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MAINTENANCE OPTIMIZATION OF FLOATING OFFSHORE WIND TURBINES: DIGITAL TWINS AND STOCHASTIC MODELING FOR UNCERTAINTY MANAGEMENT

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Abstract. Offshore wind turbines (OWTs) face high maintenance costs due to harsh and uncertain environmental conditions. Traditional maintenance strategies—whether fixed-schedule, failure-based, or risk-based—often fail to capture real-time weather impacts or gradual degradation under normal conditions. This study proposes a risk-informed, condition-based predictive maintenance strategy that incorporates environmental uncertainty to reduce costs and improve decision-making. The approach transforms the probability of failure of critical components into a condition factor used to trigger maintenance actions. Two key aspects are evaluated: (1) the cost-effectiveness of collectively maintaining spatially proximate turbines, and (2) the performance of the proposed predictive strategy versus traditional fixed-interval maintenance. Results show that grouped maintenance significantly reduces logistical costs, and the predictive strategy lowers the number of interventions while minimizing downtime, outperforming fixed-schedule approaches.

1 INTRODUCTION

Offshore Wind Turbines (OWTs) are often located far from the coast to maximize wind resource utilization and minimize interference with human activities. However, this distance poses significant challenges for maintenance operations, which are both logistically difficult and costly, accounting for up to 30% of the total lifecycle cost [1].

Traditional OWT maintenance strategies are categorized into two broad types: reactive (condition-based) maintenance and proactive maintenance. Reactive maintenance is performed after a component failure is detected. This approach is inefficient due to extended downtime and high repair costs. Proactive maintenance includes both preventive and predictive maintenance. Preventive maintenance relies heavily on expert judgment and follows a fixed schedule, which often fails to account for real-time offshore conditions or variations in weather patterns from historical trends. Predictive maintenance, on the other hand, uses historical data to forecast offshore conditions. Recent advancements include the risk-based maintenance strategy proposed by Zhang and Noshadravan [2], which introduces the method of estimating Probability of Failure (PoF) to schedule maintenance activities. This approach incorporates real-time offshore conditions through weather forecasting, and initiates inspection or intervention when the PoF exceeds a certain threshold. This can help in being more proactive in preventing catastrophic failures that may be difficult or time-consuming to repair [3].

However, even in the absence of extreme weather events—when PoF is low—OWTs continue to deteriorate due to harsh and variable environmental conditions. The inherent uncertainty in how and when this degradation occurs makes fixed, expert-judgment-based maintenance schedules less effective. This study builds upon the authors' previous work by introducing two key extensions to advance maintenance decision-making for OWTs. First, it proposes a risk-informed, condition-based predictive maintenance framework that explicitly addresses normal degradation processes, even in the absence of forecasted extreme weather events. The framework leverages real-time and forecasted environmental data and incorporates uncertainty in offshore weather conditions to support more adaptive and data-driven maintenance planning. A Digital Twin—serving as a dynamic digital replica of physical assets—facilitates data collection, transmission, and decision-making support. Second, recognizing that maintenance strategies must be tailored in multi-OWT installations due to spatial and temporal variability in weather and operational profiles, the study extends the framework to optimize maintenance across multiple turbines. By accounting for site-specific uncertainties and interdependencies, this extension enables more efficient and coordinated maintenance scheduling at the wind farm scale. Section 2 presents the proposed risk-informed, condition-based predictive maintenance framework. Section 3 provides a case study to demonstrate the effectiveness of the method. Section 4 presents the results and discussion. Section 5 concludes the paper.

2 RISK-INFORMED CONDITION-BASED PREDICTIVE MAINTENANCE

The overall framework is illustrated in Figure 1. OpenFAST, a high-fidelity simulation tool for OWTs, is employed to model turbine responses under varying offshore weather conditions. Environmental inputs, such as mean wind speed and mean wave height—following the settings in [2]—are used in conjunction with TurbSim to generate realistic wind and wave spectra. These spectra serve as inputs to OpenFAST, enabling the simulation of structural responses of OWT components.

The resulting mechanical responses are used to estimate the PoF using a Limit State Function (LSF), typically defined as $g = R - S$, where R represents structural resistance and S denotes the applied loading. The PoF is then computed as the probability that $g < 0$, which can be numerically estimated using Monte Carlo Simulation. Additionally, variability in the generated wind and wave fields introduces stochasticity into the OpenFAST outputs, further contributing to uncertainty in the response.

The computed PoF is then transformed into a condition factor that reflects the current degradation state of the component or system. This condition factor is updated at each time step and reintroduced into the LSF to inform subsequent PoF evaluations. Maintenance decisions are guided by comparing the condition factor to predefined threshold values.

2.1 Limit State Function and PoF Estimation

To illustrate the proposed framework, the tower component of the OWT is employed as a representative subsystem, with simulated dynamic responses generated using the OpenFAST aero-hydro-

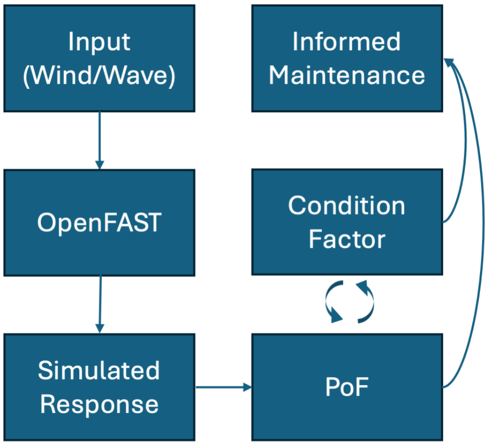

Figure 1: The framework of the risk-informed condition-based predictive maintenance.

servo-elastic modeling tool. A common failure mode of the tower is local buckling. The LSF representing this failure can be expressed as [2, 4, 5]:

$$g_1 = \gamma_1 \left(1 - 0.84 \frac{D}{t} \frac{X_{y,ss} F_y}{X_{E,ss} E}\right) \frac{1}{6} \left(D^3 - (D - 2t)^3\right) X_{y,ss} X_{cr} F_y - Y_{L1} Y_{M1} M_T \tag{1}$$

where γ_1 is the condition factor associated with loading for the tower. E is the Young's Modulus. $X_{y,ss}$ and $X_{E,ss}$ are scale effect uncertainties for yield strength and Young's modulus, respectively. D is the tower diameter, t is tower thickness. F_y is the yield strength. X_{cr} is the modeling uncertainty for the test result. Y_{L1}, Y_{M1} are modeling errors associated with loading and material properties. M_T denotes the base bending moment of the tower (obtained from OpenFAST simulations).

Table 1 summarizes the statistical distributions of these model parameters, including means and coefficients of variation (COV).

Table 1: Parameters used in general modeling in the reliability analysis[4, 5].

Parameter	Mean, COV	Distribution
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, Y_{L1}	1.0, 0.22	Lognormal
Modeling error associated with the material properties for tower, Y_{M1}	1.0, 0.03	Lognormal

Using Equation 1, the PoF, $P_f = P\left(g \leq 0\right)$, can be evaluated through Monte Carlo simulation or efficiently approximated using surrogate models [2].

2.2 Mapping Risk Metrics to Condition Factors

The predicted PoF is converted into a condition factor, reflecting the real-time health status of the component. Initially, a linear deterioration model is considered, with a PoF threshold of 0.25

representing the failure limit. However, linear models often lead to an unrealistic, rapid reduction in resistance after early degradation. To address this limitation, we introduce a nonlinear deterioration function that captures a more gradual and realistic decay, particularly under low PoF conditions. The function is designed to accelerate degradation only as the PoF approaches the failure threshold. The proposed decay model is:

$$\gamma_1{}' = \gamma_1 \times \left(1 - (1 - \mathrm{CF}_{\mathrm{min}}) \left(\frac{p_f}{p_{f,\mathrm{max}}}\right)^m\right) \tag{2}$$

where:

- γ_1: current condition factor,
- $\gamma_1{}'$: updated condition factor,
- p_f: current PoF,
- $p_{f,\mathrm{max}}$: PoF threshold (default 0.25),
- $\mathrm{CF}_{\mathrm{min}}$: minimum allowable condition factor (default 0.999),
- m: decay curve exponent (default 2.0).

2.3 Risk-informed Condition-based Maintenance Decision-making

By transforming the PoF into a condition factor, the proposed approach accounts for both the environmental conditions (e.g., wind and wave conditions) and the structural response metrics to support more informed and objective maintenance decision-making. This method helps avoid unnecessary interventions during extended periods of benign conditions, while ensuring timely action when degradation accelerates—even in the absence of extreme events. Moreover, it reduces reliance on subjective expert judgment by introducing a quantifiable, risk-informed decision variable tailored to site-specific conditions.

In practice, since maintenance is generally infeasible during extreme weather, the framework assumes that if the condition threshold is exceeded during such periods, maintenance is scheduled immediately afterward. This ensures that all interventions occur during relatively calm conditions, resulting in consistent transportation costs regardless of the exact start date. The remaining cost variability is primarily attributed to fluctuations in labor and electricity markets, which may influence the optimal timing of maintenance. As a result, maintenance activities can be initiated a few days prior to the predicted threshold breach, depending on prevailing market conditions.

Additionally, it is assumed that each maintenance operation involves inspection and partial repair of all turbines within the affected vicinity, not only those exceeding the condition threshold. Post-maintenance, each turbine's condition is assumed to recover to 90% of its original state, acknowledging that not all degradation can be fully addressed during a single intervention.

3 CASE STUDY

The 5MW OC4 wind turbine used in this study shares the same design—featuring three blades—as the monopile-based NREL 5MW reference turbine. Detailed turbine parameters are provided in Table 2. Three turbines are considered in the simulation. To simplify the analysis, this study focuses solely on the tower component of the OWT, specifically considering failure due to local buckling. A condition threshold of 70% is used to trigger maintenance decisions.

Table 2: Parameters for the 5MW OC-4 OWT in this study.

Parameter	Value	Distribution	References
Rated power (kW)	5000	Deterministic	[5, 7]
Cut-in, cut-out speed (m/s)	3 and 25	Deterministic	
Blade rotor diameter (m)	126	Deterministic	
Hub height (m)	90	Deterministic	
Tower base section diameter and thickness (m)	6.5 and 0.027	Deterministic	
Young's Modulus, E (GPa)	Mean = 210, COV = 0.02	Lognormal	[4, 5]
Yield Strength, F_y (MPa)	Mean = 240, COV = 0.05	Lognormal	

3.1 Environmental Inputs for OpenFAST

To simulate extreme conditions representative of a hurricane season, modifications were applied to the original dataset between days 50 and 100. During this period, wind speed was increased by 35 m/s and wave height by 10 meters, mimicking a hypothetical hurricane scenario. These modifications are illustrated in Figure 2, which presents the adjusted wind and wave profiles.

Environmental data were collected from a buoy located at 26.055° N, 93.646° W in the Gulf of Mexico, obtained through the National Data Buoy Center (NDBC). Wind speed data (WSPD) were recorded every 10 minutes, and significant wave height (WVHT) data were collected hourly. The dataset covers the period from January 1, 2022, to December 31, 2022. Wind speeds were measured at an anemometer height of 4.1 meters above sea level. Wave height represents the average of the highest one-third of wave heights recorded during a 20-minute sampling interval and was used as the mean wave height for each time step in this study.

3.2 Multi-OWT System Configuration

Since upstream OWTs influence the local wind field through wake effects, the turbines in this study are arranged as shown in Figure 3, such that the wake from an upstream turbine affects those downstream.

Turbine 1 is not influenced by any other turbines and thus directly experiences the original environmental conditions. Turbine 2 is placed farther downstream, where the wind and wave conditions are slightly attenuated due to wake effects. Turbine 3 is positioned closer to Turbine 1 and is more strongly affected by the wake. Based on the Gaussian analytical wake model [8], the wind and wave inputs for Turbine 2 are modeled as Gaussian-distributed with a mean of 0.98 and standard deviation of 0.01, while Turbine 3 follows a distribution with a mean of 0.95 and the same standard deviation.

3.3 OpenFAST Simulation and PoF Estimation

After defining wind and wave conditions for Turbine 1 and adjusting them via Gaussian distributions for Turbines 2 and 3, inputs for OpenFAST simulations were established. Given the computational cost of running OpenFAST for an entire year with full uncertainty quantification, a simplification strategy was adopted.

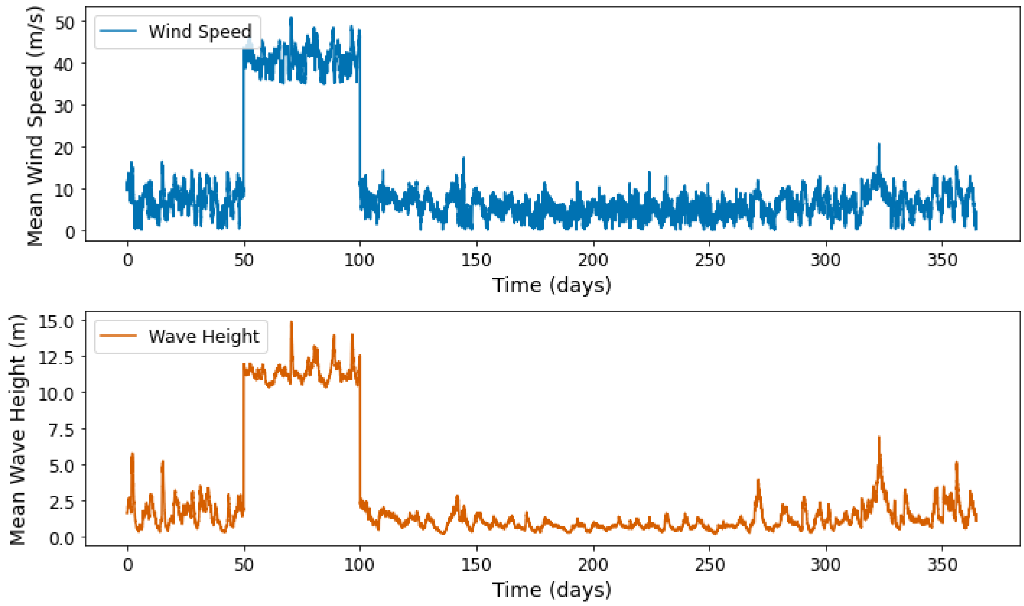

Figure 2: Wind and wave conditions, including synthetic hurricane scenario.

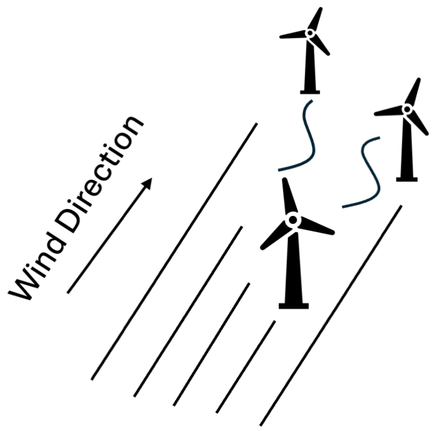

Figure 3: Turbine layout and wake interaction.

A set of representative environmental scenarios was preselected, encompassing wind speeds from 3 to 65 m/s (specifically 3, 5, 10, 15, 20, 25, 35, 45, 55, and 65 m/s) and wave heights of 5, 10, and 15 meters. All wind-wave combinations within this set (e.g., 3 m/s wind with 5 m waves, 3 m/s with 10 m, etc.) were simulated 100 times each using OpenFAST. These simulations captured the mechanical responses and power outputs of the OWT under various operating conditions. For each scenario, a Gumbel distribution was fitted to the 100 output samples, serving as a surrogate model for that specific environmental condition.

When new wind-wave conditions arose in later simulations, the nearest precomputed scenario was identified based on a proximity search within the predefined set. The corresponding Gumbel distribution was then used in place of rerunning OpenFAST, substantially reducing the computational burden.

Finally, a Monte Carlo Simulation with 100,000 iterations was conducted using these pre-defined Gumbel distributions to estimate the PoF for each turbine. This approach efficiently balances computational feasibility with the need for uncertainty-aware reliability assessment.

4 RESULT AND DISCUSSION

Assuming that each maintenance operation includes condition assessments for all neighboring turbines, the PoF is shown in Figure 4, with the corresponding condition factors are presented in Figure 5.

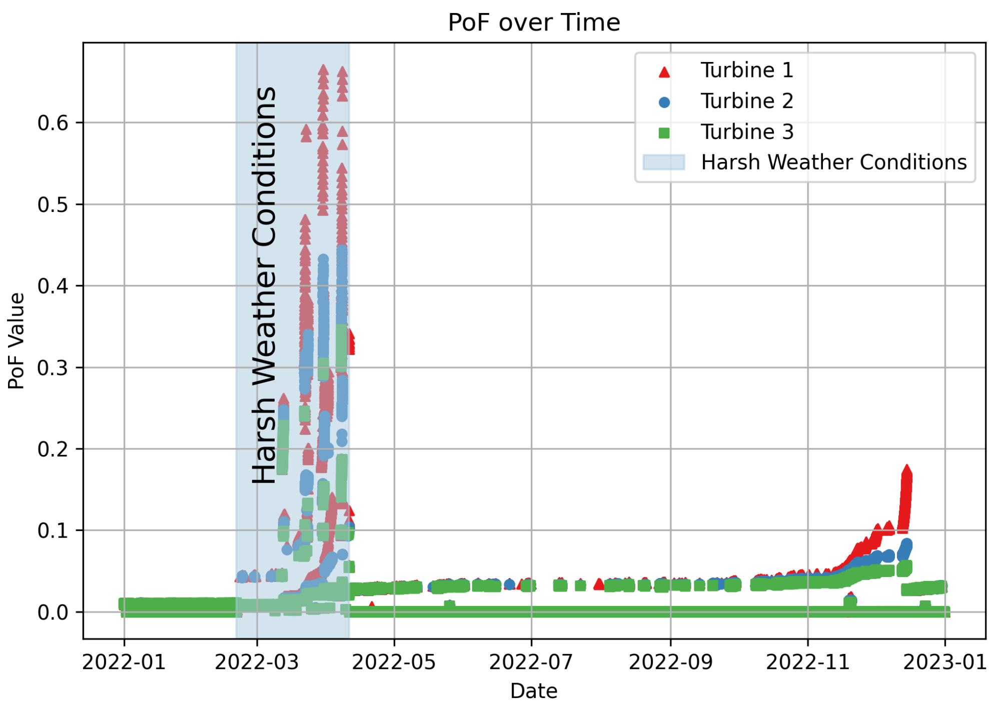

Figure 4: Probability of Failure when turbines are maintained together.

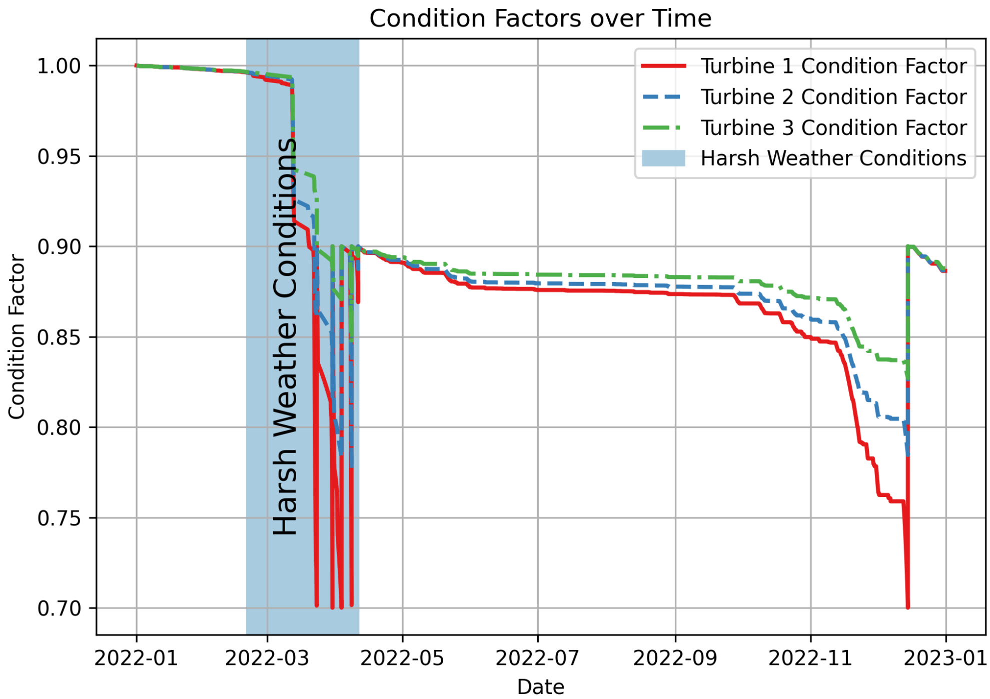

Figure 5: Condition factors when turbines are maintained together.

4.1 Comparative Maintenance Strategies: Single vs. Multiple Turbines

For comparison with the scenario in which each turbine is assessed independently, the temporal evolution of PoF is shown in Figure 6, with the corresponding condition factors presented in Figure 7.

Comparison of Figures 5 and Figure 7 reveals that each turbine exhibits a distinct deterioration rate driven by varying wind and wave conditions. As a result, condition factors differ across turbines. If maintenance is only performed on turbines reaching their condition limits, separate mobilization efforts are required, leading to increased costs. Alternatively, performing condition assessments and partial maintenance on all nearby turbines during a single offshore visit may slightly extend operational time but can significantly reduce overall transportation expenses. Given that offshore labor costs are generally lower than transportation costs, this study advocates a clustered maintenance approach as a more cost-effective strategy. Furthermore, while deterioration rates vary, turbines located in close proximity typically experience similar environmental loading, supporting the practicality and efficiency of collective maintenance operations.

4.2 Comparison of Fixed-Interval and Condition-Based Predictive Maintenance

To evaluate the proposed risk-informed, condition-based predictive maintenance strategy, three approaches are compared:

- Bimonthly Maintenance + Failure-Based Repair: Fixed inspections every two months with additional repairs upon failure.
- Half-Yearly Maintenance + Failure-Based Repair: Less frequent inspections (every six months)

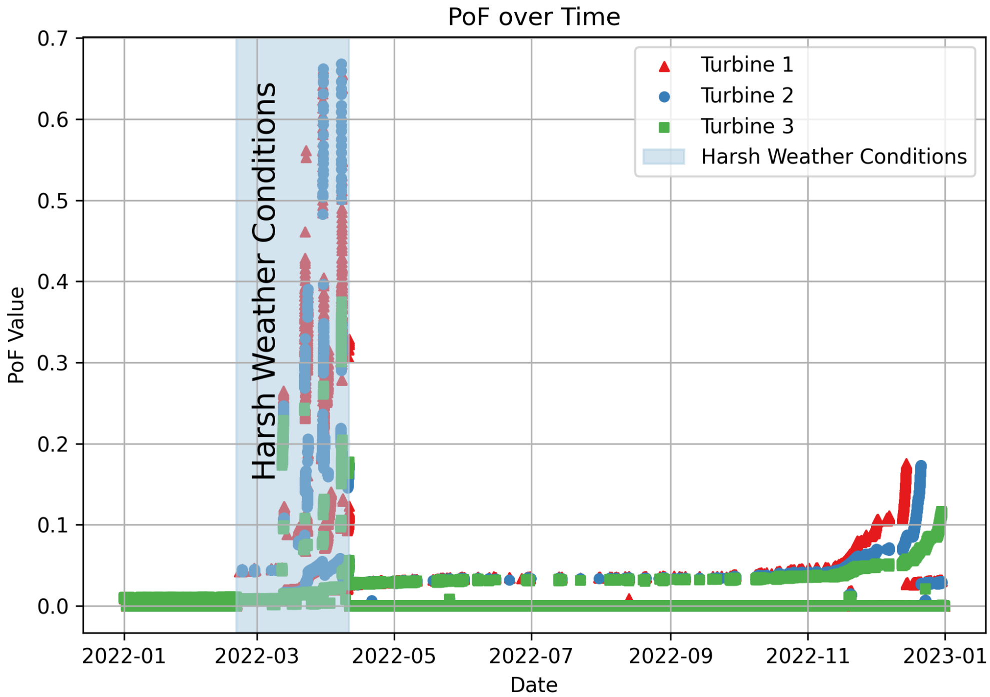

Figure 6: Probability of Failure when turbines are maintained separately.

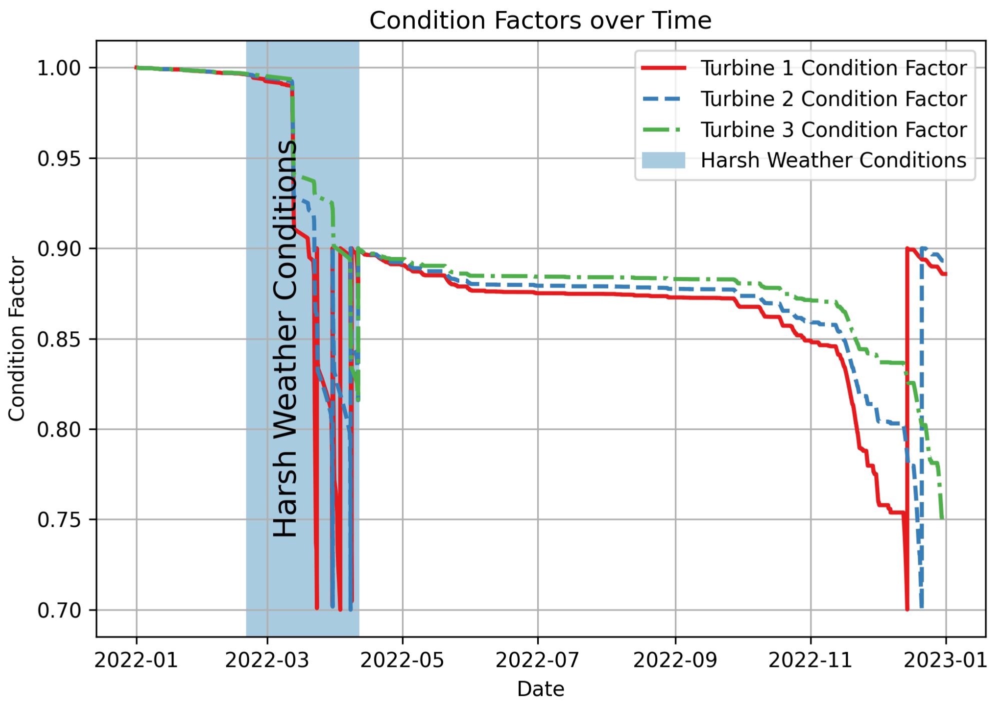

Figure 7: Condition factors when turbines are maintained separately.

with reactive repair upon failure.

- Proposed Risk-Based Condition Monitoring: Maintenance is triggered based on a predictive model using condition factors informed by environmental data.

Table 3 summarizes the comparison. Although bimonthly maintenance results in the highest number of inspections (six per year), it still carries risks of unexpected failures and associated downtime. The half-yearly approach reduces the number of inspections but increases the likelihood of severe failures due to delayed detection. The proposed method, as illustrated in Figure 5, results in two maintenance events, driven by predictive modeling of turbine condition based on weather forecasts. This approach significantly reduces both inspection frequency and the likelihood of catastrophic failure.

Table 3: Comparison of maintenance strategies in the year of the case study

	Bi-Monthly + Failure-Based	Half-Yearly + Failure-Based	Risk-Based Predictive
Risk	Moderate: Failures may occur between checks	High: Longer intervals increase failure risk	Low: Depends on weather prediction accuracy
Maintenance Frequency	6 times/year	3 times/year	2 times/year
Proposed Cost	\$72,000	\$36,000	\$24,000

Assuming each maintenance event includes 10 crew members, with a major turbine requiring 3 days of work and checking nearby turbines requiring 1 additional day, the cost can be estimated. At a daily labor cost of \$100 per crew member and a transportation cost of \$8,000 per visit, the proposed strategy demonstrates substantial savings over traditional approaches, as shown in Table 3.

5 CONCLUSIONS

Reducing the maintenance cost of Offshore Wind Turbines remains a key challenge, primarily due to the high cost associated with offshore operations. This study addresses this challenge by incorporating uncertainty in offshore weather conditions into a risk-informed, condition-based predictive maintenance framework. Using high-fidelity OpenFAST simulations to estimate the probability of failure of OWT components, a condition factor is derived to guide maintenance decision-making.

A comparison between individual and grouped turbine maintenance strategies reveals that coordinated maintenance of neighboring turbines enhances operational efficiency and reduces overall costs. Furthermore, when benchmarked against traditional fixed-interval maintenance, the proposed predictive strategy demonstrates clear advantages—reducing the frequency of inspections while maintaining system reliability, thereby minimizing both downtime and total maintenance expenditure.

Overall, this study demonstrates the feasibility and effectiveness of integrating environmental uncertainty into maintenance planning and highlights the potential for substantial cost savings through a risk-informed approach to offshore wind turbine asset management.

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