Efficient Lifecycle Reliability Assessment of Offshore Wind Turbines using Digital Twin

XUKAI ZHANG and ARASH NOSHADRAVAN

ABSTRACT

The objective of this study is to develop a reliability assessment framework for the maintenance optimization of offshore wind turbines (OWTs) using an uncertainty-aware digital twin framework. OWTs are typically located far from the coastline to optimize wind utilization efficiency and minimize disruption of human activities. However, the greater distance between OWTs and the coast can increase maintenance costs due to accessibility and exposure to harsh weather conditions. Effective planning is crucial in managing these costs. Therefore, employing digital twin models for OWTs can provide potential benefits. A digital twin framework creates a virtual replica of the turbine and leverages multi-source data for real-time simulations, enabling assessment of the turbine's performance under various loading conditions, which can substantially enhance the maintenance decision-making process. The proposed framework has two main contributions: (1) uncertainty quantification in the long-term performance of OWTs at both the component and system levels, and (2) digital twin decision support leveraging OWT failure probabilities under various scenarios, which is used to provide maintenance recommendations aimed at optimizing system profitability and structural integrity. Additionally, the digital twin model provides clear and concise warnings regarding potential OWT failures.

INTRODUCTION

OWTs are strategically placed at a considerable distance from the coastline to harness the vast wind energy available in the ocean while minimizing interference with human activities. Wind farms, typically composed of multiple turbines, are experiencing significant growth. [1] However, the remote location of OWT poses a challenge in terms of maintenance due to the limited accessibility, leading to increased costs. And the maintenance of OWTs is expensive, accounting for up to 30% of the total operation cost. [2] Therefore, it is imperative to develop effective maintenance strategies and

Xukai Zhang, PhD Student, Email: zhxukai@tamu.edu. Zachry Department of Civil and Environmental Engineering, Texas A&M University, College Station, TX, USA.
Arash Noshadravan, Assistant Professor, Email: noshadravan@tamu.edu. Zachry Department of Civil and Environmental Engineering, Texas A&M University, College Station, TX, USA.

solutions to tackle the issue of soaring maintenance costs.

In conventional practice, maintenance strategies are categorized into two types: failure-based maintenance (also known as condition-based maintenance) and proactive maintenance. Condition-based maintenance is a reactive approach that involves performing maintenance tasks only after detecting a failure. Although several studies have focused on developing condition-based maintenance approaches, it has been demonstrated that this method is impractical and inefficient due to recurrent downtimes, costly repairs, prolonged waiting and repair times, and other associated factors [3–5]. Furthermore, real-time monitoring of OWT may be hindered by inclement weather and challenging environmental conditions.

Proactive maintenance can be further classified into two types: preventive maintenance and predictive maintenance. Preventive maintenance is typically reliant on expert experience and is scheduled based on the duration of operation or power generation. Since the actual condition of the wind turbine or any other operational data is not taken into account, it can be less efficient and more expensive. For instance, offshore weather conditions can be severe, and adhering to a predetermined maintenance schedule can be challenging. On the other hand, predictive maintenance leverages the advantages of constantly calculating the Probability of Failure (PoF) at the component level, utilizing information such as weather conditions and operational data. When the PoF exceeds a predetermined threshold, predictive maintenance is initiated to restore the component to its original condition. [3]

Despite the development of numerous maintenance logistics approaches in recent years, such as storing easily failed spare components on-site or in nearby locations, maintenance vessels and crews still need to access the OWTs. Therefore, while these solutions are beneficial, the current methods cannot effectively resolve the issue of high maintenance costs. Also, it is not feasible to have the maintenance team always available to address high PoF or non-critical component failures. Furthermore, the timing of maintenance should be carefully considered, taking into account unfavorable weather conditions, such as high wave height, that may increase the potential risk of transporting components.

This paper introduces an approach that concurrently displays both the reliability of individual components and the overall system within the digital twin model. This substantial enhancement aids in maintenance decision-making by incorporating critical factors such as weather conditions and power generation. By encapsulating all pertinent information within a digital twin model, the process of scheduling maintenance teams will be expedited, thereby augmenting the potential benefits of a wind farm.

SYSTEM AND COMPONENT RELIABILITY OF OWTS

The PoF for a wind turbine system is directly linked to the PoF of its individual components. To investigate, Kang et al. [6] conducted both qualitative and quantitative Fault Tree Analysis on OWTs, which consist of several assemblies that form a parallel system. These assemblies include support structures, pitch and hydraulic systems, gearboxes, generators, speed trains, electronic components, blades system, and yaw systems. Li and Soares [7] also examined the reliability of OWT by assessing its configuration,

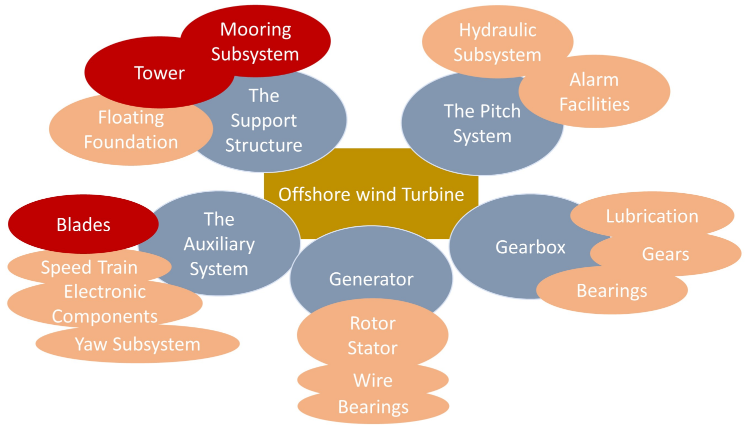

Figure 1. OWTs configuration with five subsystems depicted in blue. The subsystems are further divided into components, each with its own unique failure types. For this study, Tower, Blade, and Mooring Subsystems were Selected, along with their corresponding primary failure modes.

whereby each component in a configuration has its own sub-malfunction types, either parallel or series, which can result in system failure. However, current literature on OWT reliability assessment relies on historical data, which is unsuitable for real-time maintenance decision-making. In light of this, a method based on a high-fidelity OWT model is proposed to determine both system reliability and component reliability. The OWT configuration is divided into five parts: support structure, pitch system, gearbox, generator, and auxiliary system, each of which has its own subsystems, as illustrated in Figure 1. Through the identification of failure types for each subsystem, the risk assessment can be conducted for both individual subsystems and the system as a whole, utilizing a combination of parallel or series system analysis. The primary step in this process involves the construction of a limit state function for each failure type. This approach facilitates the computation of the PoF for every component within an OWT and the system at large, which can subsequently be utilized for predictive maintenance purposes.

This research identifies three main failure types that correspond to the three main components of an OWT: local buckling of the tower (Equation 1), bending stress on the blade root (Equation 3), and breaking of the mooring line (Equation 4). [8,9] Whenever a new limit state function is established for a specific failure type, it can be incorporated into the system failure function. Moreover, the effects of component deterioration have been considered, assuming linear deterioration for each component, which is reset to its original state after every maintenance session.

$$g_1 = \gamma_1 M_{cr} - Y_{L1} Y_{M1} M_T \tag{1}$$

$$M_{cr} = \left(1 - 0.84 \frac{D}{t} \frac{X_{y,ss} F_y}{X_{E,ss} E}\right) \frac{1}{6} \left(D^3 - (D-2t)^3\right) X_{y,ss} X_{cr} F_y \tag{2}$$

$$g_2 = \gamma_2 I_{b,r} \sigma_{b,f} / R_{b,r} - Y_{L2} Y_{M2} M_B \tag{3}$$

$$g_3 = \gamma_3 Q - Y_{L3} Y_{M3} T_M \tag{4}$$

$$P_{sys} = 1 - \prod_{i=1}^{n} [1 - p_i] \tag{5}$$

In the presented equations, γ_1, γ_2, and γ_3 are utilized as deterioration factors to account for the weakening of the structure over time. Assuming linear deterioration, the strength of the structure will decrease to 70% after one year of operation. This is represented mathematically as $\gamma_i = -0.0000133x + 1$, where x represents the time interval in 10-minute increments. The necessary data derived from the high-fidelity model of OWTs comprises the bending moment at the base of the tower, denoted by M_T, the bending moment at the blade root, denoted by M_B and the force exerted on the mooring line, denoted by T_M. These quantities are to be determined using the maximum values obtained during a one-hour modeling exercise, as recommended by [9]. M_{cr} is the critical bending moment capacity as shown in Equation 2. $X_{y,ss}$ and $X_{E,ss}$ are going to quantify the uncertainties for scale effect between test specimens and full-scale structures. D is the diameter of the tower while t is the thickness. F_y is the yield strength of the material. X_{cr} accounts for the natural modeling error of the test result. $I_{b,r}$, $R_{b,r}$, and $\sigma_{b,f}$ are respectively the second moment of the blade root section, the radius of blade root section, and blade tensile strength. Q is the breaking load capacity. Finally, as the OWT system consists of the blade, tower, and mooring line in a parallel configuration, the PoF of the OWT system can be expressed in Equation 5. p_i represents the PoF of the i -th (g_i) component (blade, tower, or mooring line) in the system, and n is the total number of components in the system. The distributions of the parameters used in the reliability analysis are defined in Table I.

DIGITAL TWIN FOR THE MAINTENANCE OPTIMIZATION OF A WIND FARM

OpenFAST, a high-fidelity wind turbine simulation tool developed by the National Renewable Energy Laboratory (NREL), is utilized to compute the response of the OWT under varying weather scenarios. OpenFAST is used to generate the time history of the structural response by inputting the mean wind speed and mean wave height. However, to ensure accurate results and account for transient effects during startup and initial operation, a burn-in period was necessary. In this study, a one-hour burn-in period was chosen, and the peak value was taken after a 30-second burn-in period, as recommended by literature [9]. With a single run of OpenFAST, a response of the OWT can be accessed, including the peak moments and forces necessary for calculating the PoF, as well as power generation in the period of time.

By executing OpenFAST multiple times, Monte Carlo Simulation can be utilized to determine the PoF for the subsystem using Equations 1, 3, 4, and for the systems using Equation 5. However, the Monte Carlo Simulation approach can be computationally expensive and inefficient, as it requires a large number of OpenFAST simulations to be executed. An alternative approach is to use a surrogate model, which can reduce

TABLE I. PARAMETERS USED IN THE RELIABILITY ANALYSIS [8, 9]

Parameter	Mean, covariance	Distribution
Young's Modulus, E (GPa)	210, 0.02	Lognormal
Yield Strength, F_y(MPa)	240, 0.05	Lognormal
Scale effect for yield strength, $X_{y,ss}$	1.0, 0.05	Lognormal
Scale effect for Young's Modulus, $X_{E,ss}$	1.0, 0.02	Lognormal
Modelling error for the adopted numerical model, X_{cr}	1.0, 0.1	Lognormal
Modeling error associated with the loading for tower and blade, Y_{L1},Y_{L2}	1.0, 0.22	Lognormal
Modeling error associated with the material properties for tower and blade, Y_{M1},Y_{M2}	1.0, 0.03	Lognormal
Blade tensile strength, $\sigma_{b,f}$ (MPa)	518, 0.03	Normal
Modelling error associate with the loading for mooring lines, Y_{L3}	1.0, 0.17	Lognormal
Modeling error associated with the material properties for mooring lines, Y_{M3}	1.0, 0.03	Lognormal
Breaking load capacity, Q (kN)	7334, 0.05	Lognormal

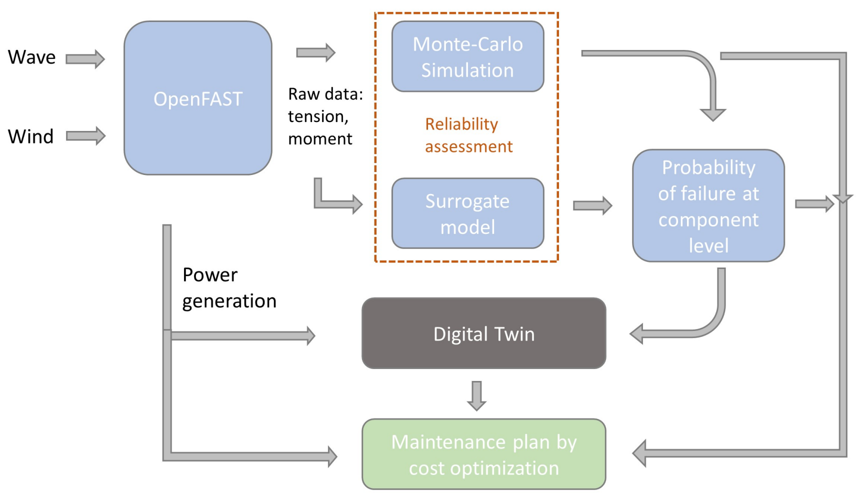

Figure 2. The framework of the digital twin aided maintenance optimization model.

the required number of samples and increase computational efficiency. [10] Reliability assessment by Monte Carlo Simulation or surrogate models can then be passed to visualization of digital twin models as it is shown in the framework in Figure 2.

Unreal Engine 5, a real-time 3D creation tool, is utilized to construct the digital twin display. The Message Queue Telemetry Transport (MQTT) protocol is employed to facilitate seamless data transmission between OpenFAST, reliability assessment, and Unreal Engine. MQTT protocol facilitates the rapid exchange of information between models. By visualizing the PoF for subsystems and systems of the OWT, critical components, and system reliability can be easily identified. Additionally, the digital twin display provides information on current weather conditions, power generation forecasts for future periods, past earnings, and maintenance costs in the user interface. The inclusion of current labor market information in the digital twin is also feasible. These data points can be leveraged to aid expert decision-making in planning future maintenance schedules and providing automatic warnings.

CASE STUDY FOR THE DIGITAL TWIN MODEL

In the case study, the modeling of the wind farm consists of 5 wind turbines, and the type is the 5MW OC4 DeepCwind semi-submersible wind turbine [11], which is included in the OpenFAST test archive and detailed parameters presented in Table II. The wind speed in the vertical directions is calculated using the logarithm law [12].

Historical data obtained from the National Data Buoy Center (NDBC) is utilized for predicting the mean wave height and mean wind speed in the wind farm area for a future period. However, this study did not involve making predictions based on historical data, but rather assumed acquired data as new for the purposes of analysis. This approach does not impact the validity of future studies that aim to make predictions based on historical data, as several studies have explored the use of historical data for wind and wave prediction [14,15]. The dataset includes the mean wind speed (represented every 10 minutes) and the mean significant wave height (represented every hour) recorded at 26.055N 93.646W, corresponding to station 42002 from NDBC. It is assumed that each data point represents the mean wind speed and significant wave height for a ten-minute interval and a one-hour interval, respectively. By feeding data into the OpenFAST, the response of OWTs can be obtained, such as moments and forces, and power generation prediction results. As shown in Figure 3, OpenFAST simulation results for the tension in the mooring lines have been shown under mean wind speed of 15 m/s and mean wave height of 5 meters, as well as the PoF analysis for the mooring line tension of a single OWT within 250 days period. Notably, the maximum PoF values for the tower base flapwise moment and the blade root flapwise moment are both 0, while for the mooring lines tension, it is found to be 0.000150. PoF escalates over time due to the gradual process of deteriora-

TABLE II. PROPERTIES OF THE NREL 5MW OC4 WIND TURBINE [9,13]

Rated power (kW)	5000
Cut-in, cut-out speed (m/s)	3 and 25
Rotor diameter (m)	126
Hub height (m)	90
The radius of blade root section, $R_{b,r}$(m)	1.77
Second moment of blade root, $I_{b,r}(m^4)$	0.566
Base section diameter and thickness (m)	126 and 61.5
Nominal diameter of mooring lines, d (mm)	77.9

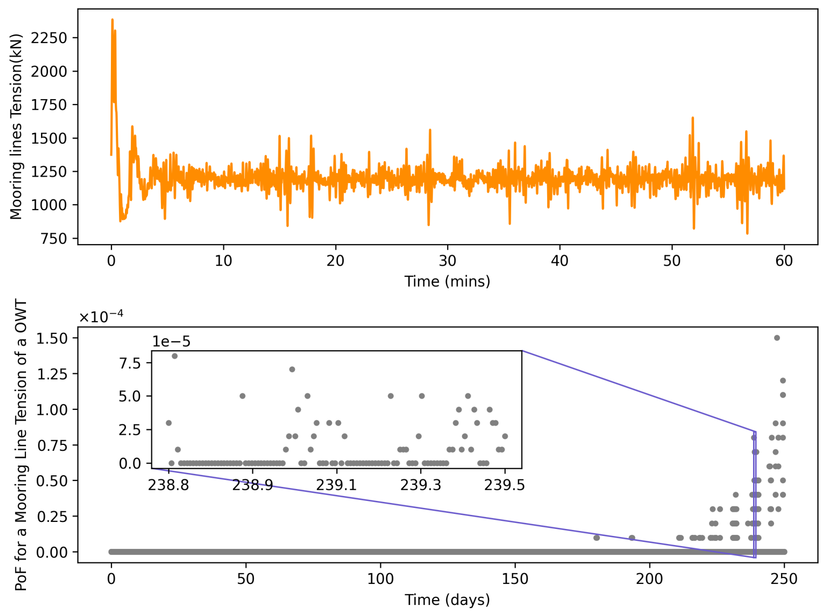

Figure 3. The OpenFAST simulation results for the tension (kN) in the mooring lines and the PoF analysis for the mooring line tension of a single OWT within 250 days period. The inset plot displays the PoF during a partial day between day 238 and day 239.

tion, while it remains low owing to the absence of severe weather conditions. Moments and forces will go into reliability assessment to calculate PoF using Equation 1-5, which will be transmitted to the digital twin model. By explicitly defining the threshold for the warning limit, the model can automatically assess the reliability of the component and issue an alert regarding the health status of the OWTs. Knowing the potential power generation, the digital twin model currently utilizes a fixed price for the power market, rather than incorporating imported market pricing data. However, in future work, it may be beneficial to incorporate labor market pricing data for repair work and component pricing, in addition to potential revenue data for the power market. Consequently, maintenance decisions can be readily made by subject matter experts armed with all necessary information, thus contributing to the cost optimization of maintenance.

CONCLUSIONS

This study introduces a novel approach based on the digital twin model for the reliability assessment of OWTs. The digital twin model offers decision-makers a comprehensive and timely risk-based decision-support tool with visualization of the critical information required to make informed decisions regarding OWTs maintenance. The approach integrates a wide range of data sources, including component failures, weather conditions, and market factors, which are displayed in a digital twin model.

The digital twin framework provides decision support based on predictive maintenance by providing real-time monitoring of the condition of OWTs in a wind farm, enabling preparation for potential events and ensuring that necessary resources are available. Additionally, the model incorporates data on harsh weather conditions and provides warnings directly on the screen, allowing stakeholders to make timely decisions regarding OWTs shutdowns in the event of any impairment. Moreover, the model can utilize advanced on-site sensors to import additional information, further enhancing OWTs' condition monitoring. Finally, the approach supports informed maintenance decisions that consider not only the conditions of OWTs but also market and weather conditions, thereby enabling profitable decision-making. It can also aid in assessing the profitability of a new wind farm using historical weather data.

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