Journal of Frontiers in Multidisciplinary Research

A Risk-Based Reliability Model for Offshore Wind Turbine Foundations Using Underwater Inspection Data

Dulo Chukwuemeka Wegner [1*], Valentine Omine [2], Aigbe Vincent [3]
[1] Deepwaterz, Nigeria
[2] Addax, Nigeria
[3] University of Benin, Benin City, Nigeria

* Corresponding Author: **Dulo Chukwuemeka Wegner**

Article Info

E-ISSN: 3050-9726
P-ISSN: 3050-9718
Volume: 02
Issue: 02
July – December 2021
Received: 31-08-2021
Accepted: 01-10-2021
Published: 03-11-2021
Page No: 300-313

Abstract
Advancements in offshore wind energy have augmented concerns related to the structural integrity and reliability of turbine foundations as they interface with the energy conversion systems and the hostile marine environment. Conventional deterministic approaches to the design and maintenance of foundations do not typically account for the uncertainties posed by the marine biofouling, corrosion, and fatigue accumulation in due course over time. This work presents a risk-based reliability model that assesses the underwater inspection integrity of offshore wind turbine foundations to derive improved probabilistic long-term stability evaluation. The model uses inspection data from ROV imagery, cathodic protection, and corrosion depth profiles to derive salient statistical relationships among structural performance and degradation processes. Thickness of marine growth, rate of corrosion, and fatigue crack initiation in the turbine operational life model are treated as stochastic phenomena. The model integrates finite damage and vibration response (FDVR) analysis with standard Integrity Element-Imager (IX) simulations and geospatial information systems (GIS) to derive site-based risk analytics within a wind farm. The model also enables failure probability analysis considering specific environmental loads in the site, like wave and biofouling, under different operational conditions.
The projected outcomes lead to the development of a decision framework based on reliability analysis for targeted maintenance and life extension planning for inspections. Unlike traditional threshold-based methods, the risk-based approach shifts the management paradigm toward examining the greatest probability of interrelated system failure. It economically improves the management of offshore wind assets by correlating actual inspection data to predictive reliability models, thus reducing uncertainties and enhancing operational reliability. The fusion of theoretical probabilistic models, risk analysis, and remote digital inspection data consolidates the resilience of offshore wind infrastructure, advancing the development of renewable energy to make it safer, more sustainable, and socially responsible.

DOI: https://doi.org/10.54660/.IJFMR.2021.2.2.300-313

Keywords: Offshore Wind Turbines, Foundation Reliability, Risk-Based Modeling, Underwater Inspection

1. Introduction
In the quest for renewable energy, offshore wind power is strategically critical to the sector's global transition to sustainable energy systems (Weiss *et al*., 2018; Gielen *et al*., 2018) [90]. The key benefits of offshore wind farms as compared to onshore wind farms include stronger and more consistent wind resources, reduced conflicts for land, and proximity to demand centers on the coast. As countries try to meet their decarbonization goals, offshore wind energy is rapidly emerging as a key source of renewable energy (GORDON, 2020; Victoria *et al*., 2020) [32, 87]. Offshore wind capacity is expected to expand more than fifteenfold by 2040 according to the International Energy Agency, which positions offshore wind as a central element of the future energy mix. The constructive and operational challenges posed by offshore wind infrastructure, particularly the long-term structural reliability of turbine foundations, pose as unique engineering problems (Igwemezie *et al*., 2019; Barter *et al*., 2020)

[38, 14]. Turbine foundations represent the primary connector between the energy-conversion superstructure and the intricate and highly dynamic marine environment (Karimirad *et al*., 2019; Vicinanza *et al*., 2019) [86]. These can be monopile, jacket, or gravity-based, and all foundations face ongoing hydrodynamic force, variable load, and corrosive seawater. They also prevent the turbine from being tilted by high winds, waves, and currents while maintaining vertical position for net energy capture (Liu *et al*., 2019; Tong, 2019) [54]. Given the aforementioned factors, foundation integrity remains a cornerstone for asset management for offshore wind farms (Lian *et al*., 2019; Köhler, 2020) [52, 44]. Any failure at the foundation level creates the potential for a catastrophic collapse, as well as exposing people, the environment, and the economy, especially subsequent investments in large-scale renewable energies, to massive risk (Avin *et al*., 2018; Keller and DeVecchio, 2019) [10, 43].

Strong engineering designs notwithstanding, structures' foundations are still prone to deterioration over time (Agrawal *et al*., 2018; Frangopol and Soliman, 2019) [4, 27]. The growth of organisms (marine life) on submerged structures, commonly referred to as biofouling, and the associated increase in surface roughness and mass, make hydrodynamic loading conditions more severe by altering loading conditions and increasing fatigue stresses. The processes of corrosion, greatly enhanced by the saline atmosphere of the splash zone and by variable concentrations of atmospheric oxygen, attack the corrosion-resistant linings on the submerged steel, and in particular, the submerged splash zone steel. Structural fatigue, as a result of millions of waves, currents, and turbine operational cycles, induces and propagates cracks on the structure and may eventually result in reduced operational load (Costa *et al*., 2020; Mehmanparast *et al*., 2020) [19, 59]. The corrosion, in addition to biofouling, and the structural fatigue, interact to create highly complex and stochastic corrosion processes. Static and deterministic approaches could only estimate and predict to.

Standard offshore foundation condition assessment techniques are based on concrete safety margins, scheduled timing, and pre-defined maintenance strategies with associated triggers (O'Carroll *et al*., 2019; Wanki *et al*., 2020) [67, 89]. These models, while quick and easy to comprehend, do not resolve the uncertainty associated with the marine atmosphere and the disassociated environmental degradation at disparate locations. Under uncertainty models either significantly underestimate the risk of loss, and hence the chance of failure, or overestimate the risk and hence the chance of loss, leading to overdesign, unintentional failure, and excess expenditure (Crisp *et al*., 2019; Holland *et al*., 2020) [20, 35]. Equally, assuming and working with a scheduled timetable eliminates and avoids the circumstantial data obtained from the underwater data-supplying sensors and devices. Hence, there is a requirement for a paradigm shift that fundamentally focuses on uncertainty boundaries, incorporates data, and continuously evaluates site-specific foundation reliability.

This focuses on formulating a model for reliability assessment and risk analysis with respect to offshore wind turbine foundations using probabilistic methods and data gathered from underwater inspections. The model determines the probability of failure during changing scenarios by incorporating the variables of marine growth, corrosion, and fatigue as stochastic processes rather than deterministic processes. Such modeling and ascription of probabilities facilitates more accurate long-term projected assessments of stability, coupled with the ability to formulate optimized maintenance (Melchers and Beck, 2018; Zhu *et al*., 2019) [60, 100]. The model explains the real physical processes of offshore foundations because coupling the model with Inspection Data, such as ROV (Remotely Operated Vehicle) inspection footage, corrosion survey data, and cathodic protection assessments, adds a robust data-driven framework for model calibration and parameter refinement.

Advanced computation techniques have been embedded within the framework to improve the precision of modeling and its practical use. Macro marine growth, modal response, and the multifaceted fatigue accumulation under fluctuating dynamic loads at sea are simulated using the FDVR software. Integrity Element models the progressive corrosion of structural elements, probabilistic crack growth, elements of structural integrity, and the corrosion and fracture inspection-reliability integration to estimate fracture reliability. Then, the spatial distribution of conditions across entire wind farms is stored and analyzed using GIS to visualize spatially the degradation patterns, assisting operators in risk-based ranking and planning of offshore wind resources Merem *et al*, 2019; Lazoglou and Angelides, 2020) [61, 48].

The risk-based reliability model, which is proposed in this case, is an advancement of the previously mentioned model to improve its inspection integration, probabilistic computations, and advanced computation techniques. The model improves predictive analytics and introduces preemptive and economically favorable maintenance strategies and life cycle management of the offshore wind infrastructure. The improvement of the reliability and resilience of the turbine foundations, the advancement of this work, simplifies the sustainability and offshore wind energy viability as a dominant renewable resource in global energy transformation.

2. Methodology

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology was applied to ensure a rigorous and transparent approach in developing the risk-based reliability model for offshore wind turbine foundations using underwater inspection data. A systematic search strategy was employed across leading academic databases, including Scopus, Web of Science, IEEE Xplore, and ScienceDirect, alongside relevant industry reports and technical guidelines from organizations such as DNV and IEC. Keywords and Boolean search strings combined terms related to offshore wind turbines, structural reliability, underwater inspection, marine growth, corrosion, and probabilistic modeling. Duplicate records were identified and removed to ensure data accuracy.

Inclusion criteria were established to select studies that directly addressed the structural reliability of offshore foundations, incorporated underwater inspection or remotely operated vehicle (ROV) data, and applied quantitative risk-based or probabilistic methods. Exclusion criteria removed publications that focused solely on onshore turbines, general marine infrastructure unrelated to wind energy, or studies lacking empirical data on degradation processes such as corrosion or fatigue. Both peer-reviewed articles and high-quality industry reports were considered to capture academic insights as well as operational practices.

The screening process was conducted in two stages. First, titles and abstracts were assessed to filter irrelevant studies. Second, full texts were reviewed in detail to confirm methodological relevance and data applicability. Studies meeting the criteria were then coded and categorized according to themes, including types of degradation mechanisms, reliability modeling approaches, and the integration of inspection data into risk assessment frameworks. A PRISMA flow diagram documented the study identification, screening, eligibility, and inclusion process to ensure transparency and reproducibility.

Data extraction involved systematically collecting information on study context, inspection data types, reliability assessment methods, statistical techniques, and outcome measures. Emphasis was placed on models that linked marine growth, corrosion progression, and structural fatigue with long-term foundation stability. Special consideration was given to approaches that incorporated geospatial mapping, GIS integration, and software-based reliability assessment tools such as FDVR and Integrity Element.

The extracted data were synthesized qualitatively and quantitatively to identify prevailing trends, gaps in current methodologies, and opportunities for enhancing risk-based reliability assessment. Particular attention was paid to the extent to which underwater inspection data improved model calibration, reduced uncertainty, and informed probabilistic predictions. The synthesis informed the development of the proposed framework, which combines inspection-based inputs with probabilistic modeling and digital mapping to support predictive maintenance and long-term offshore wind farm reliability.

2.1. Background and Literature Review

Groundbreaking advancements in turbine technology, offshore reliability assessment, and foundation design have supported the global expansion of offshore wind energy. Offshore wind turbine foundations, in particular, serve as the primary structural elements interfacing with the turbine tower and the seabed, responsible for maintaining the entire platform's stability under dynamic offshore conditions (Bhattacharya, 2019; Yang *et al.*, 2019) [15, 96]. However, environmental degradation processes, which are structural weakening factors, have been proven to compromise the long-term durability of these foundations. Risk-based inspection frameworks, especially the type pertaining to foundations and their deterioration processes, necessitate systematic examination of accuracy, reliability, and remaining useful life to be efficient.

Monopole, jacket, and gravity-based structures are the primary designs for offshore wind turbine foundations. Each type of structure has unique characteristics and degradation susceptibilities. In shallow waters, monopole foundations are the most popular. They have the most simplistic and most cost-effective designs relative to the other options. They consist of large-diameter steel tubes that are driven deep into the seabed and are able to resist lateral and vertical loads (Sanchez, 2019). Maynard, 2019) [58]. Even though they are very popular, the monopole foundations are very prone to marine growth as well as corrosion, especially within the tidal and splash zones. Where monopile foundations become pricy and difficult to construct, jacket foundations are used. They are used for deep waters and consist of lattice frameworks that are anchored by piles. Each of the individual pipes adds to the support of the structure, but they also offer large areas for the marine biofouling as well as crevice corrosion to be deposited. Concrete caissons, which are also considered gravity-based foundations, offer more self-restraint relative to the other wind turbine anchors. They are more self-weighted caissons and are also more prone to corrosion. Caissons are steel-based and prone to scour around the bottom, as well as biofouling, which alters the relative stability of which hydrodynamic. Understanding the different pathways of degradation for each structure will help assess the reliability for long periods of time.

On the contrary, the phenomena that lead to Structural deterioration for these Offshore foundations are the interplay of the most critical among which are? – The fatigue, corrosion, and marine growth. Also known in the scientific circles as Biofouling, marine growth is the phenomenon of accumulation of certain life forms on submerged surfaces. These life forms such as algae, barnacles, mussels, and even tubeworms. The life processes, which influence the hydrodynamic loading, result in an increase in the surface drag inertia and component structures formed of member diameter. They increase surface roughness. The constructs, which are jacket structures, as illustrated by Shittu *et al*, 2020, and Aeran *et al*, 2020 [3], as well as slender members, are affected the most due to the increment in the load. In addition to that, Shittu *et al* 2020 and Aeran *et al* 2020 [3] show that, the phenomena of the marine growth, in addition to the members formation of the jacket structures, is also the phenomena which leads to complication for other marine structures due to the obscurity of the inspect ability and increase in the shroud cover obstructions for the simple objective of the Non-Destructive Testing as well as condition monitoring.

Corrosion is a significant source of degradation, particularly within steel-based structures. The interaction of steel surfaces with seawater electrolytes leads to a slow but steady depletion of cross-sectional material and whole thickness. Epoxy and cathodic epoxy coatings offer some level of protective measures, though disbandment, mechanical damage, depletion of anodes, and time significantly undercut their protective power. Localized corrosion and crevices which pitting form during corrosion of coatings greatly diminish the Material's fatigue resistance. These factors are the most predictive of crack initiation (Larrosa *et al*, 2018; Akpanyung and Loto, 2019) [47, 5]. The splash zone is particularly harsh. The cyclic wetting and drying at the splash zone drastically increase corrosion rates, increasing the complexity of long-term exposure.

The degradation caused by fatigue is part and parcel of all operations done offshore on wind turbines. This is mainly because of the numerous stress cycles. The stress cycles result from the various operations and environmental conditions acting upon the turbines. The wind, waves, and current together impose certain varying stresses on the foundational components of the wind turbines. This is further complicated by the operations of the turbines, including starting, braking, and yawing. There is also the additional cyclic loading. This also works on the turbine yawing and can result in broken components. The limited P repairs greatly increase the chances of damage becoming too great. This is 'The Rule of Miner.' The addition of corrosion, as well as fatigue, is critical to the decrease in turbine resilience. For example, the loss of wall thickness increases the load on the surface. This corrosion is then 'bio-fouled', and the load increases further. This was presented by authors such as Morris and Resnik in 2019 and 2020 [64, 75] (Morris *et al*., 2019; Resnik *et al*., 2020) [64, 75]. Such multi-physics degradation makes simple design assumptions increasingly better in predictive ability.

To resolve these uncertainties, methods of reliability-based design have now been adopted in offshore engineering. Foundations are designed to meet ultimate, serviceability, and fatigue limit states over their intended design life. These are calculated using the limit state design (LSD) approach and are supplemented with probabilistic safety factors. The reliability index, along with failure probabilities in random loading and degradation scenarios, uses advanced models like the FORM and Monte Carlo simulation. The DNV, IEC, and API guidelines contain partial safety factors from probabilistic calibration and emphasize balanced safety and economy. More complex techniques combine environmental load models with structural response simulations to obtain reliability indices of fatigue life and corrosion allowances. (Alexander and Beushausen, 2019; Adasooriya *et al*, 2020) [7, 1]

Even with modern technology and systems in place, how reliability is defined and used in the process of decision-making is still being scrutinized. In the majority of situations, the decision-making process is still mechanistic in nature and relies on the time intervals assigned to an activity, like underwater inspections, regardless of the conditions. These time intervals disregard the conditions in basins that dictate how materials and conditions break down, salinity, the temperature of the water, and excess biological growth. Insufficient control can place a focus on systems that may cost a lot of money and time without gaining substantial value from, or investing far less resources and getting reduced value, or unchecked decay (Blanc, 2018; Xie *et al*., 2020) [16, 94]. Also, underwater inspections that are conducted using divers and remotely operated vehicles (ROV) often lack quantitative statistical values, making them less useful.

Another challenge is the gap between inspections and reliability-centered maintenance (RCM) planning. Most methods still maintain conservative assumptions on the rates of degradation. This can lead to component overdesign and premature retirements. While condition-based maintenance (CBM) is gaining traction, it still struggles to integrate and harmonize disparate data from inspections, sensors, and environmental monitoring (Quatrini *et al*. 2020, Atta and Talamo 2020) [73, 9]. Additionally, empirical data is often used to calibrate models, reducing predictive reliability. The absence of consistent methods for evaluating degradation evidence from inspection reliability assessments creates additional uncertainties for operators and regulators.

The foundations of offshore wind turbine structures can undergo progressive deterioration from marine growth, corrosion, and fatigue, which pose deep-rooted issues for structural reliability and operational safety. While the theory behind existing reliability-based design methods is sound, the gap between inspection-derived decision making is a significant barrier (Huang *et al*. 2019, Xiang and Yang 2019) [37]. Closing these gaps requires advanced models that can calculate the probability of failure and leverage real-world inspection data to minimize uncertainty, optimize offshore wind asset maintenance, and prolong operational life.

2.2. Data Sources and Input Parameters

The marine degradation of offshore turbine foundations poses a multi-faceted complexity, and hence has a composite of physical, environmental, and operational perturbations that evolve with the Foundation, depend on Systems, the standing of the underwater effectiveness of the inspection, and postulating operationalization of predictive, monitoring surveys, and a multi-section operational document of systematic architectural logs as shown in Figure 1. This focuses on bathymetric foundations, automated log devices, and assesses their assignment to mechanical operationalized and means of autonomous functionality, ultrasound observational logging with supportive sensorised recording log devices. The process similarly outlines the preliminary operational stages for uncertainty calculation of data gleaned from Research, pragmatic consistency, and autonomous observation/shadowed log devices with pad-sensed architecture recorder and hierarchical data-structure operationalized vats for shredded dissymmetrical data becoming a formulated relayed log on mechanical data with multi-sectioned cloud-inclusive centralization of fluid operationalized battalizations rounded into firm composite logs.

Fundamental to the health monitoring of offshore wind turbines is the two-tiered approach of Remote Underwater Observation and Sonar Imaging, otherwise known as ROV Imagery and Sonar Scanning, and Diver Observation and Inspection. ROVs conduct their tasks with minimal disturbance to the environment and a high degree of precision, covering significant areas on the foundations of the turbines and accumulating both visuals and sound. These ROVs have a camera and sometimes a sonar unit that allows the user a closer scan of the livestock that thrives on the turbines, detects submerged steel fractures, and visually maps the marine growth on the turbines. Sonar is especially useful in sonar-vs-water visibility contests, as it can detect strange surfaces caused by tube pit, monopile scour, and fatigue cracks (Shen *et al*. 2018, Packer and Reeves 2020) [79, 71]. ROVs create datasets that are geo and time-referenced, which allows users to monitor the degradation of a wind farm over time. This becomes especially useful in the predictive modeling of the density of the covering marine life, as well as in estimating the rate of fractures and cracks, which are important in assuring the structural reliability of the farm.

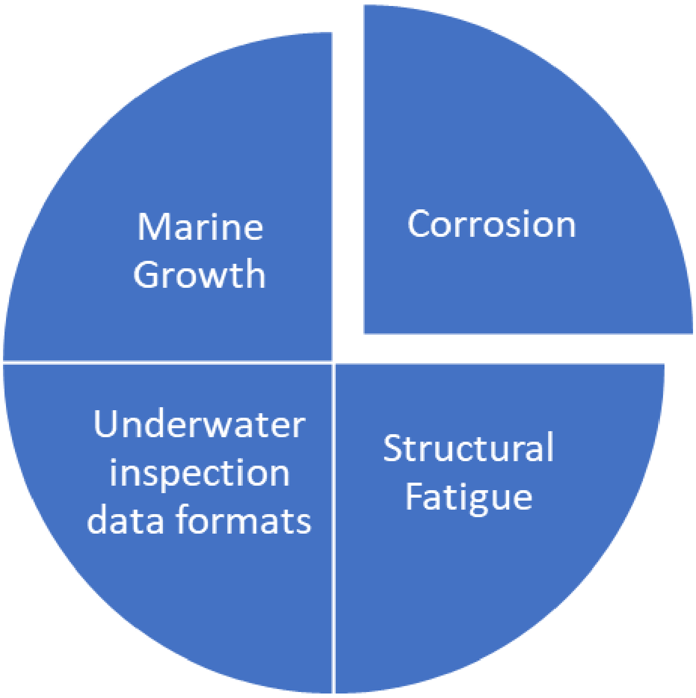

Fig 1: Data Sources and Input Variables

Unlike ROV technology, diver-based approaches are still important for the detailed corrosion profiling and localized assessment of the structure's condition. With ultrasonic testing equipment, divers are able to carry out direct tactile inspections and measure thickness, allowing for the quantification of wall loss and coatings' performance. Diver-based techniques are especially useful in splash zones and in transition pieces, which suffer regionally accelerated corrosion because of intermittent wetting with sea chartered aerated seawater. Although more resource-intensive and more dangerous than ROV surveys, diver inspections are the only means of obtaining precise datasets useful for mapping and validating remote sensing probabilistic models.

Corrosion is one of the most prevalent mechanisms of failure for offshore foundations, and the offshore foundation corrosion control, for the most part, is achieved through cathodic protection systems, sacrificial anodes, and impressed current systems. Cathodic protection survey data acts as fundamental input for the computation of electrochemical degradation processes.

The critical parameters include voltage measurements, which are the protection level achieved as reflected on the electrochemical potential of steel surfaces in comparison to reference electrodes. The level of protective current and anodic dissolution is indicated with current density measurements. The condition of protective barriers, which are coating systems, paint, and epoxy layers, dissipated, detached, or ruptured, is also an indicator of protective barrier effectiveness (Morozov *et al*. 2019, Dhawan *et al*. 2020) [63, 20].

The incorporation of these data into the probabilistic model allows for a more refined representation of the temporal variability of corrosion rates. In addition, the changes in the performance of cathodic protection over time can be linked to the loss of wall thickness, which allows for data-driven improvements to be made for models of corrosion progression.

The effects of environmental factors on the degradation of the turbine foundations and the responses of the structures themselves are significant. Environmental loading data accounts for waves, currents, salinity, and temperature, all of which need to be acquired for evaluating degradation explaining factors and stochastic variability. Wave and current data serve as inputs for the hydrodynamic load modeling and the fatigue analysis. These forces govern the stress cycles imposed on the foundation and, over the course of decades of operation, the foundation as a whole accumulates a certain amount of fatigue damage. The salinity data directly influence the corrosion kinetics, as the higher salinity levels enhance the rates of the electrochemical reactions and thus the corrosion protection coatings become less effective (Zhu *et al*. 2019; Yu *et al*. 2020) [100, 97]. The data temperature alters the corrosion rates of materials as well as the temperature fatigue properties of the materials with the thermal stress sequences as well and amplifies the physical stresses and speeds up the chemical reactions.

Such datasets are usually obtained from metocean monitoring stations, floating buoys, or satellite-based oceanographic models. Use of data collected from the environment allows for the adjustment of the variability of the site to the generic assumptions so that more specific data can be incorporated into the reliability assessments.

Apart from external elements, internal operational mechanisms within wind turbines are also crucial for assessing foundation reliability. Operational data records are critical for understanding loading histories and vibration responses. Turbine load histories retain data on the axial and bending wind/ wave-induced loads and torsional loads aloft and below the foundation within the tower. This serves as valuable data for modeling fatigue life, as the total number of loading cycles is a major determining factor for crack initiation and propagation. Vibration logging records capture the fundamental behavior of the structure when subjected to external and internal loads and shifts. The monitoring of natural frequencies and mode shapes can also flag a major stiffness drop due to fatigue or loss of materials, which assists with degradation management strategies (Banerjee *et al.*, 2019; Kaur *et al.*, 2019) [11, 42].

As a norm, operational datasets are archived with the aid of SCADA systems, as well as structural health monitoring and any internal sensors within the turbine itself. These streams of information allow for the continuous development of reliability assessment models and the advancement of fatigue damage predictive mechanisms.

Reliability assessment is a complex process, and much data is needed for a fully integrated model. This data can differ from photographs taken, chemical infusions, and the weather, all of which require preliminary preprocessing to be usable data for a cohesive reliability assessment model.

The stages, such as cleaning and filtering, as well as removing noise, outliers, and redundant records, especially in large ROV image sets, are examples of data preprocessing. It is the case with normalization, the standardizing of data across diverse sources to common units and scales, such as for probabilistic analysis. In interpolation and extrapolation, gaps within the records of both the environment and the operation are filled, frequently via statistical imputation or a physics-informed framework of modeling (Rasheed *et al.*, 2020; Jain *et al.*, 2020) [74, 39].

After integration of the data sets is accomplished, the next step is to determine how much background is missing and how this impacts the data, especially measurable data, within the complex spatial and temporal setting of the ocean. Marine environments are highly variable, and data related to inspection are frequently both sparse and error-prone. Bayesian updating, with its other set of approaches such as the Monte Carlo method and probability density function estimation, offers statistical methods to account for uncertainty in the degradation parameters. For example, corrosion rates can be treated as variables with a lognormal distribution, whereas fatigue crack growth can be treated as a stochastic phenomenon having random loaded cyclic histories. Quantifying uncertainty offers assurance that most reliability predictions will fall within a more reasonable cushion of error.

The reliability and operational characteristics of underwater tidal turbines are based on the integration of several information streams, such as environmental loads, structural history, and inspections (Nicolussi and Cazzaro, 2019; Luger, 2020) [66, 55]. Operational history documents, accompanied by ROV imaging and diver-based cathodic protection surveys, provide insight into complex dynamic structural responses and aid in contextualizing degradation mechanisms, enhancing the understanding of active and passive tidal turbine loads and cathodic protection. The separation of external data into coherent probabilistic variable components by preprocessing and quantifying the uncertainties self-calibrates the risk-based reliability models. The holistic study of the combined datasets provides a practical framework allowing foundation region inspection and remotely operated vehicle-based data collection.

2.3. Probabilistic Reliability Model Development

Offshore wind turbine foundations' structural performance is governed by multifaceted interactions among operational requirements, material degradation, and environmental loading. Such phenomena require the use of probabilistic modeling because the interactions are too complex for deterministic design approaches to capture for design reliability. Reliability probabilistic modeling approaches outlined by Cai and Mahadevan (2018) [17] and Shrivastava *et al.* (2019) [81] capture the uncertainties and predict failure probabilities for the service life of the foundation. These models define random variables and statistical and simulation models to derive and apply probabilistic approaches that enable performance-based decisions to be made regarding maintenance, inspections, and life extension plans, as shown in Figure 2.

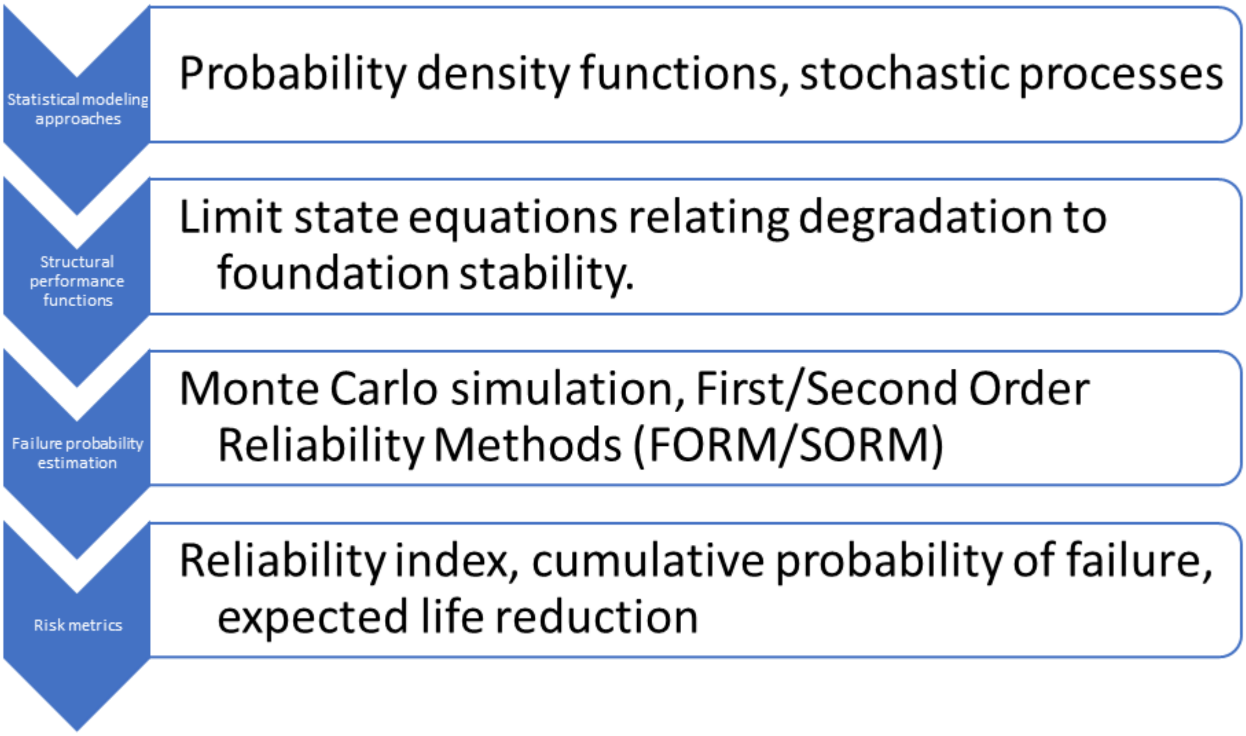

Fig 2: Probabilistic Reliability Model Development

The development of probabilistic models hinges on identifying pivotal random variables that encompass the degradation mechanisms' stochastic traits. One such variable of interest is the marine growth thickness, which is marked by prominent spatiotemporal variability. Growth rate and biofouling are sluggish and sluggish respectively and depend on water temperatures, nutrients, and seasonal cycles; thus, the processes are considered non-deterministic. Another significant random variable is the corrosion depth, which is representative of electrochemical material loss on steel elements. Variability in coating efficiency, protection efficiency, and micro-environmental factors in tidal zones contributes to variability in zones. The initiation of cracks is considered a probabilistic phenomenon of degradation caused by the concentration of stresses, material dissimilarities, and the combined effects of degradation processes (Larrosa *et al*., 2018; Zeng *et al*., 2020) [47, 98]. In the end, fatigue life is treated as a random variable as a result of accumulated deformation cycles from the wind, wave, and operational stresses; however, the fatigue cycles suffer from considerable variations in the imposed cumulative range as well as the S-N curve parameters. These variables serve as the probabilistic basis for assessing the reliability of the entire structure.

Robust statistical modeling approaches are necessary because of the stochastic characteristics of these degradation processes. Assigned random variables are represented by probability density functions (PDFs). Marine growth thickness, for example, may be lognormally distributed due to the shift to the right that occurs during biological blossoms (skewness). General and localized corrosion dominate; thus, corrosion depth is represented by the normal and Weibull distributions, respectively. Within the realm of crack initiation, times are modelled by extremes, either exponential or Weibull, and these are aligned with the reliability theory specified with failure-time analysis. Fatigue life distributions are obtained mostly from probabilistic S–N models. The loss of the very large, or highly stressed, components, which exceed the lognormally or Weibull distributed proportions, is more of the contributions with the stress amplitudes and material parameters. Aside from the static PDFs, stochastic processes are used to capture dynamic variables. For degradation processes, futuristically models such as Markov Chains and Gamma processes enable the forecasting of upcoming conditions, which integrates the information from attended inspections (Giorgio *et al*., 2018; Chiachío *et al*., 2020) [30, 18]. Such random models enable the continuous updating of reliability assessments conditioned on new evidence.

Predictive reliability analysis starts from the structural performance function, also known as the limit state function. This function, in a controlled manner, takes some degradation variables and, using them, draws a line between `safe` and `failure` states. In reliability models from biofouling, marine growth auxiliary SS may be related to hydrodynamic load amplification factors, and, as a result, biological fouling is associated with increased stress ranges and reduced fatigue life. It is through the above formulations that structural performance is probabilistically linked to the degradation variables, which is sufficient to initiate the estimation of failure probabilities.

Estimation of failure probabilities is done through computational techniques that assess the crossing of the performance function into the failure zone (Kordestani *et al*., 2019; Xiao *et al*., 2019) [93]. The computational technique that is most prevalent is called Monte Carlo simulation (MCS). In this technique, samples are taken from the distributions of the independent variables, and the failure cases are used as the basis for estimating the probability of failure. While this form of simulation is computationally expensive, it is flexible and accurate for highly nonlinear limit state functions. Analytical techniques, which are more computationally efficient, are approximations such as the First Order Reliability Method (FORM) and the Second Order Reliability Method (SORM). Reliability indices are calculated at the most probable point of failure, where FORM approximates the performance function by linearizing it at the point of the most probable failure. SORM extends this by including the effects of curvature and nonlinear limit states, which is more accurate. These methods enable engineers to cut the cost of simulation in relation to precision, which is important in sensitivity analyses or updating simulations with new data from inspections.

Models that utilize risk metrics to construct a probabilistic function on the operational aspects of a foundation shed light on the intricate operational aspects of its foundations. The reliability index β is one of the metrics used for the quantification of sustention safety levels. Higher values of β foretell a lower probability of failure, and the target values are often set as per the design codes. The cumulative probability of failure is yet another perspective of failure in the operational lifetime of the foundation (Leimeister and Kolios, 2018; Doan *et al*., 2020) [50, 23]. This, among the rest of the failure indicators, is critical to the life-cycle analysis, and especially to the comparison of different lines of maintenance. The expected life reduction metric, as per probabilistic fatigue and corrosion life cycle models, expresses the reduction of available service life due to degradation in the conditions of corrosion. These risk metrics enhance the process of decision-making with respect to the timing of the inspections, the upgrade of cathodic protection, or even the retrofitting of the structure. Many contemporary risk metrics allow updating the foundation model, aiding the prediction accuracy and enabling timely risk assessment and continual management plans.

The foundations of offshore wind turbines are subjected to probabilistic modeling followed by formulating reliability models while considering random variables, considering the degradation processes. Statistically based degradation models include the construction of limit state equations that associate degradation and the capacity of the structure. Risk assessment that includes probabilistic models translates the failure probabilities defined using Monte Carlo simulation or FORM/SORM to useful engineering outputs. Offshore wind foundation reliability is improved and scientifically rationalized through the proposed framework. It is computationally efficient and serves as a practical aid for the risk-aided inspection and maintenance of offshore wind energy systems, thus prolonging their operational sustainability (Montewka *et al*., 2018; Langdalen *et al*., 2019) [62, 46].

2.4. Software and Computational Framework

In constructing a risk-centric reliability model on offshore wind turbine foundations, sophisticated computing systems that have the capability to deal with various degradation processes, stochastic variability, and extensive spatial datasets will be a necessity. Deterministic and static approaches will struggle to model the reliability of the foundation, and will require the integration of numerical approaches, geospatial visualization, and probabilistic assessment (Aldosary *et al*., 2018; Xiong and Huang, 2020) [6, 95]. The backbone computing systems of the proposed framework will use Finite Damage and Vibration Response to model the response to fatigue and dynamic loads, the Integrity Element to simulate structural integrity and corrosive materials, and a Geographic Information System (GIS) to spatially represent risk. The integration of these systems allows for an extensive and multi-layered analysis of the degradation of the foundation, and streamlines the decision-making processes for inspection, maintenance and maintenance, asset preservation, and management, as shown in Table 1.

Table 1: Software and Computational Tools in Offshore Asset Management"

Tool / Software	Primary Function	Key Applications / Benefits
FDVR (Fatigue Damage and Vibration Response)	- Models fatigue accumulation in structural components under cyclic loading - Analyzes vibration response of assets in dynamic offshore environments.	- Predicts structural fatigue life of offshore platforms, turbines, and pipelines.- Supports maintenance planning and load management.- Reduces risk of unexpected structural failures.
Integrity Element	- Models corrosion progression and defect growth in metallic assets - Performs probabilistic reliability analysis to estimate failure likelihood over time.	- Enables risk-based inspection scheduling.- Supports life-extension studies and reliability-based maintenance.- Integrates inspection and monitoring data for informed decision-making.
GIS Mapping	- Spatial visualization of inspection results, environmental exposures, and asset locations.- Integrates multiple data layers (bathymetry, marine traffic, environmental zones).	- Facilitates site planning, hazard identification, and regulatory compliance.- Enables risk distribution analysis across multiple turbine sites.- Enhances communication of complex spatial data for stakeholders.

In offshore wind turbine foundations, fatigue damage is one of the most critical degradation processes. The Finite Damage and Vibration Response (FDVR) software allows for the modeling of accumulated fatigue damage under operational and dynamic environmental conditions.

FDVR models the history of stress due to the interactions of winds, waves, and currents, as well as the application of rain flow counting methods to the accumulation of stress cycles over time. These cycles are then correlated with the onset and the subsequent growth of fatigue cracks using fracture mechanics. Unlike deterministic design fatigue curves, FDVR incorporates the stochastic variables of fatigue design curves, such as variable wave heights, irregular current profiles, and correlated turbine load fluctuations to provide fatigue life estimates at probabilistic, rather than single-point, predictions (Faghihi *et al*., 2018; Ozguc, 2020) [26, 70]. This treatment of uncertainty improves the fidelity of reliability estimates by reducing the uncertainty in the estimated crack growth for the stochastic history of loadings.

An important aspect of FDVR's innovation is the capacity to incorporate the effects of marine growth on vibration modes. Biofouling changes the effective mass and stiffness of the submerged structural constituents and thus changes the natural frequencies of the system and increases the dynamic response of the system to resonance. By applying hydrodynamic coefficients modified by the thickness of marine growth, FDVR has the first-order approximation of how biofouling accelerates the accumulation of fatigue damage (Murallidharan, 2018; Earnest and Rachel, 2019) [65, 24]. This feature is important because most empirical fatigue models neglect the indirect, yet substantial, cumulative effects of biofouling and thus underestimate the rate of degradation. The FDVR approach captures the synergistic effects of marine growth and structural fatigue on the environmental loading to provide a more realistic prediction of the service life of the foundation.

Focusing on fatigue and dynamic responses, FDVR is complemented by Integrity Element, a structural integrity modeling platform, especially for the advancement of corrosion and probabilistic crack growth. The foundations of offshore wind turbines are steel structures that are very susceptible to electrochemical degradation in saline environments. Integrity Element models corrosion processes through the simulation of cathodic protection, the condition of protective coatings, and environmental factors like salinity and oxygen (Liu and Kelly, 2019; Andrade, 2019) [53, 8].

The software manages corrosion as a stochastic process that is a function of time. Different corrosion rates may be assigned to various foundation zones (e. g. splash zone, submerged zone, and mudline). The software allows users to define and allocate statistical distributions to the measurements of corrosion depth, reflecting in the predictions of the loss of wall thickness as a function of time (Hazra *et al*. 2020, Vachtsevanos 2020) [34, 85]. This method captures the fundamental corrosion uncertainties, which are dependent upon the microclimate, flow regime, and microclimate of individual sites, as well as the effectiveness of the corrosion control coatings.

Integrity Element also offers capabilities for modeling probabilistic crack growth (Ma *et al*. 2020, Tee and Pesinis 2020) [82]. The software also features the ability to simulate the propagation of cracks and other structural failures that appear as a result of cyclic loadings, by using the widely known Paris' law and other elements of fracture mechanics through the theory of structures, by means of incorporating randomness of the factors of the material, the stress intensity, and the history of loading. Outcomes of this ability allow for the risk of structural failures to be assessed, as crack growth behavior can be associated with certain reliability indices and failure probabilities. Combining the model of corrosion progression with the model of fatigue cracks, Integrity Element simultaneously resolves the corrosion loss and stress concentration problems associated with structural elements, providing a more comprehensive deterioration rate of the structure.

The Integrity Element facilitates the connection between inspection data and reliability modeling (OGUNNOWO *et al*., 2020; Lee *et al*., 2020) [68, 49]. For instance, inspection data, such as ultrasonic wall thickness measurements or ROV-based crack detections, can be used to update probabilistic models using Bayes' theorem. Thus, reliability predictions are aligned with actual observed structural conditions, which decreases epistemic uncertainty and increases decisional confidence.

In addition, while FDVR and the Integrity Element offer precise, detailed numerical modeling of the underlying degradation processes, the addition of Geographic Information Systems (GIS) mapping enhances the spatial dimension of the reliability assessment, allowing operators to assess degradation across an entire offshore wind farm. Offshore wind assets are geographically dispersed, and the degradation processes at different locations are associated with different spatial distributions due to environmental exposure, seabed conditions, and local hydrodynamics. GIS provides a spatial framework for integrating inspection data, model predictions, and environmental datasets (Gong *et al*., 2015; Wang *et al*., 2019) [31, 88].

Using GIS, metrics of degradation like corrosion depth, marine growth thickness, and fatigue damage index can be represented in geospatial layers and create intuitive illustrations of farm-wide foundation conditions and their development over time. These illustrations are instrumental for risk-based foundation prioritization by geolocating high-risk foundations needing urgent inspection or maintenance. Moreover, GIS correlation inspection data by risk grade so that spatial patterns and degradation drivers can be analyzed (Barman *et al*. 2020; Senanayake *et al*. 2020) [13, 77]. For instance, some foundations adjacent to tidal channels are fully subjected to increased fatigue loading due to stronger currents, while other foundations in shallow zones suffer accelerated biofouling.

Supporting predictive modeling from Environmental datasets (GIS integrated), wave heights, salinity, and currents with degradation models yielded risk maps with the ability to inform inspection schedules, resource allocation, and maintenance. Dually, GIS allows for the seamless support of decision-making for stakeholders by visualizing the geo-referenced models into decision-making tools that can be easily interpreted and manipulated to change maintenance and resourcing allocations (Wyszomirski and Gotlib, 2020; Li, 2020) [31].

The risk-based reliability model will be supported using the data up to October of 2021 for the FDVR, Integrity Element, and geospatial information system (GIS) functions of the system, each of which handles one side of the temporal, probabilistic, and spatial factors of foundation degradation and fracture, respectively. FDVR predicts biofouling impacts on vibration response and fatigue accumulation under stochastic loading. Integrity Element, primarily, assesses corrosion, probabilistic fracture, and data-driven modeling to corrosion inspections, modeling the voids in data-driven predictive corrosion modeling. The foundation trust assessment GIS incorporates numerically driven risk predictions and loss spatial data to allow for spatial risk assessment visualization, facilitating risk-informed decision-making across entire offshore wind farms (David *et al*, 2019; Peri and Tal, 2020) [21, 72].

The FIM and GIS Spatial Foundation Risk Model system enhances the operational agility of the offshore wind assets' foundation reliability. Barriers of deterministic, operational frameworks for investment appraisal, risk-informed strategic decision-making, and predictive risk modeling are integrated (Barlow *et al*, 2018; Seyr and Muskulus, 2019) [12, 78]. The windsocks of the offshore structure are interstate and wind-limited, standing as a cost-saving brute force fracture risk prediction model. This risk-based offshore foundation system increases the geospatial sustainability of offshore wind energy maintenance without structural failure.

2.5. Case Study / Model Application

In illustrating the case study for which the applicability of the risk-based reliability framework is employed for the foundations of offshore wind turbines, it utilizes a novel offshore wind farm in the North Sea. This hypothetical site is close enough to northern European offshore sites, as it experiences strong tidal currents, is moist with varying salinity levels, and is subject to immense wave energy, along with other northern European offshore structures. Although it is a hypothetical case, it still utilizes datasets available in the public domain which is reported in offshore wind projects in the literature, thus guaranteeing enough freedom while still anchoring the model's practicality.

The wind farm in question has an operational area of around 150 square kilometers and 60 turbines, each with a monopole or jacket foundation. The turbines sit in waters around 25 to 45 meters deep, in which both waves and tidal currents create an intense flow of energy and immense stress to the underwater structures. The site has been operational for eight years, during which various inspections have been documented by ROV surveys, diver inspections, and cathodic protection monitoring. These inspections provide valuable datasets and, as such, they are critical for the modeling of the probabilistic reliability model.

The case study tackles the integration of inspection data with a probabilistic modeling framework using a probabilistic approach.

Evidence supports the use of ROVs to take images and sonar scan monopile surfaces for marine growth thickness, which data suggests is between 5 and 15 cm in depth. Operators diving for ultrasonic inspections report evidence of corrosion to the cylinder walls, with the most damaged areas being located in the splash zones. These areas experienced a loss of corrugated thickness of up to 12%. Cathodic protection has measured fluctuating potential values for retraction of some monopile foundations less than others, which suggests decreases in protection (Adedoja *et al* 2018; Habibzadeh *et al*, 2019) [2, 33]. SCADA systems provided data on turbine loads and vibrations to correlate with operational data.

Data was cleaned, normalized, and interpolated. Missing corrosion data was identified and was reconstructed based on reasoning provided by Bayesian updating, which drew heavily on the work done on cathodic protection.

Finite Damage and Vibration Response (FDVR) is applied under a specific context with wave spectra and turbine load histories to simulate fatigue accumulation. Wear and tear corrosion simulation and spindle crack simulation integrated elements forwards and backwards, determining on inspection which wall thickness data serves as the most relevant baseline measures. Other probabilistic analysis was undertaken on Monte Carlo simulations of lower subsystems.

Gains from the FDVR and Integrity Element were then visualized as a final product, converting them to layers in a GIS file.

The analysis revealed risk profile variances for the monopile and the jacket foundations.

Monopile foundations exhibited higher fatigue risk due to larger diameters and increased hydrodynamic loading. Marine growth also considerably increased modal mass, thus amplifying vibration responses. Classifying approximately 20\% of monopiles as "high risk" poses an alarming fact, considering their probability of failure index is nearing acceptable boundaries within a decade if no measures are taken.

Although jacket foundations are structurally more redundant, their bracing joints are susceptible to localized corrosion (Okoro and Kolios, 2018; Gholami *et al*., 2019) [69, 28]. The effectiveness of cathodic protection varies within the farm, with 15% of jackets classified as "medium risk" due to accelerated wall loss in splash zones.

The remaining foundations classified as low risk are the monopiles and jackets located in deeper water, where biofouling is less intense, and cathodic protection is more effective. These foundations also maintained reliability indices above safety thresholds with high confidence.

This categorization, in turn, justified the allocation of inspection and maintenance resources to the high-risk monopiles, while the medium-risk jackets were kept under surveillance.

In order to analyze the complex outputs that result in actionable and strategic outputs, results were superimposed on top of the farm's layout using Geographic Information Systems (GIS). Each foundation was georeferenced, and risk categories were assigned color-coded symbols, with high-risk foundations colored in red, medium-risk risk in orange, and low-risk risk in green.

The GIS visualization showed spatial clustering of how patterns of degradation developed and spread. High-risk monopiles were clustered predominantly in the shallowest water regions near the tidal channels with the highest intensity of hydrodynamic loading and marine growth. Medium-risk jackets were also clustered near the periphery of the farm, where the rate of degradation of the cathodic protection anodes was greater due to increased current flow.

This form of spatial analysis was aimed at providing operators with better decision-making capabilities. For instance, GIS maps helped operators locate the "hotspot zones" that required inspection the quickest, as well as the rest of the regions deemed to be low risk, where inspection intervals could be extended. The synthesis of numerical models and geospatial visualizations, and direct inspection integrated raw inspection data to create an effective system of asset management to be used proactively (Mallela *et al*., 2018; Jones, 2019) [57, 40].

The case study demonstrates the application of a probabilistic, risk-based reliability framework on the inspection and operational data of the offshore wind turbine foundations. The model incorporated Fatigue, disbanded, Virtual Reality, corrosion, and simulation of random (stochastic) crack processes from Operated Vehicle (ROV) imagery, diver measurements, SCADA records, cathodic protection surveys, and integrity element simulations in a stochastic framework. Integrating Geographical Information Systems (GIS) to reliability outcomes visualization helped to improve the model's practical usefulness, which allows non-expert spatial risk assessment across the wind farms. The model gives the operators a new way to improve safety and regulatory compliance while decreasing maintenance costs, foundation lifecycle, and operational costs.

3. Conclusion and Future Work

The completion of a risk-based reliability framework for offshore wind turbine foundations, along with the marine risk analysis, is a milestone in the governance of enduring structural behavior performance in an indeterministic marine atmosphere. The suggested model combines underwater inspection data with probabilistic modeling and goes beyond the standard assessment and threshold assessment approaches that are contingent on deterministic models. Degradation mechanisms — marine growth, corrosion, and fatigue — and loss of stability and safety in the structural limit states of the foundation systems that govern the marine indeterminacies are what the model aims to measure. A calculated and sophisticated foundation reliability assessment is what the model aims to deliver by transforming the insight foundation behavior reliability from prescriptive to probabilistic. The assessment delves into the variability often omitted by deterministic models to streamline inspection, maintenance, and life extension efforts and make informed decisions.

The risk-based probabilistic framework has many distinct benefits compared to contributions made using deterministic approaches or threshold-based approaches. Unconditional approaches of estimating risk usually assume a safety factor of margins bounded above by specific limits set in advance of a given period of time. These rigidly set boundaries do not correlate with the actual conditions and may set off unnecessary countermeasures or pose severe shortcomings. On the other hand, the accuracy of a probabilistic model is said to be improved by performing more elaborate data collection and processing during actual inspections and reliability evaluations, resulting in the quantified reduction of various types of epistemic and aleatory uncertainties. Maintenance planning is improved with the ability to use real situational assessment to predict outcomes that incorporate timing and scheduling of inspections and maintenance. These technologically driven systems offer significant cost savings by targeting the most critical assets and components in use as well as improving the safe operational life of the systems and assets, all while safety is not compromised. In addition, the elastic framework encourages more open and frank discussion with governing bodies, potential or current backers, and other interested parties on the current structural status by offering measures such as indices of estimated life, reliability of system components, and system failure occurrence probabilities.

The asset managers can schedule maintenance which are data data-driven and which reduces downtime and catastrophic failures. Operators can counteract degradation trends and avoid downtimes, which lowers operational costs. Furthermore, the regulators can quantify and substantiate the evaluation of safety standard compliance, which fosters confidence for offshore wind investment. All these cases demonstrate the need for incorporating inspection-based reliability assessments, which are probabilistic, for inspections of offshore wind turbines that are to be deployed for extended periods, which are numerous w.r.t the growing offshore wind industry.

The expansion of restated inspection datasets aids in the statistical degradation of the proposed model. Numerous datasets from various regions and divergent environments, which, along with empirical data, enhance the framework for corrosion and, specifically, marine growth to strengthen the probabilistic deformation of the model.

The next possible step is how Digital Twin technology can be used for real-time structural health monitoring. Digital twins can integrate sensors, inspections, and probabilistic models to create dynamic working models of offshore foundations. This facilitates the continuous updating of reliability, real-time risk estimation, dynamic maintenance scheduling, and liability splitting, which it still predictive management of offshore assets.

Lastly, machine learning can help boost predictive reliability and detection of anomalies. Complex algorithms can assess inspection photos, acoustic data, and sensor data to capture levels of degradation that human operators may not detect. Also, machine learning models may be used to predict degradation profiles, working alongside probabilistic models and therefore further diminishing uncertainty. The integration of machine learning, digital twins, and probabilistic reliability modeling can be seen as offshore structural integrity management's leap forward.

The proposed risk-based reliability model is both scientific and practical for use in the offshore wind energy sector. The integration of inspection data and probabilistic reliability models makes it possible to devise more effective, efficient, and flexible maintenance strategies. With offshore turbine foundations expected to be used for long periods, integration with machine learning and digital technologies will further enhance their predictive reliability, ensuring safe and cost-effective maintenance.

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