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Title	Surrogate-assisted reliability-based design optimization of reinforced concrete gravity-based foundations for offshore wind turbines
Author(s)	Lehky, David; Amlashi, Hadi; Novák, Drahomír et al.
Relation	Proceedings of the 10th International Symposium on Reliability Engineering and Risk Management (ISRERM 2026), June 28 - July 1, 2026, Sapporo, Japan
Citation	Proceedings of the 10th International Symposium on Reliability Engineering and Risk Management (ISRERM 2026)
Issue Date	2026-07-01
Doc URL	https://hdl.handle.net/2115/100437
Type	conference paper
File Information	C000043_1.pdf

Hokkaido University Collection of Scholarly and Academic Papers : HUSCAP

ISRERM 2026

10th International Symposium on Reliability Engineering and Risk Management (ISRERM 2026),
28 June-01 July 2026, Sapporo, Japan
Kitahara, T., Miyamori, Y. & Beer, M. (editors)

Surrogate-assisted reliability-based design optimization of reinforced concrete gravity-based foundations for offshore wind turbines

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Given the rising demand for sustainable energy sources, optimizing the design of offshore wind turbines is becoming increasingly important to ensure their efficiency and reliability throughout their service life. Traditional reliability-based design optimization approaches are often extremely computationally intensive. To address this, the paper describes a surrogate-assisted methodology employing an artificial neural network to approximate an inverse reliability function. This approach allows for the direct identification of design parameters satisfying target reliability indicators, such as reliability indices or failure probabilities. The method's effectiveness is demonstrated through a case study of a reinforced concrete gravity-based foundation. The required areas of mild steel reinforcement and prestressing tendons are identified while adhering to reliability constraints for ultimate and serviceability limit states. Results confirm that the methodology offers a transparent and time-efficient framework for the probabilistic design and assessment of engineering structures.

Keywords: Offshore wind turbine, reliability-based optimization, inverse analysis, artificial neural network, reliability index.

1 Introduction

The growing demand for sustainable energy solutions has highlighted the necessity of optimizing the design of offshore wind turbine (OWT) structures. For offshore and land-based wind turbines to become competitive with other energy supply methods, it is essential that they exhibit the high reliability while reducing their cost of production. To achieve a consistent reliability level for all structural components, probabilistic design methods should be employed. These methods explicitly account for uncertainties in loads, materials and computational models. While forward reliability methods have been widely applied in engineering, inverse reliability approaches have not received the same level of attention or application. However, they are useful due to their important role in engineering design. They are, however, mathematically more challenging and computationally intensive. With the development of advanced reliability and machine learning methods, it is now possible to perform reliability-based design optimization (RBDO) in a transparent and time-efficient manner.

The traditional RBDO approach is the double-loop approach, where an outer loop optimizes design parameters considering reliability constraints while an inner loop assesses the failure probability under these parameters (Lehký et al. 2018, Wang et al. 2025). To avoid time-consuming reliability analyses, a fast-to-evaluate surrogate model is often employed. This paper uses a surrogate model differently. Rather than using forward optimization, the proposed method obtains design parameters using an inverse reliability function. This function is approximated by a machine learning–based meta-model that is trained using data from a limited set of reliability analyses generated using a Latin hypercube sampling (LHS) scheme. The surrogate model then provides design parameter values for specified reliability indicators. Owing to its efficiency and practical applicability, the method is suitable for designing or assessing the reliability of offshore wind turbines and other engineering structures, as demonstrated in the case study presented in the paper.

2 Inverse reliability analysis

The design of a structure or a structural component to achieve a required level of reliability is a typical example of an inverse problem. The aim is to find input design parameters $\mathbf{d} \subseteq \mathbf{X}$ (where $\mathbf{d}$ may contain deterministic design variables and/or statistical parameters of random variables) which yield the corresponding structural safety described by probability indicators – failure probabilities $\mathbf{p}_f$ or reliability indices $\boldsymbol{\beta}$ – related to different limit states. Then, calculation of failure probabilities for multiple limit states $\mathbf{g}(\mathbf{X})$ can be formally generalized as:

$$\mathbf{p}_f = \mathbf{F}(\mathbf{X}). \tag{1}$$

Note that function $\mathbf{F}$ involves a rather complex calculation–including repeated evaluations of the limit states $\mathbf{g}(\mathbf{X})$, which are necessary for estimating reliability. In case of probabilistic analysis of a structure, the analytical solution of

an inverse problem or the utilization of a trial-and-error procedure is time-consuming and inefficient, or even impossible. In such cases, it seems necessary to use advanced methods such as those described, e.g., in Wang et. al. 2025. In this paper, the design parameters $\mathbf{d} \subseteq \mathbf{X}$ are obtained via inverse transformation:

$$\mathbf{d} = \mathbf{F}^{-1}(\mathbf{p}_f). \tag{2}$$

Since finding an analytical formulation of the inverse functions $\mathbf{F}^{-1}$ in (2) is possible only in extremely simple cases, an artificial neural network (ANN)-based surrogate model $\mathbf{F}_{\mathrm{ANN}}^{-1}$ is utilized instead. To reduce computational effort to an acceptable level, the ANN is coupled with a small-sample stochastic simulation of the Monte Carlo type employed to generate the training data. Once the ANN has been trained, it represents an approximation that is subsequently utilized to provide the best possible set of design parameters corresponding to the prescribed reliability. A flow chart of the ANN-based inverse reliability method is depicted in Figure 1. For detailed description of the method see Lehký et al. (2018).

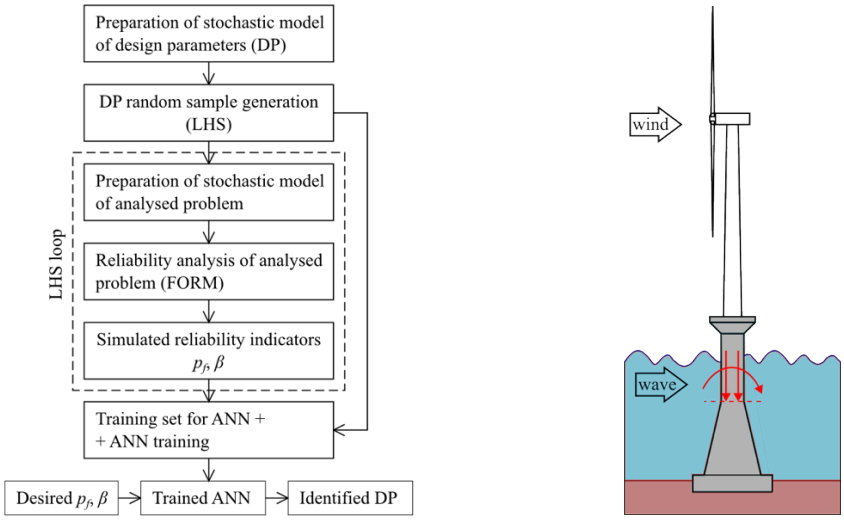

Figure 1. A flow chart of the ANN-based inverse reliability method (left); a schematic view of offshore wind turbine with a gravity-based foundation (right).

3 Case study

3.1 *Analyzed structure*

The reinforced concrete gravity-based foundation (GBF) supporting OWT is selected to demonstrate potential of the small-sample ANN-based inverse reliability method to identify the design parameters while satisfying reliability constraints. For the analyzed structure, an optimal combination of mild steel reinforcement and prestressing tendons is desired assuming that overall geometry of the concrete structure is already known. The OWT is installed at a mean water depth of 25 m annual mean sea level. Figure 1 shows a schematic view of the analyzed OWT, indicating the critical ring beam section of GBF, which has outer and inner diameters of 6.5 m and 5.5 m, respectively.

The GBF was made from concrete with a mean compressive strength of 53.3 MPa (strength class C45/55) and mild and prestressing steel with mean yield strengths of 560 and 1643 MPa, respectively. Simplified load model is based on extreme load distribution, which was derived using environmental contour method (Winterstein et al. 1993) for a reference offshore site. Model assumes both maximum wind speed and maximum significant wave height from which the annual extreme bending moment M_e at a critical section was derived, see Velarde et al. (2019) for more details.

Table 1 summarizes all the deterministic and stochastic input variables of the analyzed GBF, including the model uncertainties that reflect the simplifications of load and resistance models. The statistical characteristics were considered according to Velarde et al. (2019) and JCSS model code (2001).

3.2 *Reliability assessment*

The structural reliability is assessed for two limit states: (i) concrete compressive failure and (ii) concrete crack initiation. Note that, due to the limited scope of this paper, only ultimate and serviceability limit states are considered. Fatigue failure, which also plays an important role in OWTs, is not addressed.

For the first limit state, the concrete compressive strength of the critical cracked section R_1 is evaluated as:

$$R_1 = \frac{M_R \cdot c}{I_{cr}} \tag{3}$$

where the moment resistance M_R and the moment of inertia for a cracked section I_{cr} are:

Table 1. Stochastic and deterministic variables of analyzed gravity-based foundation.

Variable	Distribution	Mean	Stand. dev.
Material properties:			
Concrete compressive strength f_c (MPa)	Lognormal	53.3	5.33
Concrete tensile strength f_t (MPa)	Lognormal	3.8	0.38
Yield strength of mild reinforcement f_y (MPa)	Normal	560	30
Yield strength of prestress reinforcement f_{py} (MPa)	Normal	1643	41
Modulus of elasticity of steel E_s (MPa)	Lognormal	210000	6300
Modulus of elasticity of concrete E_c (MPa)	Lognormal	29600	1776
Structural parameters:			
Cross-section area A_c (mm^2)	Deterministic	9420000	–
Area of mild reinforcement A_s/A_{s0} (mm^2)	Deterministic	? / 200000	–
Area of prestress reinforcement A_{ps}/A_{ps0} (mm^2)	Deterministic	? / 120000	–
Radial distance to critical point c (mm)	Deterministic	3250	–
Moment of inertia of the concrete section I_0 (mm^4)	Deterministic	4.27×10^{13}	–
Section outer diameter d_0 (mm)	Deterministic	6500	–
Distance of reinf. from top of the section d_{As} (mm)	Deterministic	6250	–
Radial distance to mild reinforcement d_s (mm)	Deterministic	3000	–
Load actions:			
Extreme annual bending moment M_e (MNm)	Gumbel	186.7	40.4
Gravity loads F_G (MN)	Normal	22.0	0.5
Model uncertainties:			
Concrete resistance model uncertainty X_c (–)	Lognormal	1	0.10
Steel resistance model uncertainty X_{rs} (–)	Lognormal	1	0.05
Prestressing model uncertainty X_{ps} (–)	Lognormal	1	0.05
Load model uncertainty X_E (–)	Lognormal	1	0.10
Load statistical uncertainty X_N (–)	Lognormal	1	0.05

$$M_R = \mathrm{X}_{rs} A_s f_y \left(d_{As} - \frac{1}{2} \frac{\mathrm{X}_{rs} A_s f_y}{\mathrm{X}_c d_0 f_c} \right) \tag{4}$$

$$I_{cr} = \frac{I_0}{2} + n_{sc} A_s d_s^2 \tag{5}$$

where the modular ratio $n_{sc} = E_s/E_c$ is used to transform A_s to equivalent concrete area. The load action E_1 is governed by the extreme annual bending moment M_e, additional compressive stress from prestressing and gravity loads:

$$E_1 = \frac{M_e \cdot c}{I_{cr}} X_E X_N + \frac{0.8 A_{ps} f_{py}}{A_c} X_{ps} + \frac{F_G}{A_c} \tag{6}$$

The second limit state relates to concrete tensile cracking and ensures the durability and serviceability of the structure under extreme environmental conditions, particularly with regard to the initiation of reinforcement corrosion. The resistance to concrete crack initiation R_2 and the load action E_2 can be expressed as:

$$R_2 = X_c f_{ct} \tag{7}$$

$$E_2 = \frac{M_e \cdot c}{I_{cr}} X_E X_N - \frac{0.8 A_{ps} f_{py}}{A_c} X_{ps} - \frac{F_G}{A_c} \tag{8}$$

The ultimate limit state function for compressive failure and the serviceability limit state function for concrete crack initiation is then defined as:

$$g_i(\mathbf{X}) = R_i - E_i \tag{9}$$

where $i = 1, 2$ indicates the limit state number. The RBDO aims to determine the area of mild reinforcement A_s and prestressing reinforcement A_{ps} (see question marks in Table 1) as design parameters (DPs). These are optimized to ensure target reliability levels for both limit states, defined in accordance with JCSS recommendations as reliability index values $\beta_{1t} = 3.7$ and $\beta_{2t} = 1.7$. These target values correspond to moderate consequence of structural failure and normal relative costs of safety measures. The calculation of reliability is performed using the first order reliability method (FORM).

3.3 *Results*

The results of RBDO for the two limit states are summarized in Table 2 and depicted in Figure 2, where variations in the reliability indices β_1 and β_2 are depicted as functions of DPs (A_s and A_{ps}). To check the accuracy, DP values were used in Eq. (9), and reliability indices were calculated; see their comparison with target values in Table 1.

Table 2. Identified values of design parameters and corresponding reliability indices.

Design parameter	Identified	Reliability	Value	Target
A_s (mm^2)	227015	β_1	3.697	**3.7**
A_{ps} (mm^2)	137436	β_2	1.698	**1.7**

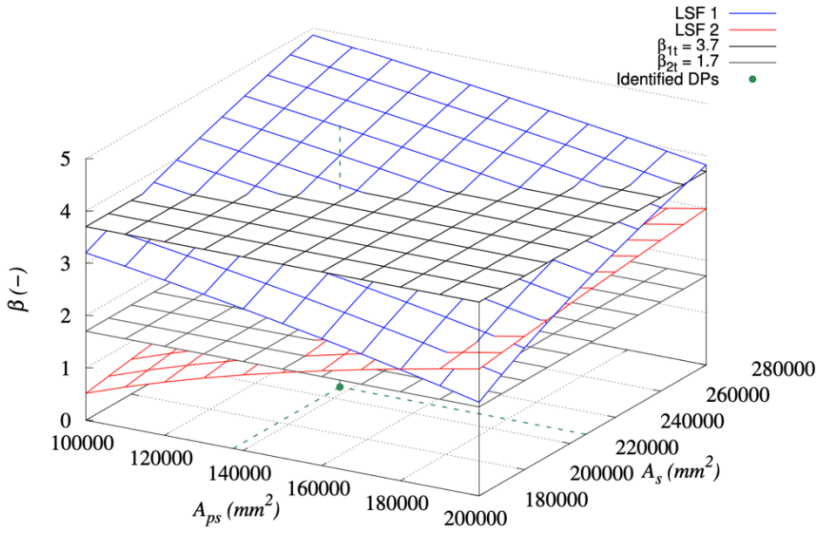

Figure 2. Variations in the reliability indices with respect to design parameters for concrete compressive failure (blue) and crack initiation (red).

4 Conclusions

This study confirms that the proposed surrogate-assisted RBDO framework provides a robust and efficient solution for the probabilistic design of offshore wind turbine structures. By utilizing an ANN to approximate the inverse reliability function, the methodology effectively bypasses the high computational costs associated with traditional double-loop optimization approaches and allowed for the precise identification of critical design parameters. Application to a gravity-based foundation case study demonstrated that the optimized areas of mild steel reinforcement and prestressing tendons successfully met the target reliability indices. The results confirm the high accuracy and reliability of the ANN-based predictions. These findings highlight the approach as a transparent, time-efficient, and practical tool for structural engineering that explicitly accounts for uncertainties. Ultimately, this framework offers significant potential for the assessment and optimization of a wide range of complex engineering structures beyond the offshore energy sector.

Acknowledgments

David Lehký, Drahomír Novák and Bohumil Šplíchal acknowledge the support of the Interreg Austria-Czechia 2021-2027 Programme, Project IREC No. ATCZ00068 and the Project No. 24-10892S awarded by Czech Science Foundation. Hadi Amlashi acknowledges the received funding from the research area Energy, Climate, and Environment at the University of South-Eastern Norway, project No. 2754084.

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