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Uncertainty analysis of ageing structures under a spatio-temporal degradation process

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This study proposes a methodology for uncertainty analysis of structural capacity that accounts for the spatio-temporal deterioration process. The nonstationary and non-uniform behaviour of capacity degradation is modelled using a stochastic Gamma process combined with random field theory. The proposed framework integrates non-linear finite element analysis with a surrogate modelling approach to enable accurate and efficient probabilistic assessment of ageing structural performance. The application problem investigated is the probabilistic assessment of the ultimate compressive strength of corroded plates, accounting for the variability in geometry, material properties, initial imperfections, and the corrosion process. The proposed methodology offers a more realistic assessment of the ultimate strength of ship plates compared to current state-of-the-art approaches.

Keywords: Uncertainty analysis, Stochastic process, Random field, Surrogate model, Corrosion.

1. Introduction

Aggressive environmental conditions and natural hazards can affect civil and marine structures and infrastructure throughout their service life. These environmental or hazard factors may alter the resistance and stiffness of structures, reducing structural capacity over the service life. The degradation of structural resistance is inherently nonstationary due to the interacting effects of random material deterioration, multiple degradation mechanisms, and uncertainties in the degradation process (Kakaie et al., 2026b; Li et al., 2015). In addition, the degradation process is spatially non-uniform due to variations in material properties, structural configuration, and local environmental exposure.

Due to uncertainties in geometry, material nonlinearity, initial imperfections, residual stresses, and complex load combinations that may trigger multiple collapse modes (Guedes Soares and Søreide, 1983), the ultimate strength of ship structural components is inherently probabilistic (Guedes Soares, 1998). To establish a more reliable basis for evaluating structural integrity under variable operating conditions, numerous studies have developed probabilistic models to represent both structural strength and load effects in ship structures, accounting for the inherent randomness of the parameters governing ultimate strength (Anyfantis, 2020; Kakaie et al., 2024; Parunov et al., 2022). These probabilistic approaches contribute to improved safety, reliability, and robustness in the structural design and maintenance of ships.

During their service life, ship hull structures are often exposed to severe operational and environmental conditions, which may result in a gradual loss of structural capacity. Corrosion is widely regarded as the most significant cause of age-related degradation in ship structures (Guedes Soares et al., 2009, 2008). The structural performance of ships is affected by various forms of corrosion, including general corrosion, pitting corrosion, erosion–corrosion, crevice corrosion, and galvanic corrosion. It should be emphasised that, with the exception of general corrosion, most corrosion mechanisms are highly localised. Consequently, corrosion-induced degradation can be considered a stochastic process, as it is governed by many influencing factors and exhibits substantial uncertainty in both time and space (Kakaie et al., 2026a; Teixeira and Guedes Soares, 2008).

The non-linear corrosion wastage models developed by Guedes Soares and Garbatov (1999) have been widely used in the literature to describe corrosion degradation. Furthermore, Garbatov et al. (2007) proposed a probabilistic corrosion model based on corrosion measurements from plate elements of different bulk carriers. Paik (2012) also examined corrosion degradation using a probabilistic framework and suggested the Weibull distribution to characterise corrosion depth based on the data collected from seawater ballast tanks. These investigations primarily focused on general uniform corrosion. In contrast, several studies have examined the stochastic nature of corrosion degradation and its influence on the reduction in ultimate strength associated with pitting corrosion (Silva et al., 2014; Wang, 2021; Wang et al., 2018).

Additionally, the spatial variability of the corrosion process has been modelled using random field theory. The collapse strength of steel plates has been investigated using a spatial distribution modelled by a uniform and isotropic Lognormal random field (Teixeira et al., 2013; Teixeira and Guedes Soares, 2008). A theoretical foundation for random field modelling of corrosion-induced thickness loss was established through power spectrum analyses of corroded surfaces (Garbatov and Guedes Soares, 2019; Melchers et al., 2010). Furthermore, random field theory has been employed to estimate both the constitutive behaviour of steel (Wang et al., 2022) and the mechanical properties of corroded plates (Woloszyk and Garbatov, 2020).

The nonlinear finite element (FE) method underpins most current numerical research on the ultimate strength assessment of ship structural elements. A key challenge in probabilistic modelling of ship structures is the need for large sample sizes to obtain reliable results. However, generating such a large number of samples requires numerous non-linear FE simulations, which can be computationally expensive. One effective approach for addressing complex and time-consuming engineering problems is metamodeling, where simplified models are constructed to act as surrogates for the full problem (Afshari et al., 2022; Teixeira et al., 2021).

For probabilistic modelling of plate ultimate strength, basic polynomial response surface models (RSM) have been used for their computational efficiency, though they are limited in global interpolation accuracy (Kmiecik and Guedes Soares, 2002). Kriging metamodels have also been widely employed for reliability analysis, offering higher accuracy than polynomial RSMs in structural reliability assessments (Gaspar et al., 2017). More advanced Kriging-based approaches, such as Bi-fidelity Kriging and active learning polynomial chaos Kriging (PC-Kriging), have recently been used for ultimate strength assessments, demonstrating high precision and effectiveness in quantifying uncertainties in complex engineering systems (Kakaie et al., 2026a; Lima et al., 2023; Okoro et al., 2021).

The deterioration in marine structures is monotonic (non-decreasing), non-stationary over time, and non-uniform across space, excluding restoration, maintenance, and other strengthening measures (Kakaie et al., 2025). Therefore, considering both temporal and spatial variability in corrosion improves prediction accuracy and supports more effective maintenance and decision-making. This study aims to introduce a framework for the probabilistic analysis of the ultimate strength of ship structural plates, incorporating the spatio-temporal variability of corrosion. The approach integrates nonlinear FE analysis with surrogate models to facilitate uncertainty propagation and sensitivity analysis, accounting for variability in geometry, material properties, initial imperfections, and the corrosion process.

2. The proposed methodology

The framework shown in Fig. 1 is used to probabilistically analyse the plate's ultimate strength, accounting for the spatio-temporal stochastic corrosion process and the variability in geometry and material properties. Initially, given the uncertainties associated with the input variables, design of experiments (DOE) points are generated. The plate is then partitioned into discrete elements with a set of uniform locations. Random plate structures are generated using the spatio-temporal corrosion model for each set of DOEs. Subsequently, the ultimate strength of the stiffened plate for each set of DOEs is estimated using the nonlinear FE analysis.

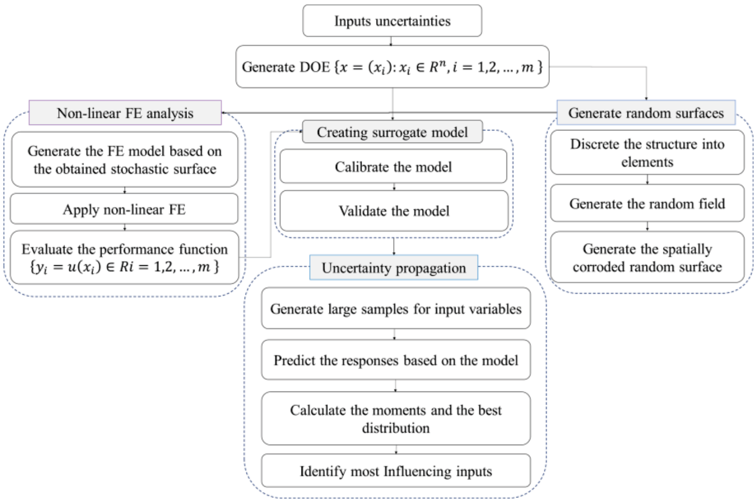

Fig. 1. Flowchart of probabilistic analysis of plate's ultimate strength

This step involves conducting an FE analysis of the randomly generated surface using ANSYS APDL, integrated with Python code. In this study, a PC-Kriging model is used as a surrogate for the probabilistic evaluation of the plate's ultimate strength. Subsequently, the model parameters are calibrated using the DOE points, and the model's performance is evaluated on a separate dataset. The developed PC-Kriging model, combined with Monte Carlo simulation, is used to predict the ultimate strength of numerous random plates while accounting for input uncertainties. The resulting ultimate strengths are then analysed to estimate their statistical properties and to determine the best-fit distributions. In addition, total Sobol indices are computed from the PCE representation to assess the relative influence of each input parameter.

3. Spatio-temporal corrosion process

The corrosion process can be divided into three distinct stages: the coating-free life, the transitional phase, and the corrosion progression stage (Paik et al., 2003a). The nonlinear model defines the corrosion-induced reduction in plate thickness as a time-dependent function.

$$d(t) = d_\infty \left(1 - e^{-\frac{(t-T_c)}{T_t}}\right) \qquad t > T_c \qquad (1)$$

The corrosion depth is denoted by $d(t)$, the coating lifetime by T_c, the transition time by T_t, and the long-term corrosion depth by d_∞. Also, the standard deviation of the corrosion thickness loss is estimated as:

$$\sigma_d(t) = \mathrm{A}t + B \quad ,\mathrm{t} > T_c \qquad (2)$$

where A and B are constant. The corrosion depth on a ship plate surface increases monotonically over time, assuming no restoration, maintenance, or other strengthening interventions. Several studies have shown that using the Gamma process effectively captures this positive progression over time (Kakaie et al., 2025, 2026b, 2026a; Li et al., 2015; Yang et al., 2022). Assuming a Gamma distribution for the thickness reduction caused by corrosion at time *t* with the same scale parameter α and shape parameter $\eta(\mathrm{t})$ the probability distribution of $d(t)$ is:

$$f_{d_t}(x) = \frac{\alpha^{\eta(t)}}{\Gamma(\eta(t))} x^{\eta(t)-1} \, exp(-\alpha x) \qquad (3)$$

where $\Gamma(.)$ refers to the Gamma function. If $\eta(t)$ varies linearly with time, the process is stationary, with mean and standard deviation increasing linearly. If $\eta(t)$ is nonlinear, the process becomes non-stationary and non-homogeneous.

Spatial variability of corrosion growth is commonly modelled using Gaussian homogeneous random fields to capture uneven structural degradation. The Karhunen–Loève (K–L) expansion (Phoon et al., 2005) and the circulant embedding matrix approach, also known as the discrete spectral method (DSM) (Chiles and Delfiner, 2012), are the main approaches for random field generation. DSM uses the discrete Fourier transform to efficiently generate random fields while preserving spatial correlation at grid points (Dietrich and Newsam, 1997). This spectral approach is highly flexible and can be interpreted through a stochastic Fourier integral representation of Gaussian random fields $H(x)$ based on:

$$H(x)= \sqrt{2\sigma^2}\left(\int_0^\infty \cos(2\pi kx)\sqrt{E(k)}\,dW_1(k) + \int_0^\infty \sin(2\pi kx)\sqrt{E(k)}\,dW_2(k)\right) \tag{4}$$

where $dW(k)$ is a complex-valued white noise random measure and $S(k)$ is the spectrum. Also, $E(k) = S(k)/\sigma^2$ is the normalised spectrum or the spectral density function and $W_1(k)$ and $W_2(k)$ are two independent real-valued Wiener processes. The Fourier method, which is based on the Riemann sum discretisation of Eq. (4), is the most straightforward and most robust discretisation approach and is easy to implement. Regarding a finite symmetric partition of N intervals having equal widths ΔK, Eq. (4) can be approximated as follows (Heße et al., 2014):

$$H(x) = \sqrt{2\sigma^2}\sum_{i=1}^{N}\sqrt{E(k_i)}\left(cos(2\pi k_i x)\,\Delta W_{i,1} + sin(2\pi k_i x)\,\Delta W_{i,2}\right) \tag{5}$$

where $\Delta W_{i,n} = Z_{i,n}\sqrt{\Delta K}$ and $Z_{i,n}$ is an independent normal random variable. The randomisation method used in this study is a variant of the Fourier method. Its key difference lies in how the wave numbers k_i are generated. In the Fourier method, k_i are sampled from a finite interval, which completely excludes higher-frequency components. In contrast, the randomisation method samples k_i as random variables following a density distribution defined by the spectral density $E(k)$.

The stochastic Gamma process can be generalised into a spatio-temporal random field by allowing its parameters, such as the scale parameter or shape function, to vary spatially as random fields. Considering the scaling property, the separable stochastic model of thickness loss can be expressed as (Oumouni et al., 2019; Yang et al., 2022).

$$d(t,s) = d(t)\,\alpha(s)^{-1} \tag{6}$$

where $d(t)$ is the Gamma process with a shape function of $\eta(\mathrm{t})$ and a scale parameter of 1, $\alpha(s)$ is a positive spatial random scale and s is the spatial variable of x, y, z. The positive spatial GRF $\alpha(s)$ is assumed to be independent of $d(t)$. A Log-normal distribution has been proposed for a random scale to ensure a positive distribution for the spatial random field.

$$\alpha(s) = e^{\gamma+\zeta H(s)} \tag{7}$$

The constant e^{γ} is the deterministic component of the scale parameter and ζ represents the standard deviation of the scale parameter's random field. The parameter ζ characterizes the intensity of spatial variability in the thickness loss during the corrosion process. A small ζ corresponds to relatively uniform corrosion, while a larger ζ indicates that certain regions corrode significantly faster or slower than others. It quantifies the degree of non-uniformity in corrosion over the plate surface. In this study the squared exponential correlation function is used for the two-dimensional Gaussian random field.

Generating a discrete random field for each time step may fail to capture the realistic cumulative nature of corrosion, which is inherently monotonic over time. To address this issue, in this study, a lognormal spatial scale field $\alpha(s)$ is generated once per simulation and kept fixed throughout all time steps.

4. PC-Kriging surrogate model

PC-Kriging is a hybrid metamodeling technique that integrates Kriging with polynomial chaos expansions (PCE). In this approach, PCE captures the system's global behaviour through orthogonal polynomial expansions, whereas Kriging models local deviations within a Gaussian process framework. The combination of these two methods enhances predictive performance by effectively accounting for both global trends and local variations in the computational model. Mathematically, the PC-Kriging can be expressed as (Schöbi et al., 2017):

$$U^{PCK}(x) = \sum_{\alpha\in\omega} \beta_\alpha \psi_\alpha(x) + \sigma^2 Z(x) \tag{8}$$

where U^{PCK} is the model response, ψ_α denotes the multivariate orthogonal polynomial basis functions, α is a multi-index that identifies the components of the multivariate polynomials and β_α denote the corresponding expansion coefficients, ω is a certain set of selected multi-indices of multivariate polynomials. The polynomial basis $\psi_\alpha(x)$ in PCE is constructed using multivariate polynomials formed from a set of univariate orthonormal polynomials $\Phi_{\alpha_i}^{(i)}$ as:

$$\psi_\alpha(x) = \prod_{i=1}^{m} \Phi_{\alpha_i}^{(i)}(x_i) \tag{9}$$

Building a PC-Kriging model involves two key steps: selecting the optimal polynomial set for the regression part and calibrating the Kriging parameters. A sequential approach is adopted, in which the Least Angle Regression (LAR) algorithm is first applied within a pure PCE framework to identify a sparse set of orthonormal polynomials (Efron et al., 2004; Schobi et al., 2015). These polynomials define the trend in a universal Kriging model, which is subsequently calibrated based on the DOEs.

Global sensitivity analysis includes regression-based and variance-based methods. The variance-based approach employs the functional analysis of variance (ANOVA) decomposition, which expresses the model output as a combination of contributions from individual input variables and their interactions. The PCE coefficients contain crucial information about the surrogate model's ANOVA structure, and since the polynomial chaos (PC) representation of the model is already available, Sobol indices can be derived analytically (Sudret, 2008).

4. Numerical example

A plate with the length $a = 2.55m$, and the width $b = 0.85m$ under uniaxial compression is considered. Four-edge simply supported boundary conditions and initial geometric imperfection mode indicated in Fig.2 are applied in the nonlinear FE analysis. The geometry, material properties and initial imperfection variabilities are shown in table 1.

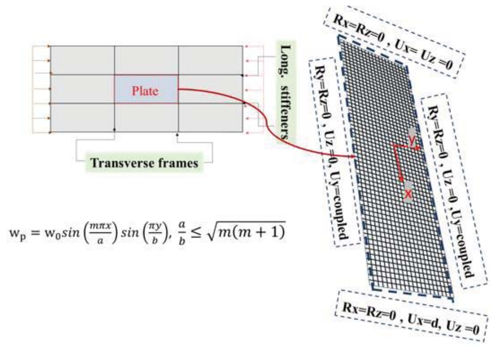

Fig. 2. Boundary condition and initial imperfection

The corrosion parameters, T_c, T_t and d_∞ were estimated as 5, 1.64 and 1.07 years receptively using corrosion data in various operational bulk carriers (Paik et al., 2003b). The parameters A and B are -0.0237 and 1.1016, respectively. Also, the correlation length of $l_c = 0.2$b and the coefficient of variation of the scale parameter's $CV = 0.5$ are considered in the random field model.

Table 1. The input variables

Variable	Mean	CV	Distribution
$t_p(mm)$	16	0.02	Normal
σ_y(MPa)	348	0.06	Lognormal
E(GPa)	205.8	0.06	Lognormal
w_0(mm)	3.9	0.50	Lognormal
$d(t,s)$	Eq. (6)	-	Gamma

To account for asymmetric material removal, the method proposed in (Teixeira et al., 2013) is adopted. One-sided corrosion is modelled by introducing an eccentricity to the element midsurface, ensuring that the lower surface of the plate remains straight. Fig. 3 illustrates the spatiotemporal evolution of corrosion-induced thickness loss across the plate, showing three realisations at 6, 8, and 10 years of service. The spatial distribution demonstrates a consistent progression, with corrosion patterns at earlier stages developing into more severe losses over time.

In this study, a PC-Kriging surrogate model is developed using ANSYS, Python, and the UQLab framework (Lataniotis et al., 2021). A DOE set comprising 200 samples is generated to account for the probabilistic modelling of the input parameters listed in Table 1.

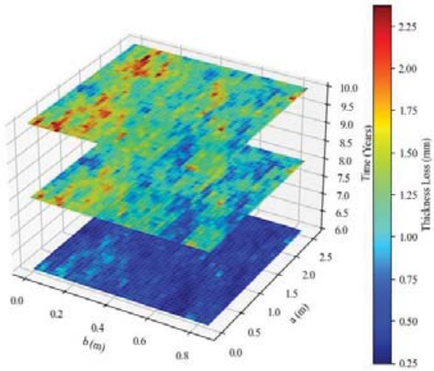

Fig. 3. Spatiotemporal corrosion on plate surfaces

The resulting random plate realisations are analysed using nonlinear FE analysis. Of the generated samples, 75% are used to train the surrogate model, while the remaining 25% are reserved for validation. The performance of the surrogate model is assessed using the Leave-One-Out error ELOO and the validation error computed based on the test dataset. Table 2 presents the surrogate model validation results for the intact and corroded plates after 10 years of service. The constructed models exhibit appropriate performance.

Table 2. Validation of the surrogate model

	E_{LOO} error	Validation error
Intact	8.30e-06	2.36e-04
corroded	8.36e-03	7.74e-02

The calibrated PC-Kriging surrogate model is employed to predict the ultimate strength of 10^5 generated random plates. Fig. 4 presents the histogram and statistical description of the predicted ultimate strength for intact and corroded plates after 10 years of service. As expected, Corroded plate has lower ultimate strength than intact plates and show greater variability. The Weibull distribution provides a good fit for the generated data for the corroded plate, which can be attributed to the long-tail behavior of the Gamma process used to model corrosion thickness loss.

The sensitivity of the plate's ultimate strength to the input variables is shown in Table 3. The total Sobol indices are computed from the PCE coefficients obtained from the surrogate models.

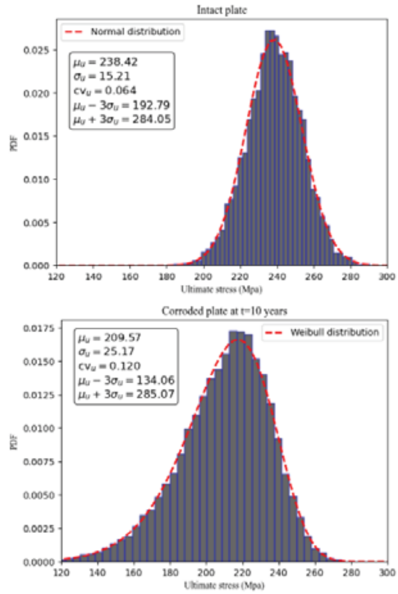

Fig. 4. Probabilistic modelling of ultimate strength

For the intact plate, the uncertainty in ultimate strength is mainly governed by the initial local imperfection and the material yield strength. However, for the corroded stiffened plate, the reduction in corrosion thickness exhibits the highest Sobol index, indicating that variability in corrosion loss is the dominant contributor to the variance in ultimate strength.

Table 3. Sensitivity analysis

	t_p	σ_y	E	w_0	d
Intact	0.066	0.352	0.122	0.471	-
corroded	0.025	0.088	0.037	0.099	0.77

An additional analysis is conducted to examine the assumption of uniform corrosion, which neglects spatial variability. Table 4 compares the statistical results of the ultimate strength of plates with uniform and non-uniform corrosion at t=10 years. Compared with uniform corrosion, the non-uniformly corroded plate shows a lower mean ultimate strength, along with a higher coefficient of variation and total Sobol index. This indicates that spatial variability in corrosion affects the probabilistic response. The reduced strength can be attributed to critical corrosion patterns that lead to localised thinning and failure, which are more likely to occur under non-uniform corrosion conditions.

Table 4. comparison between uniform and non-uniform corrosion

parameter	Uniform corroded t=10	Non-Uniform corroded t=10
μ_u	217.84	209.57
σ_u	20.92	25.17
CV_u	0.096	0.12
S_{dt}^T	0.62	0.77

5. Conclusion

This study presents an integrated framework for quantifying the uncertainty in the ultimate strength of corroded ship structural plates, taking into account the temporal and spatial variability of the stochastic corrosion process. By combining nonlinear finite element analysis with PC-Kriging surrogate modelling, the approach enables efficient and accurate probabilistic assessment of structural performance. The methodology is applied to the ultimate strength analysis of corroded plates under compression, considering uncertainties in geometry, material properties, initial imperfections, and corrosion evolution. The results highlight that spatially variable corrosion can trigger localised failures and reduce ultimate strength, underscoring the importance of realistic corrosion modelling. The probabilistic outcomes provide valuable support for reliability analysis, maintenance planning, and inspection strategies over the service life of ship structures.

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