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Structural reliability assessment of deteriorating offshore wind turbine monopiles for extreme limit states

Ali Khodam

Department of the Built Environment, Aalborg University, Denmark. E-mail: alkh@build.aau.dk

Jannie Sønderkær Nielsen

Department of the Built Environment, Aalborg University, Denmark. E-mail: jsn@build.aau.dk

Abstract: Offshore wind turbines are exposed to various deterioration mechanisms in harsh marine environment. Steel corrosion in sea-water is one of the major and most expensive challenges for their long-time structural integrity. This degradation introduces significant uncertainty in predicting structural performance over time, making structural reliability analysis and uncertainty quantification necessary for safe and cost-effective design, maintenance and life-extension strategies. In this study, a bi-modal corrosion model is utilized to estimate corrosion-induced material loss in offshore wind turbine monopiles and to model uncertainty for assessing their structural reliability. The model is able to capture variability and uncertainty in corrosion loss, which makes it suitable for reliability analysis under realistic conditions. Furthermore, the model is calibrated based on seawater temperature, allowing the consideration of temperature/climate effects on corrosion loss and structural reliability of deteriorating monopile foundations supporting offshore wind turbines. Structural reliability of both pristine and deteriorated components which have been designed using safety factors provided by IEC 61400-1 ed. 4 are estimated for several extreme load cases. For each load case, reliability is evaluated for two representative mean annual sea-water temperature conditions corresponding to different wind farm locations. The reduction in reliability level due to corrosion in the final year of the planned lifetime of OWTs, which can be used for life extension studies, is also quantified. Results illustrate that corrosion loss can result in up to 18% reduction in the reliability level of the considered OWT monopile. The results contribute to a more comprehensive understanding of how environmental factors and material degradation affect structural reliability and performance, supporting site-specific risk-informed decision-making for inspection, maintenance, and life-extension strategies in offshore wind energy infrastructure.

Keywords: Target reliability; Extreme load; Reliability of deteriorated structures; Offshore wind turbine deterioration, Steel corrosion.

1. Introduction

Structural elements of offshore wind turbines (OWTs) that are influenced by ageing and deterioration experience a reduction in load-bearing capacity and an increase in their fragility under both extreme and operational loading conditions (Brijder et al., 2022). This increase in vulnerability is particularly important because OWTs operate in highly degradation-prone marine environment where they are continuously exposed to environmental loads such as wind and wave loads and may also be subjected to natural hazards like earthquakes.

Among various deterioration mechanisms, corrosion is one of the most critical and costly challenges for offshore wind infrastructure (Duguid, 2017). The marine environment, especially in regions such as the North Sea, is characterized by high corrosion rates that accelerate the degradation of steel components (Khodabux et al., 2020). Field observations have revealed that corrosion-protection and paint systems on OWT structures may fail after a few years of service (Khodabux et al., 2020), leaving the underlying steel surface exposed to corrosive seawater and harsh climatic conditions. This not only increases inspection and maintenance demands but also poses significant risks to structural integrity, fatigue life, and overall safety (Brijder et al., 2022). Consequently, estimating corrosion degradation is essential for assessing the long-term structural reliability and economic viability of offshore wind energy systems.

A critical factor intensifying steel corrosion is the rise in sea-water temperature, which has been shown to significantly increase corrosion rates in steel structures (Melchers, 2003a). While previous studies have primarily concentrated on corrosion-fatigue and its implications for structural performance (Mehmanparast & Vidament 2021; Shamir et al. 2023), the direct impact of corrosion-induced metal loss on the fragility and reliability of OWT monopiles needs to be addressed. This makes deterioration modeling more accurate and comprehensive, which is essential for time-dependent fragility assessments, particularly when evaluating life-extension strategies for existing wind farms. Without incorporating corrosion loss into structural reliability assessment, predictions of failure probability may be optimistic, potentially compromising structural safety and economic feasibility. This paper evaluates the impact of corrosion loss on the structural reliability of OWT monopiles. A bimodal corrosion model is utilized to estimate corrosion-induced material loss. The effect of sea-water temperature on corrosion loss and its associated uncertainty is also investigated through the corrosion model. Reliability of both pristine and deteriorated OWT monopiles designed using partial safety factors provided by IEC 61400-1 ed. 4 (International Electrotechnical Commission, 2019) are assessed for extreme design load cases. The reduction in structural reliability level due to corrosion in the final year of the planned lifetime of OWTs, is also quantified.

2. Corrosion modelling

Corrosion in steel offshore structures progressively reduces metal thickness, diminishing structural load-carrying capacity and increasing the likelihood of failure under various loading conditions. Accurately predicting corrosion-induced metal loss throughout the service life of OWTs is therefore crucial for obtaining realistic structural response, reliability estimation and maintenance planning. This task is, however, highly complex due to the stochastic nature of steel corrosion progression, which depends on multiple environmental and operational factors. To address this challenge, several corrosion models were developed, primarily within the maritime, oil and gas, and shipping industries, leveraging extensive datasets collected from ship hulls and ballast tanks. For instance, Kim et al. (2020) introduced a time-dependent probabilistic corrosion model for steel structures based on the data from ballast tank deterioration in ships. Their approach estimates the parameters of corrosion-loss probability distributions as a function of exposure time, capturing the uncertainty associated with corrosion evolution. Zayed et al. (2018) proposed a corrosion model for steel plates of ship hulls based on limited information on local environmental conditions. They used corrosion data from ballast and cargo tanks for calibration of their proposed model. Melchers (2003a) proposed a bi-modal corrosion model that has been widely used in various structural applications. This model, developed using real-world data and grounded in fundamental corrosion principles, includes two modes: an aerobic mode and an anaerobic mode associated with microbiologically induced corrosion (MIC). The aerobic mode consists of phase 0 (activation), followed by cathodically controlled corrosion in which oxygen diffusion controls the corrosion process: first by oxygen diffusion through the water near the steel surface (phase 1) and then through the increasing corrosion products (phase 2). The anaerobic mode includes a transient phase with decreasing hydrogen diffusion (phase 3) and a long-term steady-state corrosion phase (phase 4) characterized by a linear behaviour. In this study, the bi-modal model is utilized due to its capability to account for sea-water temperature and the uncertainty associated with corrosion. This model effectively captures the long-term corrosion loss, providing a realistic representation of time-dependent degradation. The model is formulated based on sea-water temperature, allowing corrosion loss to be evaluated at any point during OWTs lifecycle. Corrosion loss is expressed as a function of the exposure time, t, using the following general formulation (Melchers, 2003b):

$$c(t) = b(t)f(t) + \varepsilon(t) \tag{1}$$

where $f(t)$ is the mean corrosion-loss function, $b(t)$ is a bias function with a unit mean value, and $\varepsilon(t)$ is a zero-mean uncertainty term. The probability bounds for the expected corrosion loss can be estimated using the following expression for the variability (standard deviation) of corrosion loss, σ_c, as given in (Melchers, 2003b):

$$\sigma_c = (0.006 + 0.0003T)(\frac{t}{t_a}) \quad (2)$$

where T denotes sea-water temperature, t is the exposure time (in year), and t_a represents the time at which anaerobic corrosion initiates. The uncertainty was estimated based on field data and the corrosion model bias. Since this study focuses on long-term corrosion, the corrosion loss is estimated using the Phase 4 formulation of the bi-modal corrosion model, which is linear in time:

$$c(t) = r_s t + c_s \quad (3)$$

where r_s is the corrosion rate in phase 4 and c_s is the intercept at $t = 0$ on the corrosion-loss axis. Once the corrosion loss is obtained using the bi-modal corrosion model, cross-sectional properties such as section modulus and cross-sectional area are updated. r_s and c_s are both formulated in terms of mean annual sea-water temperature (T) as follows (Nielsen et al., 2025):

$$r_s = 0.039 \exp{(0.0254T)} \quad (4)$$

$$c_s = 0.141 - 0.00133T \quad (5)$$

3. Structural reliability assessment

This section details the structural reliability assessment framework for OWT components designed in accordance with the partial safety factors specified in Edition 4 of IEC 61400-1 (calibrated for a reliability target of $\beta = 3.3$).

3.1. *Reliability model*

The design equation for extreme design load cases (DLCs) is as follows (IEC TS 61400-9, 2025):

$$G = z\frac{1}{\gamma_M}R_k - \gamma_n \gamma_f F_k \geq 0 \quad (6)$$

In this equation, z refers to the design parameter, for example cross-sectional area and section modulus. The terms R_k and F_k represent the characteristic values of structural resistance and load effect, respectively. γ_M, γ_n, and γ_f are partial safety factors. The partial safety factor for resistance, γ_M, is taken as 1.2 for the characteristic value corresponding to the 5% fractile. γ_n is the partial safety factor accounting for the consequence of failure, and its value is taken as 1.0 in this study (corresponding to the component class 2). The load safety factor for normal design situations is γ_f=1.35. As an exception, this safety factor for DLC 1.1 (with load extrapolation) is reduced to γ_f=1.25. For the load case with only gravity loading, the load safety factor is γ_f=1.1. The characteristic value of load effects corresponds to the 98% quantile of the annual maximum load distribution. The only exception is gravity loading where the mean value is applied. For the typhoon class defined in IEC 61400-1, the safety factor for normal situations can be used for the design. However, it specifies (in a footnote) that this factor assumes a coefficient of variation (COV) of annual maximum wind speed below 15% and if COV exceeds this threshold, the load safety factor can be linearly increased by a multiplier η, ranging from 1.0 at COV of 15% to 1.15 at COV of 30%. However, since it is not a requirement, the design may be performed based on the safety factor of γ_f=1.35 for normal situations (Nielsen et al., 2023). Using the design equation (together with the safety factors), the design parameter z is calculated for the given characteristic values associated with resistance and load effects. Reliability analysis is performed to compute the annual reliability index associated with the given design parameter z. The limit state for reliability assessment is formulated as:

$$g = z\delta R X_{Str} - X_{Site}X_{Aero}X_{Dyn}X_{Mat}X_{Wind}X_{Sim}F \quad (7)$$

where z denotes the design parameter, R represents the resistance, and F represents the load effect. The term δ captures model uncertainty in the resistance model, while X_{Str} reflects uncertainty in the stress/strain model. Additional uncertainty parameters include X_{Site} for site and atmospheric conditions, X_{Aero} for aerodynamic properties, X_{Dyn} for structural dynamics, X_{Mat} for material and geometric variations, X_{Wind} for the wind model, and X_{Sim} for statistical uncertainty due to limited wind condition simulations. The stochastic model parameters for load effect and resistance variables are summarized in Tables 1 and 2, respectively. For the load case with Typhoon, a COV of 50% is assumed for the load effect, corresponding (approximately) to a COV of 25% for wind speed (Nielsen et al., 2023). In this study, wind pressure/speed is modeled using a Gumbel distribution. The reliability model is in accordance with (IEC TS 61400-9, 2025).

Table 1. Statistical parameters for load effects (Nielsen et al., 2023)

Variable	Distribution	Mean	Characteristic value	COV	COV	COV	COV
				DLC 1.1 & 1.3	DLC 6.1	DLC 6.1 (Typhoon)	Gravity Loading
X_{Site}	Lognormal	1.00	μ	10%	10%	10%	0%
X_{Aero}	Lognormal	1.00	μ	10%	10%	10%	0%
X_{Dyn}	Lognormal	1.00	μ	5%	5%	5%	0%
X_{Mat}	Lognormal	1.00	μ	5%	5%	5%	5%
X_{Wind}	Lognormal	1.00	μ	10%	10%	10%	0%
X_{Sim}	Lognormal	1.00	μ	5%	5%	5%	0%
F	Gumbel/ Gumbel/ Gumbel/ N		98%/ 98%/ 98%/ μ	5%	23%	50%	5%

Table 2. Statistical parameters for resistance (Nielsen et al., 2023)

Variable	Distribution	Mean	Characteristic value	COV
δ	Lognormal	1.00	μ	5%
R	Lognormal	-	5%	5%
X_{Str}	Lognormal	1.00	μ	5%

When the limit state function and the reliability model are completely characterized, the annual reliability can be assessed using structural reliability techniques, such as the First-Order and Second-Order Reliability Methods (FORM and SORM), and advanced simulation-based methods. In this paper, reliability index is obtained by FORM. Limit state function for reliability analysis of deteriorating monopiles is modified by incorporating a strength retention factor into the first term on the right-hand side of Equation (7).

3.2. First-Order Reliability Method (FORM)

Structural reliability assessment aims to estimate the probability of failure or the reliability index associated with predefined limit state (LS) function (Shayanfar et al., 2014). This function is defined as $g(\boldsymbol{X})$, where $g(\boldsymbol{X}) \leq 0$, represents the failure region. In this function, $\boldsymbol{X}$ is the vector of random variables. Failure probability is computed through the multidimensional integral:

$$P_f = \int_{g(\boldsymbol{X})\leq 0} \dots \int f_{\boldsymbol{X}}(\boldsymbol{X}) d\boldsymbol{X} \tag{8}$$

where P_f denotes the failure probability and $f_{\boldsymbol{X}}(\boldsymbol{X})$ shows the joint probability density function of the vector $\boldsymbol{X}$. Because closed-form solutions are not generally available for solving the integral, approximate methods such as FORM, SORM, and Monte Carlo Simulation are employed. In structural reliability analysis, reducing the number of limit state function evaluations is usually desired. FORM generally requires only 5–10 function evaluations to achieve an accurate approximation (Koduru & Haukaas, 2010), making it widely used in structural reliability and reliability-based design (RBD) frameworks (IEC TS 61400-9, 2025). Accordingly, this study uses FORM implemented in OpenSees (McKenna et al., 2010) for reliability calculations. FORM begins by mapping the original random variables to standard normal variables through a probabilistic transformation:

$$\boldsymbol{u} = T(\boldsymbol{X}) \qquad T: \boldsymbol{R}^m \rightarrow \boldsymbol{R}^m \tag{9}$$

where T denotes the probabilistic transformation that converts original (non-normal) random variables into standard normal variables. In this study, Nataf transformation implemented in OpenSees is utilized for this purpose. In the standard normal space, the limit state surface is linearized using a first-order Taylor expansion. The method then identifies the so-called design point, or the most probable point (MPP). Determining the MPP converts the reliability assessment into a constrained optimization problem:

$$\beta = \min \ \|\boldsymbol{u}\| \quad \text{subject to} \quad G(\boldsymbol{u}) = g(\boldsymbol{X}(\boldsymbol{u})) = 0 \tag{10}$$

where $G(\boldsymbol{u})$ is the limit-state function formulation in the standard normal space, and β is the reliability index, representing the Euclidean distance between the design point and the origin in the standard normal space. This optimization problem can be solved using several nonlinear algorithms available in OpenSees, such as iHLRF, the Polak–He algorithm, the gradient projection method, and sequential quadratic programming. In this study, the iHLRF algorithm is utilized to obtain the design point.

4. Numerical example

This example evaluates the impact of corrosion affected by sea-water temperature on structural reliability of the NREL 5 MW OWT monopile (Jonkman & Musial, 2010). Reliability assessment for the pristine OWT monopile is performed using Equation (7) as the limit state function. For deterioration modelling, corrosion loss is only applied after the protective coating has failed. It is assumed that corrosion does not occur when the coating protection system is functioning. A normal distribution with the mean value of 5.5 years and standard deviation of 0.4 years is assumed for coating life (Moan & Ayala-Uraga, 2008). Corrosion loss and its associated uncertainty at the final year of the OWT service life are estimated using the bi-modal corrosion model. The corrosion loss is then used to update the monopile cross-sectional properties such as section modulus (S). The updated section modulus is integrated into the reliability analysis via a strength retention factor ($\eta = \frac{S_{Corroded}}{S_{Pristine}}$), which modifies the limit state function as follows:

$$g = z\delta\eta R X_{Str} - X_{Site} X_{Aero} X_{Dyn} X_{Mat} X_{Wind} X_{Sim} F \tag{11}$$

For each realization of the corrosion loss based on the corrosion model discussed in Section 2, the corroded section modulus $S_{Corroded}$ is computed and subsequently expressed as a retention factor η. A Monte Carlo simulation (using 1,000 samples) is performed to account for the uncertainties associated with corrosion loss and coating life, yielding a distribution of $S_{Corroded}$ values and, consequently, the statistical characteristics (mean and standard deviation) of the retention factor η. These statistics, listed in Table 3, are then used as inputs to the reliability analysis.

Since the corrosion model is calibrated as a function of sea-water temperature, and temperature varies with wind farm location, two representative temperatures corresponding to distinct wind farm sites are considered. These temperatures are used to evaluate the influence of site-specific sea-water temperature on corrosion loss and the structural reliability of OWT monopiles.

Table 3. Statistics for strength retention factor (η) at *t = 25 yr*

Temperature	Mean	std
9.4	0.963	0.0021
24.8	0.948	0.0122

Structural reliability of the pristine and corroded OWT monopile is then calculated for extreme DLCs listed in Table 4 to demonstrate the impact of deterioration on the reliability of OWTs. For each load case, reliability index is computed for two mean temperatures (9.4 °C, and 24.8 °C), corresponding to different wind farm locations. Results are illustrated in Table 4.

Table 4. Reliability index associated with the DLCs for different sea-water temperatures

Load case	Safety factor	$\beta_{Pristine}$	$\beta_{T=9.4}$	$\beta_{T=24.8}$
DLC 1.1: Normal operation Load Extrapolation	1.25	2.91	2.74	2.66
DLC 1.3: Normal operation ETM	1.35	3.26	3.09	3.01
DLC 6.1: Extreme wind	1.35	3.29	3.19	3.14

DLC 6.1 Typhoon	1.35	3.09	3.00	2.97
DLC 6.1: Typhoon (Increased)	1.485	3.31	3.22	3.18
Gravity Loading	1.1	3.23	2.88	2.72

Table 4 illustrates that DLCs involving loads with lower uncertainty result in a greater reduction in reliability index. As an example, for the monopile at a sea-water temperature of 24.8 °C, the reduction of reliability level due to corrosion is 9.4% for DLC 1.1, compared to 4% for DLC 6.1 with typhoon. This can be explained by the fact that in DLCs with low load variability, the overall variance of the limit state function is reduced, making the reliability of the structure more sensitive to changes in the resistance (due to deterioration). The reliability reductions at sea-water temperature of 9.4 °C are 6.2% for DLC 1.1 and around 3% for DLC 6.1. This shows that the temperature-induced impact of corrosion on structural reliability varies by location, illustrating the importance of site-specific risk and reliability assessment of OWTs.

5. Conclusion

This paper addresses the reliability assessment of deteriorating OWT monopiles. The deterioration occurs due to steel corrosion in sea-water. A bi-modal corrosion model, formulated in terms of sea-water temperature, is utilized to assess corrosion loss. Corrosion loss and its associated uncertainty obtained by the corrosion model are being used for updating cross-sectional properties of OWT monopiles. Then, reliability of the NREL 5 MW OWT monopile designed using the safety factors provided by IEC 61400-1 (Edition 4) for extreme design load cases is assessed. To evaluate the impact of corrosion on structural safety, the analyses are performed for cases with and without consideration of corrosion. Two different sea-water temperatures corresponding to different wind farm locations are used to estimate corrosion loss and its effect on structural reliability. Results illustrate that corrosion loss can result in a 3-12% and 4-18% reduction in the reliability level of the OWT monopile for sea-water temperatures of 9.4°C and 24.8°C, respectively.

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