked processes are used as intended to carry out AM activities and accomplish AM objectives that will last over time.
- An understanding of all stages and levels of the lifecycle.
- For AM decision-making to be successful, it must be competent, reliable, and ideal. It also necessitates

finding the optimum compromise between AM's competing themes.

AM is referred to be an interdisciplinary field of study that incorporates knowledge from all areas of the asset's lifecycle and management and requires buy-in from all players. To get a better understanding of the intricacy, the AM manager may need to take a step back.

The wind turbines and the internal grid of the farm, which includes cables and transformers, are the major assets in wind farm management. An asset system could be used to characterize the wind farm itself. Wind turbines are made up of a variety of pieces, all of which require separate management, operation, and maintenance techniques because of their vastly varying compositions, structures, and functions. The various components are referred to as asset components in this study. The various wind turbine asset components are as follows:

- Foundation
- Tower
- Gearbox
- Blades
- Transformer

It is obvious that the parts of a wind turbine might be further separated into groups, with the transformer and gearbox, in particular, having a large number of parts. But this would be outside the paper's purview.

The recent tools created[9] for the planning and coordination of renewable energy systems are examples of computational decision tools that can support complicated decision-making in the energy sector and follows a similar kind of framework as shown in Figure 1. Performance analysis of a renewable energy system serves as the foundation for this type of decision-supporting tool. Only a small portion of the current decision support systems in the wind energy industry are appropriate for offshore projects,[10] and the majority of

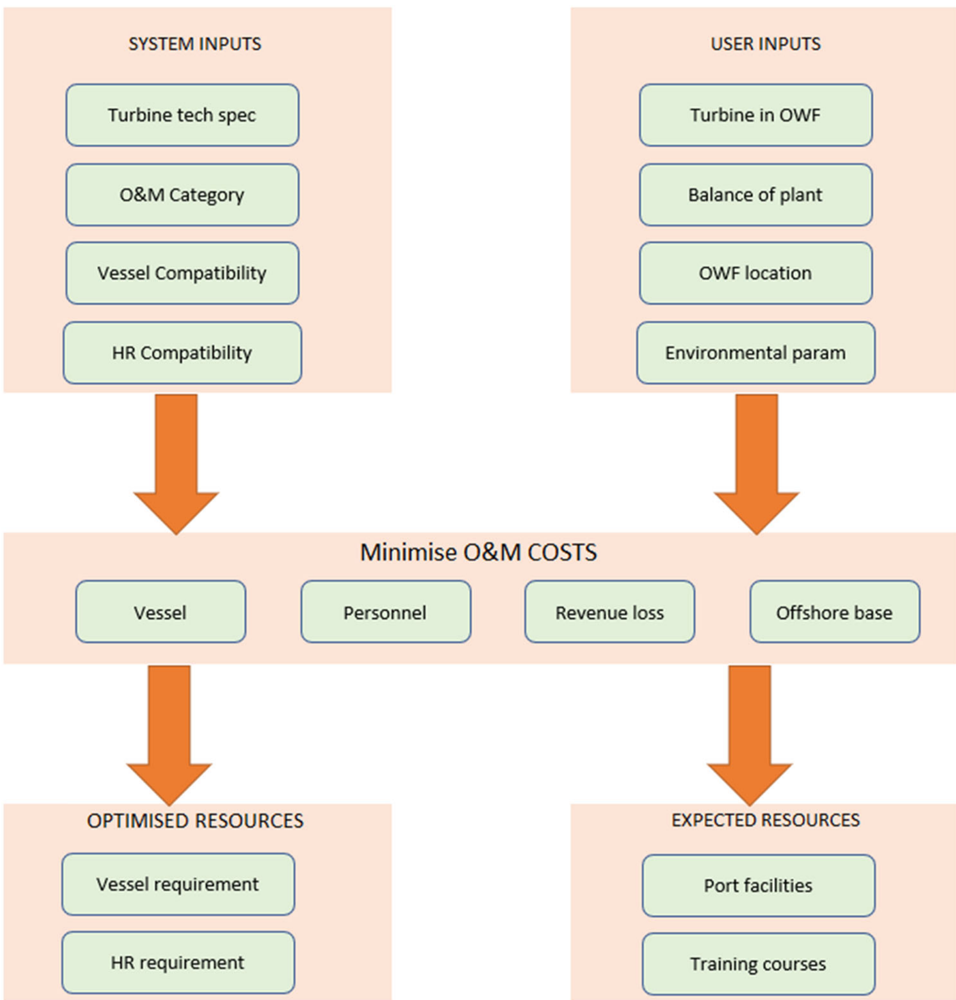

FIGURE 1 Decision support framework

these are focused on onshore initiatives. As opposed to a vast area like the North Sea, the technologies are more likely to be usable offshore in a constrained geographic area.

To achieve a considerable reduction in the cost of energy throughout the course of OWFs, cost-effective O&M techniques must be developed, as O&M expenses make up about one-third of the lifecycle cost of an OWF. In recent years, a number of researchers have developed decision support tools for various uses in offshore wind production, including forecasting a wind farm's operations,[11] estimating O&M costs including revenue loss,[12] and simulating the operational phase of an OWF with all maintenance activities and costs.[13] Finding the best maintenance strategy or planning for a specific OWF, as opposed to a general strategy for several farms, is a common goal of these tools. Levelised production cost (LPC), which is viewed as an effective method for the analysis and evaluation of risk and total cost across the life of offshore turbines, may be used by the decision tools to determine maintenance costs. In Myhr et al.,[14] examined the effectiveness of the operational and maintenance simulation models currently in use for OWFs; they also identified the fundamental model premises that influence model outcomes.

The operational phase of an OWF, including all maintenance operations and costs, can be simulated by the offshore wind cost and benefit model NOW-Icob.[13] Changes can be made to a number of input parameters in the model to examine their effects on performance parameters like O&M costs and availability. These input parameters include both controllable options and uncontrollable external factors. All strategic alternatives that the owner of the wind farm can directly choose are considered controllable options. All elements that are not directly under the control of the operator of the wind farm, such as the market environment and weather patterns, are referred to as uncontrollable external factors. Although these two factors are frequently assumed to be deterministic, the majority of the tools focus on modeling failures and repair. To mimic the variability of the failure rates of wind turbine components, stochastic modeling is recommended, however, as a deterministic approach would not produce realistic findings. One effective computational method used to address stochastic data challenges is discrete-event simulation.[15]

Operational research (OR) has a long history of helping businesses run more efficiently, especially when it comes to cutting expenses.[16] A variety of OR techniques have been used in the planning of production schedules, transportation routes, and maintenance supply chains in the field of renewable energy. An optimization approach for scheduling energy production in a wind farm, for instance,[17] was provided. Connolly et al.[18] have examined related research on the scheduling and capacity planning of renewable energy. Offshore wind O&M has also been optimized using OR approaches. To assist in making decisions on challenges involving the makeup of a vessel fleet, a mixed integer programming model with binary variables is typically used.[19] To design the vessel fleet with crews for the execution of maintenance operations in OWFs, vessel properties, and contracts should be taken into consideration. The most typical objective function is to minimize the fixed costs of the ships and ports, the variable costs associated with using the ships, the expected costs associated with expected downtime associated with delayed correct maintenance activities, as well as penalty and/or transportation costs. The number of vessels available, the amount of time needed to complete a maintenance task, the locations of the resources available for maintenance, and the sea state appropriate for O&M activities are typical constraints on the best solutions. The reliability of the wind turbines is an important factor to consider when modeling O&M procedures for OWFs because it has an impact on the project's output, including energy output and cost per unit of produced energy. The decision-making process for corrective maintenance operations is complicated by the dearth of publicly available data on OWT failure. Several models have been created to forecast costs[20] or to calculate O&M expenses[21] by taking wind turbine reliability into account. The failure rates of OWTs can be calculated using reliability models, which can also be used to determine how long it takes to fix each form of failure. Energy losses resulting from wind turbine malfunctions, downtime, and maintenance procedures are considered to be a component of maintenance costs. However, a substantial amount of failure rates utilized in earlier studies were taken from data from onshore wind farms, and the impact of the marine environment on the reliability of OWTs has not been taken into account. An examination of the decision support and optimization models for maintenance in OWFs revealed that there has not been much work done on integrating optimization models into decision support systems.

3 | DECISION-MAKING UNDER METEOROLOGICAL UNCERTAINTY

It is important to consider environmental uncertainties about factors like wave height and wind speed because they could affect installation and maintenance activities, thereby causing delays and financial costs. Appropriate models should be created to replicate an installation scenario for a large number of historical environmental data to integrate these uncertainties in the estimation.

The offshore cons studies include a wide range of topics, including both immediate (such as real-time, hourly, daily, and weekly operating decisions) and long-term perspectives (e.g., planning or policy making). The decision-making process is fed by input parameters, most of which are unpredictable. The art of handling uncertainty has undergone many developments and has most recently come into focus.

Making decisions can benefit greatly from quantifying uncertainty. It is feasible to assess various scenarios and, with a certain degree of confidence, select the best suitable one by accurately estimating the uncertainty. This can be especially helpful when making decisions about issues with significant implications. These can range from management choices involving huge offshore wind energy infrastructure assets to global policies. These issues are typically complex and have a wide variety of risk factors. Additionally, they frequently depend on one another. Therefore, analysts and decision-makers should accurately depict associated uncertainties, their reliance, as well as the combined effect of all these aspects, to ensure that the problem under investigation is sufficiently informed.

Offshore construction operations are exposed to a number of unknowns, including environmental factors, equipment and/or vessel failure, varying operation durations, availability of necessary components, and so on. However, underestimating environmental factors, including wind speed and substantial wave height, which are challenging to estimate during the planning stage, is one of the major causes of project length underestimations and delays. Due to these factors, project schedulers may employ buffers during the planning stage, which may result in an overestimation of the project's time and, consequently, its installation cost. Finding a system that would help schedulers include these uncertainties will enable them to estimate the length of offshore installation activities with greater accuracy and reliability.

The forecasting of environmental time series has been the subject of extensive research in the past. The following techniques are mentioned by Zounemat-Kermani and Kisi[22] to model the characteristics of wind and waves: statistical techniques, discrete spectral approach, stochastic simulation, numerical methods, and data-driven models (such as artificial neural networks, fuzzy wavelet model, genetic programming and fuzzy logic). Furthermore, Monbet et al.[23] surveys of stochastic models for wind and wave state time series divide these models into nonparametric models, models based on Gaussian approximations, and other parametric models. A chaotic theory-based study of wind-wave time series is also suggested by Zounemat-Kermani and Kisi.[22]

However, these approaches do not necessarily illuminate the underlying physical characteristics of a joint probability distribution. In light of the fact that environmental random variables are defined by a non-normal joint distribution, little or nothing has been said about their joint probabilities. To predict the design parameters of wind speed and wave characteristics without taking their dependence into account, univariate distributions are usually utilized. The joint distribution of wave features such as significant wave height and wave period should also be studied. To identify the relationship between significant wave height and wave time, Salvadori et al.[24] employed Copulas, Athanassoulis et al.[25] applied applications of the Placket model, and Galiatsatou and Prinos[26] looked into various bivariate distributions. Very few studies look at how wind speed and significant wave height are distributed together. In particular, Fouques et al.[27] provide two methods based on multivariate Hermite polynomials expansion of the multinormal distribution and one way utilizing simply the correlation matrix to describe the co-occurrence of those variables including the wave duration. Additionally, Bitner-Gregensen and Haver[28,29] created a joint environmental model that takes into account wind, waves, currents, and sea level and are based on the conditional modeling approach (CMA). The joint distribution based on parametric fits for each one-dimensional marginal was calculated using this model for the design and operation of marine constructions.[30] Additionally, the Nataf model[31] is frequently applied in the literature to model cosmological variables. The Nataf model, however, may result in biased results when the transformation to standard normal variates deviates from a multinormal distribution, as stated in Bitner-Gregersen et al.[32] Finally, using Copulas to estimate the joint distribution of wind speed and significant wave height without accounting for the autocorrelation—which is crucial when time series are required—Yang and Zhang[33] adopted a similar strategy to the one outlined in this article.

The perfect tool for the management of an OWF would be one that is able to determine the right maintenance strategy depending on the condition of the wind farm, the type of turbine, and the potential failures of the turbines but also to adapt its planning to the changing weather conditions at sea. The right strategy involves making a clear inventory of the wind farm and putting the right sensors in the right places in the turbine to be able to collect as much data as possible about the health of the turbine. Regarding the weather, several options are possible. First, it is possible to implement a deep learning tool as presented in this part by taking it with data from the meteorological institutes of a region close or similar to that of the wind farm and then using this tool in the planning operations and planning all possible scenarios given the weather conditions at a time t. Otherwise, set up a weather station (wind + sea) with the prediction tools that go with it and sensors throughout the wind farm, would be much more expensive.

4 | DATA USED IN THE O&M OF WIND TURBINES

To develop reliable weather window assessments, it is crucial and vital to have access to reliable met ocean data. Sometimes the data need to be created since they are not readily available. To obtain numerous realistic time series of wind speed, wave period, and significant wave height, an alternate method to sensors is studied in this chapter. These time series might be useful for more effective planning and scheduling of offshore installation activities. To identify the best vessel and equipment combination that is needed for a certain operation and to arrange the sequence of complicated offshore installation procedures. As a result, a significant number of environmental time series are required to account for environmental condition uncertainties that restrict operations. The collection of environmental time series is difficult, costly, and sometimes impossible to obtain. Moreover, even when it is possible to collect these data, there are often missing values due to failures in the measurement tools,[34] which might affect the prediction of the duration of offshore operations. Considering the relationship between the environmental parameters is crucial for creating genuine environmental time series. Data generation makes sense at that point.

The majority of the new digital solutions for offshore wind decision management are based on machine learning (ML) and data analysis, which both demand a vast quantity of data. Data collection and management are challenges that data scientists must overcome. In fact, a lot of data is necessary for ML models to be trained effectively. Large data sets are frequently challenging for businesses to obtain in a timely manner to train an effective model. It is expensive and time-consuming to manually classify data. But data scientists and businesses may get over these barriers and create trustworthy ML models more quickly by producing and using synthetic data. These techniques need a lot of data to be trained effectively, however, due to privacy concerns, this data may be difficult to get or use. To do this, numerous technologies have been created over the past few decades to generate a significant amount of data from a sample.

To generate those data, various tools are used. These tools include ML techniques like GAN,[35] generative adversarial networks, and VAE,[36] variational autoencoder, as well as approaches like SMOTE,[37] synthetic minority oversampling techniques, and the study of the nearest neighbors. ML methods will be the ones to examine due to the nature of our data, the issue encountered by the OWF, and the complexity of the distribution of our data (weather forecasting), as they are both more efficient and more accurate than other methods. In 85% of the scenarios studied in Xu's study, some variation of GAN outperformed conventional synthetic data-generating methods.[38]

The GAN, one of the most current powerful ML methods, has a lot of potential for tabular data synthesis. A type of neural network architecture for generative modeling is known as GANs. Goodfellow et al.[35] initially introduced GANs in 2014. Due to their superior performance, conditional generative adversarial network (CGAN) and CopulaGAN models are chosen over GAN for creating tabular data.[38] Traditionally, a vector sampled from a common multivariate normal distribution is given to the generator in a GAN (MVN). One finally achieves a deterministic transformation that translates the standard MVN into the distribution of the data by training alongside a discriminator neural network. The imbalance in the categorical columns is not taken into account by this technique for training a generator. The generator might not be properly trained if the training data are randomly picked since the rows that belong to the minor category will not be adequately represented. The generator in CGAN learns the resampled distribution, which is distinct from the distribution of the training data. The objective is to efficiently resample such that, during the training phase, all categories from discrete characteristics are sampled equally (but not necessarily uniformly), and to retrieve the (nonresampled) real data distribution during the test.[39] A CGAN model variant called CopulaGAN[38] makes use of Cumulative Distribution Function (CDF)-based modification to speed up CGAN model training.

Generally speaking, all models are capable of accurately capturing the relationships between features. All of the models exhibit comparable performance, demonstrating that artificial data may be used to solve ML issues in place of actual data. Both meteorological and data on wind turbine failure can be generated using these data producers. They assist in training the various decision-making models for managing vessels and predicting failures, both of which are helpful for planning maintenance.

5 | DIGITAL TECHNOLOGIES FOR OFFSHORE WIND DECISION MANAGEMENT

The everyday operations of OWTs require an efficient and dependable maintenance approach. It is hard to achieve 24-h operations with no onsite maintenance delays since personnel must go to the wind farm from a port. A maintenance crew ought to go to the wind farm periodically to prevent failures. Unnecessarily frequent visits, on the other hand, are ineffective and costly due to the substantial need for maintenance staff and vessels. A decreased visit frequency, on the other hand, can lead to a higher failure rate and, as a result, longer downtime. As a result, the frequency of maintenance involves a trade-off between hazards, vessel capacity, personnel resources, and other factors.

An effective maintenance strategy strives to maximize financial gain, increase component lifespans, lessen the need for emergency repairs, cut down on overtime labor expenditures, and lessen the stress that unanticipated equipment breakdowns cause on the job. According to the timing of maintenance, maintenance strategies are often divided into corrective (reactive), proactive, and opportunistic categories.[40] In Figure 2, these classes are displayed. The following are the meanings of the color shifts between the various lines:

- When the wind turbine changes from green to red, it stops working.
- When the wind turbine changes from red to green, it has been fixed and is now functional.

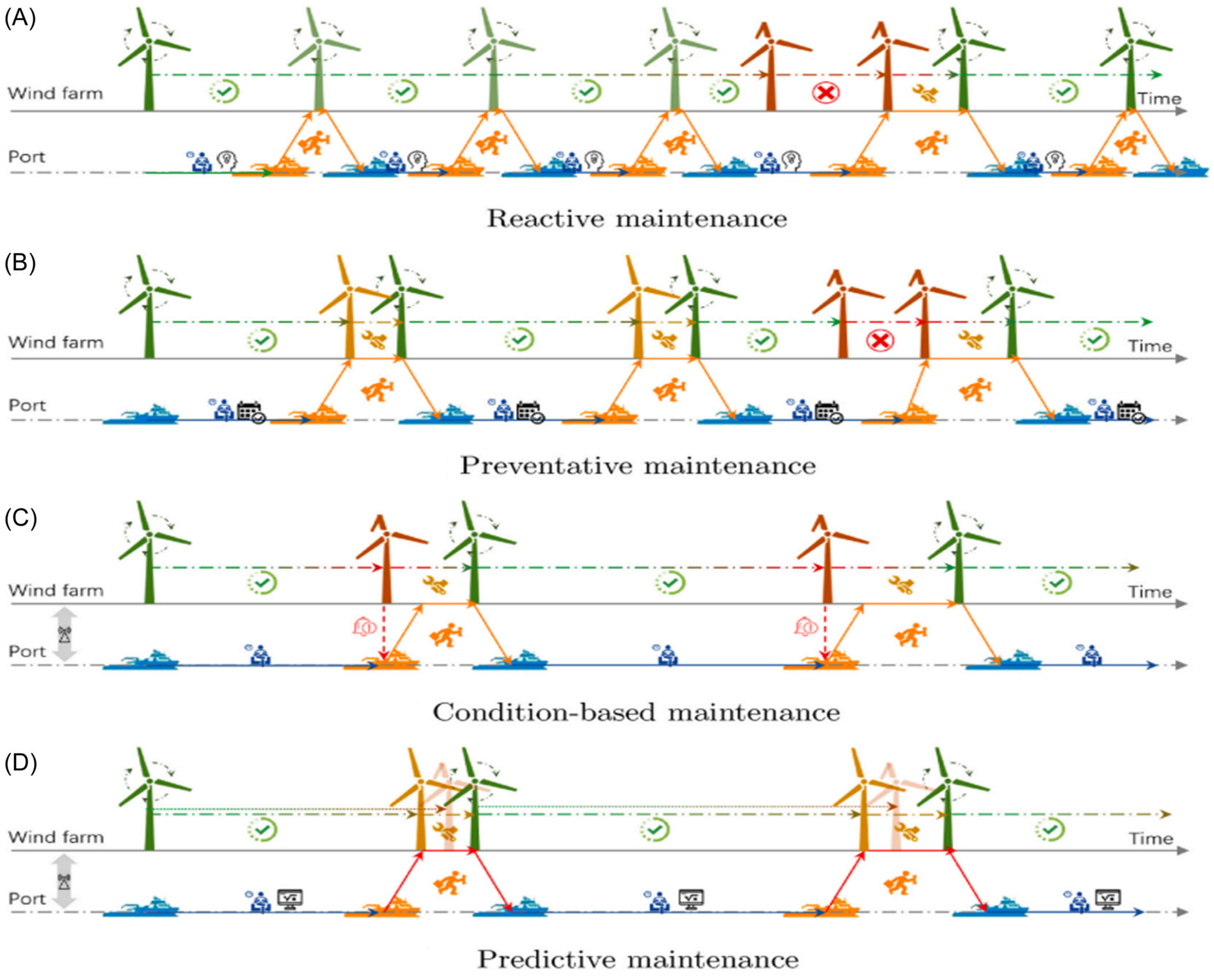

FIGURE 2 Diagrams of maintenance strategies[41]

- Tasks are carried out by a maintenance vessel, ranging in color from blue to orange.
- An upkeep vessel is back at the port and waiting for new assignments as it changes from orange to blue.

A failure-based maintenance technique known as corrective maintenance, sometimes known as reactive maintenance, only performs maintenance after a failure has already happened. High availability can be effectively attained with the corrective maintenance technique while eliminating unnecessary maintenance visits and inspections. As a result, it is appropriate for a system with little downtime loss. However, because of a high failure rate and comparatively low system reliability, the corrective maintenance technique proves to be unattractive and unworkable for large OWFs.[42] Unexpected failures could result in higher costs than anticipated downtime. Additionally, the marine environment makes equipment less accessible and less reliable; for instance, a failure might only be discovered by the maintenance team after a protracted period of downtime.

Figure 2 illustrates the maintenance strategies where the usually operating OWT, the stopped OWT due to failures, and the halted wind turbine owing to maintenance are each represented by the colors green, red, and yellow. The waiting maintenance vessel is represented by the color blue, while the task-performing vessel is represented by the color orange. Proposed in the early 1970s, proactive maintenance is a more sophisticated strategy[41] that involves routine examination and replacement before failure to stop minor faults from becoming significant failures. Only 25% of failures are major, while major failures account for 95% of downtime.[43] A practice that is still in its infancy, proactive maintenance primarily consists of preventive and condition-based maintenance strategies.

Typically, a preventive strategy refers to planned maintenance that happens at (i) a predetermined time or (ii) a specific level of power generation. Optimizing the production plan and the economical maintenance plan is the aim of the preventive maintenance strategy. The benefits of this strategy over corrective maintenance include: (1) eliminating unplanned maintenance; (2) having a good maintenance weather window; (3) minimizing the impact of unpredictable weather; (4) making reasonable use of service vessels; (5) avoiding having an excessive number of spare parts; (6) combining maintenance and repairs; (7) optimizing maintenance tasks; and (8) making a contribution to a successful asset maintenance plan.

Optimized maintenance scheduling has been implemented using data-driven methodologies, such as ML, which has gained popularity in recent years.[44] The most popular method is supervised learning. The tagged data is used to train a black-box neural network model, which may then be used for a variety of analysis, monitoring, and prediction tasks.[44] This strategy is particularly well suited for scenarios that are challenging to model because of their great complexity and ambiguity. However, there are several drawbacks to learning strategies. The procedure first heavily depends on the caliber and volume of measured data. The neural network deteriorates when the required measurements are missing. It is very challenging to demonstrate stability. The network architecture affects the robustness and speed of computation. Failure can rarely be detected if the failure scenarios are not included in the trained data. Therefore, the ability to represent the entire data sample and educate our decision tool to consider all options makes data generation helpful.

5.1 | ML models

This section examines the current applications of ML in reliability engineering and safety. When doing such an endeavor, it is impossible to claim to be thorough, but we have made an effort to sample important articles from each of the ML categories and subcategories mentioned above. A ML algorithm's fundamental components are as follows: Datasets for testing and training, an objective function or loss function to optimize, such as a sum of squared errors or a likelihood function, plus an optimization technique and a model for the data are all required (e.g., linear, nonlinear, nonparametric). It is simple to imagine the extremely broad range of ML applications for reliability and safety applications by changing any one of these components, such as by looking at various datasets in various industries, applying various ML models to various systems or components, or changing some models and algorithms to better suit the task at hand. In general, the goal is to bring new, more precise findings from datasets for improved dependability, safety-informed decision-making, and more successful accident prevention. For the estimation of an asset's remaining usable life (RUL), anomaly and fault detection, health monitoring, maintenance planning, and deterioration evaluation, ML models are utilized.

5.1.1 | Regression models

For estimating RUL and forecasting degradation, supervised regression is frequently utilized. Applications of ML to various technical products are discussed in the literature in this field, including Li-ion batteries,[45] railroad tracks,[46] turbine-cutting tools,[47] rolling bearings,[48] and aviation engines.[49] For a safety-critical system, an accurate prediction of an equipment RUL and degradation level is crucial, and condition-based maintenance is crucial to reduce system downtime and other negative effects of a run-to-failure strategy. The desire for better prognostics and health management (PHM) necessitates, among other things, a more precise calculation of the RUL. RUL prediction is a key component of PHM. Two major categories can be used to categorize approaches to RUL and deterioration level predictions, with a third hybrid category straddling the first two: (i) model-based techniques, which develop failure models based on a thorough examination of the physical characteristics of the failure mechanism in question.[50] These models need in-depth prior knowledge and subject-matter experience; (ii) data-driven techniques, which construct degradation models from old sensor data and hence do not need system-specific prior knowledge see Table 1, for example. Given the quality and quantity of the available data, these models can be created using a variety of ML techniques, and their accuracy and computing requirements can vary. The identification and diagnosis of faults frequently utilize supervised categorization.

5.1.2 | Classification models

This entails both online monitoring of equipment deterioration stages and diagnosing various failure kinds (binary and multiclass). In this context, classification sits at the crossroads of two more general issues, predictive maintenance, and PHM, and it offers vital

TABLE 1 ML regression models in reliability and safety applications[51]

ML model	Advantages	Disadvantages	Applications
SVR	**1.** Superior prediction accuracy as compared to traditional techniques. **2.** Robust to data noise. **3.** Superior efficiency than traditional methods.	**1.** Not suitable for sparse and high-dimensional data. **2.** Require prior knowledge for kernel selection.	**1.** Failure and reliability prediction of time-series data. **2.** RUL estimation. **3.** Prognostic and Diagnostic
RVM	**1.** Superior prognostic accuracy than traditional methods.	**1.** Not suitable for sparse and high-dimensional data.	**1.** System degradation prognostic.
DNN	**1.** Excellent prediction accuracy and training efficiency. **2.** Excellent long-term and short-term predictions.	**1.** Computationally expensive. **2.** Hard to interpret the 'black box' model.	**1.** RUL of aircraft degradation. **2.** Human error prediction **3.** Component reliability and degradation level estimation.
CNN	**1.** Provides excellent prediction accuracy to a highly nonlinear and complex system.	**1.** Computationally expensive.	**1.** RUL estimation
Recurrent neural network	**1.** Prior knowledge is not required.	**1.** Suffer from the vanishing gradient problem.	**1.** RUL estimation.
LSTM	**1.** No prior knowledge is required. **2.** Higher prediction accuracy as compared to traditional techniques.	**1.** Computationally expensive.	**1.** RUL estimation **2.** Time-series forecasting
CNN-based LSTM	**1.** Suitable for more complex engineering systems and high-dimensional inputs.	**1.** Computationally expensive. **2.** Prone to overfitting	**1.** Multi-scale feature selection and RUL prediction
GPR	**1.** Better accuracy than traditional models **2.** Suitable for nonlinear high dimensional system analysis	**1.** Require prior knowledge for kernel selection. **2.** Inferior computational scalability with training data set size.	**1.** Time-dependent probability failure prediction. **2.** System reliability analysis

Abbreviations: CNN, convolutional neural network; DNN, deep neural network; GPR, Gaussian process regression; LSTM, long short-term memory; ML, machine learning; RVM, relevance vector machine; RUL, remaining usable life; SVR, support vector machines.

information that supports both practices. In a variety of reliability and safety applications, such as those involving aircraft engines and electric power transformers,[52] water distribution and pipe failures,[53] bearings or rotary machines,[54] wind turbine blades,[55] software reliability,[56] and forest fires,[57] classification ML tools are used to detect and identify faults.

A variety of models, ranging from the straightforward k-nearest neighbor (k-NN) and logistic regression to more complex decision trees (DT), linear discriminant analysis (LDA), and support vector classification, enable ML classification (SVC). In addition to these single-classifier techniques, ensemble classifiers that combine numerous single classifiers for improved performance have been created. Examples of this are AdaBoost and random forest (RF) (AB). Similar to regression models, it is crucial for research in reliability and safety applications to benchmark and evaluate the performance of many classifiers before choosing the most appropriate one given the datasets employed, details are in Table 2.

TABLE 2 ML classification models in reliability and safety applications[51]

Techniques	Advantages	Disadvantages	Applications
DT	**1.** Excellent prediction accuracy and training efficiency.	**1.** Not robust to data noise	**1.** Assessing stakeholders' corporate governance. **2.** Dirt and mud detection on the wind turbine blade.
RF	**1.** Suitable for discrete classification. **2.** Excellent prediction accuracy.	**1.** More complex than DT. **2.** Hard to interpret the "black box" model.	**1.** Rank the importance of each component of an engineering system.
k-NN	**1.** Excellent accuracy and efficiency	**1.** Not robust to data noise. **2.** Not suitable for high-dimensional datasets.	**1.** Risked-based inspection screening assessment. **2.** Dirt and mud detection on the wind turbine blade.
SVC	**1.** Highly efficient with up to two orders of magnitude time saving compared with traditional methods.	**1.** Not suitable for sparse and high-dimensional data **2.** Require Prior knowledge for kernel selection.	**1.** Risked-based inspection screening assessment. **2.** Structural health monitoring. **3.** Reliability analysis of network connectivity.
RVM	**1.** High classification accuracy	**1.** Not robust to data noise.	**1.** Dynamic predictive maintenance framework for failure prognostic.
LDA	**1.** Excellent prediction accuracy.	**1.** Not suitable for nonlinear system applications.	**1.** Risked-based inspection screening assessment. **2.** Rank the importance of each component of an engineering system.
GPC	**1.** Suitable for the complex system. **2.** Excellent computational efficiency.	**1.** Require Prior knowledge for kernel selection. **2.** Inferior computational scalability with training data set size.	**1.** Reliability evaluation of the complex system.
DNN	**1.** Excellent classification accuracy in high-dimensional problem	**1.** Computationally expensive for training the datasets.	**1.** Structural reliability analysis and failure probability estimation.
LSTM	**1.** Capable of the safety analysis of the time-varying system. **2.** No need for prior assumption and knowledge.	**1.** Computationally expensive. **2.** Prone to overfitting.	**1.** Time-dependent probability

Abbreviations: DNN, deep neural network; DT, decision tree; GPC, Gaussian process classification; k-NN, k-nearest neighbor; LDA, linear discriminant analysis; LSTM, long short-term memory; ML, machine learning; RF, random forest; RVM, relevance vector machine; SVC, support vector classification.

6 | CHALLENGES ASSOCIATED WITH OFFSHORE DECISION MANAGEMENT

The difficulties involved with maintenance jobs, which are among the most important responsibilities for OWTs, stem from a variety of factors. In the first place, the separation between an OWF and a port or beach restricts accessibility and lengthens downtime. The ownership or employment of a maintenance fleet and an increased number of technicians is costly. The incorporation of bottom-fixed and floating foundations has also increased the complexity of OWTs. Additionally, the accessibility of OWTs for service vessels and personnel transfers from the vessel to the OWT is constrained by weather conditions, particularly substantial wave heights and wind speeds. Although such equipment is still bulky and expensive, motion-compensated gangways for offshore access systems have been regularly used in conjunction with service operation vessels during the past 10 years.[58] There will likely be a lengthier wait time and a bigger loss of power generation during downtime if maintenance work needs to be delayed because of weather conditions. Due to the specialized equipment needed, even without taking the effects of weather into account, OWT maintenance costs are higher than those of identical jobs performed on land. Furthermore, OWT component failure rates are increased by a harsh offshore working environment, increased wind speed, wave-induced motions, and structural vibrations. Additionally, larger and more specialized devices are needed for offshore maintenance and repairs because of the recent growth in OWT size, which aims to increase power-generating efficiency.

Given that it is anticipated that wind energy will supply 50% of the world's electricity consumption by 2050, extensive maintenance and repair work will be necessary for the coming decades.[59,60] Therefore, it is equally crucial to investigate how OWT maintenance affects the ecosystem. Hence, the overall purpose of a proper repair and maintenance strategy must balance maximizing profitability and minimizing environmental consequences, so contributing to the sustainable development of offshore wind energy over the long run. According to the discussion above, it is evident that OWT maintenance is difficult, and good maintenance will guarantee a decrease in downtime while minimizing energy production losses. The broad subject of OWT O&M can be split into a number of unconnected research problems, including overall cost management and logistical planning, on-site operations and mechanical designs for particular operations, and forward-looking evaluation of prospective consequences. Even though researchers and engineers from related fields have researched each subproblem, an amalgamation of these technologies is still in its early stages. To make computations and analyses more closely approximate reality, research in OWT maintenance entails a higher level of complexity and ambiguity. Every area of OWT maintenance has recently improved due to significant theoretical and technological improvements. A corrective maintenance method is no longer appropriate as OWFs grow in size quickly, and proactive maintenance strategies are gradually taking their place.

Maintenance jobs must be scheduled based on straightforward route planning and more complex scenarios to be carried out efficiently. By taking into account the capacity of the mode of transportation, as well as the availability of workers and parts, route planning for OWT maintenance, has been accomplished using one or more O&M bases. The goal of choosing the best route is to reduce greenhouse gas emissions while maintaining the highest level of efficiency. Additional factors that should be taken into account by ideal scheduling include reducing downtime, increasing revenue, enhancing system reliability, and fostering cooperation amongst maintenance teams.

After scheduling, the next phase is on-site maintenance, which is very different from on-shore turbine maintenance. First, erratic weather restricts the movement of employees and equipment and places stricter demands on the modes of transportation. Additionally, a second docking action is necessary. In this study, docking devices including active motion-compensated access devices and basic fenders have been studied. While weighing the significance of many crucial collision-related elements, the possibility of collision between service vessels and the turbine should be considered. Due to the unpredictable wave heights, the criteria for lifting operations are stiffer for OWTs. Specialized and expensive lifting equipment are often required, whose daily rates are higher than for onshore equivalent. To decrease the height that external cranes must lift heavy components from, it has been suggested that built-in lifting equipment be installed on OWT towers. Rombouts[61] proposed a decision-support tool to optimize the second half of the "Saint-Brieuc project" during the operational phase of the OWF located near the French coast. Their proposed tool is able to incorporate the actual status of the project and the most recent weather forecast, including its uncertainty and results suggesting that tools achieve high accuracy. In recent years, a variety of O&M simulation tools has been developed, including Shoreline O&M Design,[62] ForeCoast Marine Gamer Mode,[63] Offshore TIMES,[64] DNVGL O2M,[65] and ECN O&M Calculator[66] to support the modeling, project planning, and decision-making services. However, these are commercial products that require annual license fees, technical support, and user inputs.

7 | CONCLUSION

An offshore wind project's maintenance covers a lot of ground. Compared to onshore wind power, the cost of maintenance represents a greater portion of the overall cost of energy production. Long distances from the coast, the unpredictability of the weather (including wind and wave conditions), a lack of information from remote monitoring, unexpected malfunctions, aging, and subjective considerations are the main obstacles to OWT maintenance. Every area of OWT maintenance has recently been improved by a significant quantity of theoretical and technological breakthroughs.

It is possible to optimize OWT maintenance in two ways. Increased weather forecasting skills, which are essential for scheduling onsite maintenance, are one way to improve onsite maintenance. The alternative strategy is to use robots deployed inside the tower to do simple maintenance chores remotely or to take use of system redundancies to keep the wind turbine operating, even at a reduced capacity, and so decrease maintenance frequency. The ability to acquire data must be improved for both perspectives.

Recent advancements in computational power have created prospects for integrated and in-depth CM analytics, where many data types can be leveraged to support robust decision-making that is based on actionable knowledge of emerging dangers. Utilizing ML approaches to improve monitoring procedures can help plan ahead and reduce the need for maintenance visits to OWFs.

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