Reliability-based design optimization of a spar-type floating offshore wind turbine support structure

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\textbf{Abstract}

The application of reliability-based design optimization (RBDO) methods to offshore wind turbine systems is highly relevant regarding economic efficiency and for considering prevailing uncertainties within the design process. Furthermore, RBDO is a very promising approach in optimizing systems when classification and standardization are not fully available. The level of difficulty of design optimization already increases when including the reliability aspect, but becomes even more challenging when dealing with the highly complex system of floating wind turbines (FWTs), which has not yet been applied. Thus, this paper presents for the first time an integrated framework for RBDO of FWTs, combining concepts of optimization with reliability-based design and advanced modeling, requiring reasonable computational effort and time expenditure. In preprocessing, environmental conditions, limit states, and uncertainties are specified, an appropriate reliability assessment approach is elaborated, and response surfaces for various system geometries in the optimization design space are generated ahead of the RBDO execution. These are finally used by means of an interpolation approach for the reliability calculation integrated in the iterative design optimization. On the example of a spar-buoy FWT system, the application of the presented methodology and the feasibility of coupling FWT design optimization with reliability assessment are shown.

1. Introduction

With the end of 2018, the first renewable energy directive from 2009 [1], which set the target of a minimum share of 20% of renewable energy in the European energy demand by 2020, was revised and replaced. The new European goals – now for 2030 – are to reach at least 32% share of renewable energy [2]. A large contributor to energy generation from renewable sources is offshore wind. Its worldwide technical potential exceeds the current electricity demand by a factor of more than 18 [3]. Shallow water zones and areas of intermediate water depth such as the coastal offshore sites in German waters, are, however, an exception. The majority of the world oceans exhibits great water depths [4–6]. Thus, to exploit these sites for energy generation from offshore wind turbines, floating systems need to be utilized. Even though the costs for offshore wind has already decreased over the last few years [7], more cost reduction is required to make offshore wind energy – and especially floating solutions – economic and competitive with other renewable energy systems. In addition, more flexible design provisions would enable more innovation and allow for accelerating the market uptake of floating offshore wind. To this end, structures could adhere to a goal-setting design approach, where reliability is the key driving criterion, and concepts of structural reliability can be adopted in order to systematically account for uncertainties and different design criteria. Optimization based on structural reliability analysis concepts is highly relevant for considering the wide range of prevailing uncertainties, coming from environmental loads, manufacturing processes, or material properties [8–12]. These uncertainties may significantly affect the dynamic system response, but are not accounted for in deterministic design optimization (DDO) methods which are commonly used for offshore structures [9,11,13].

Abbreviations: DDO, Deterministic Design Optimization; DLC, Design Load Case; DNV, Det Norske Veritas; DNV GL, Det Norske Veritas and Germanischer Lloyd; Dymola, Dynamic Modeling Laboratory; FORM, First Order Reliability Method; FWT, Floating Wind Turbine; HL–RF, Hasofer Lind–Rackwitz Fiessler; IEC, International Electrotechnical Commission; ISO, International Organization for Standardization; IWES, Institute for Wind Energy Systems; LS, Limit State; LSM, Least Squares Method; MCS, Monte Carlo Simulation; MoWiT, Modelica library for Wind Turbines; NaN, Not a Number; NREL, National Renewable Energy Laboratory; NSGAII, Non-dominated Sorting Genetic Algorithm II; OC3, Offshore Code Comparison Collaboration; RBDO, Reliability-Based Design Optimization; Rkf4, Runge–Kutta fixed-step and 4th order method; SORM, Second Order Reliability Method; SSS, Severe Sea State; SWL, Still Water Level

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https://doi.org/10.1016/j.ress.2021.107666

Received 29 May 2020; Received in revised form 24 January 2021; Accepted 27 March 2021

Available online 8 April 2021

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There is a broad range of structural reliability analysis methods, which can be classified in different ways, such as local and sampling methods [14,15] or analytical and stochastic methods [16]. By means of statistical surrogate modeling methods – such as kriging, response surface method, or regression analysis – a system representation can be created [14,16]. The final reliability analysis can be performed either on the real system or on such a derived system representation. The most common analytical reliability analysis methods are FORM (First Order Reliability Method) and SORM (Second Order Reliability Method), which are based on Taylor expansion, while stochastic approaches can follow sampling methods, as for example Monte Carlo simulation (MCS), Latin hypercube sampling, or importance sampling [14–16]. Combinations of these methods, such as response surface method or Latin hypercube sampling for creation of an approximate metamodel and MCS, FORM, or SORM for finally determining the reliability, are applied – especially when it comes to offshore wind turbine systems which are of high complexity [16,17]. Consequently, alternative approaches and simplifications are required for the even more complex and computationally highly demanding reliability-based design optimization (RBDO) of offshore wind turbine systems. Thus, response surface approximation [18], fractional moment reliability analysis method [12], environmental contour method [19], surrogate modeling combined with an ensemble learning method [20], or an advanced first-order second moment method [21] can be found in studies on RBDO of offshore wind turbine system components. Even if MCS and sampling-based RBDO methods are recommended for systems with nonlinear or intricate design sensitivity [9], these are highly computationally intensive as they require a large number of iterations. Thus, MCS is often just used for the final reliability calculation, based on predetermined response surface approximation models, surrogate models, or Latin hypercube metamodels [10,11]. A stepwise refinement, as applied by Hu et al. [8], where surrogate models are just created for a more detailed RBDO at predetermined hotspots, may as well be more efficient. Finally, another approach that is adopted in some research studies – as well with the focus on efficiency enhancement – is the decoupling of the reliability assessment and the design optimization [13,22].

In some first studies on RBDO in relation to offshore wind turbine systems [8,11,19,20,22,23], the cost reduction objective is augmented by constraints addressing reliability aspects, such as reduced fatigue damage. These RBDO application examples deal with different single components of the system, such as blades [8,9], drivetrain [10], tower [21], transition piece [13], or various bottom-fixed support structures (monopiles, gravity-based foundations, or tripods) [11,18,19,22,23]; however, the only component of a floating wind turbine (FWT) system addressed in a RBDO study is the mooring system [20,24]. This emphasizes the significantly increased level of difficulty, when – in addition to including the reliability aspect into design optimization – also the much more complex system of a FWT is considered.

Thus, this study addresses the RBDO of FWTs. The paper aims to develop a proven methodology, by which means the combination of FWT system design optimization and reliability assessment is feasible, as well as reasonable with respect to computational effort and elapsed time. Due to the already high complexity and fully-coupled system dynamics of FWTs, a simple design example is elaborated in this first approach. In the highly flexible framework for RBDO, the reliability criterion can be specified as objective function or also addressed as constraint within the design optimization. The latter option is adopted in the presented application example due to computational limitations. With success of this first application example, having obtained positive results, the presented methodology and framework can – due to its robustness and modularity – be used for more complex and advanced RBDO problems on FWT systems. If expanded to real structures, this methodology can enable full RBDO where uncertainties can be considered systematically and the target reliability can be used as the single comprehensive design constraint, qualifying disruptive engineering solutions which are not currently governed by provisions of design standards. This way, the presented methodology can path the way to reliable structures of FWTs and reduced uncertainties in the system designs.

In the following, first (Section 2), the RBDO problem is presented. The challenges and solutions for the realization and numerical implementation of this RBDO problem are discussed and detailed in Section 3. The presented RBDO methodology is applied to an exemplary spar-buoy FWT system and the results are presented in Section 4 and further discussed in Section 5. At the end (Section 6), some conclusions and outlook are provided.

2. Definition of the RBDO problem

The optimization problem – as given in Eq. (1) – is to find values for the optimization variables or so called design variables $x_i$, contained in the design variables vector $X$, so that the objective functions $f_i$ are minimized, as well as the equalities ($h_i$) and inequalities ($g_i$) constraints are fulfilled.

$$
\begin{align*}
\text{minimize} & \quad f_i(X), & i = 1, \ldots, l \\
\text{subject to} & \quad h_i(X) = 0, & i = 1, \ldots, m \\
\text{subject to} & \quad g_i(X) \leq 0, & i = 1, \ldots, n
\end{align*}
$$

The RBDO is applied to the reference FWT system, presented in Section 2.1, and for certain design-critical environmental conditions elaborated in Section 2.5. In a former DDO example [25], the same system is optimized with respect to its global performance, while limiting the outer dimensions of the floater. Based on this and applying a semi-probabilistic method in the presented example, limit states (LSs) in form of characteristic values, uncertainties in form of stochastic variables, and reliability criteria – comprising both LSs and uncertain parameters – are incorporated in the optimization problem. For a RBDO problem, a target reliability has to be specified as objective function. An alternative – the reliability-constrained design optimization, as realized in this work due to computational limitations – is to address the reliability criteria in the constraints of the optimization problem.

Thus, the finally selected design variables and objective functions, LSs, environmental conditions, stochastic variables, and reliability criteria, as well as optimization constraints, are specified in Sections 2.2 to 2.8. Due to the complexity of a FWT system, the objective functions and (in-)equalities constraints are not only directly dependent on the design variables but also on the fully-coupled dynamic system response. This is indicated in the following through the term $system(X)$.

2.1. Reference FWT system

As reference FWT system, the concept from OC3 (Offshore Code Comparison Collaboration) phase IV [26] is considered. This consists of a spar-buoy floating platform that supports the NREL (National Renewable Energy Laboratory) 5 MW reference wind turbine [27] with an offshore adapted tower and adjusted controller for the floating system. The FWT has a hub height of 90.0 m, a draft of 120 m, an overall system structural mass (rotor-nacelle assembly, tower, floater including ballast) of 8.066E+6 kg, and is moored at 320 m water depth with three catenary mooring lines. The spar-buoy floater matches at 10.0 m elevation above still water level (SWL) the tower base diameter of 6.5 m. This diameter prevails down to 4 m below SWL, where it increases in an 8 m long tapered section up to 9.4 m, which then remains down to the bottom of the floater. A schematic illustration of the spar-buoy floater is presented in Fig. 1. For more details on the OC3 phase IV FWT system, the reader is referred to the definition documents [26,27].
2.2. The design variables

The floating spar-buoy platform is mainly defined through its geometry (diameters and heights) and the ballast (density and height). Not altering the transition between tower and floater base – meaning the upper cylindrical spar element down to the bottom end of the tapered part – three design variables for modifying the spar-buoy floater are defined, as indicated schematically in Fig. 1:

- the spar base diameter ($x_1 = D$),
- the spar base height ($x_2 = H$), and
- the ballast density ($x_3 = \rho$).

For the ballast design variable, the density is chosen to directly specify cheap ballast materials. This leaves the ballast height as a dependent variable to ensure floatation of the system. Other floater properties, such as material density, wall thickness, or resulting mooring stiffness, are kept unchanged.

Allowable value ranges for the three selected design variables are specified to limit on the one hand the outer dimensions of the floater, which would positively affect the required material and resulting structural costs, and on the other hand to consider only feasible design solutions with respect to existing and affordable ballast materials. Thus, the original values for the spar base diameter and height are set as upper bound for the allowable value ranges. The lower bound for the spar base diameter is prescribed by the tower base diameter to avoid any constriction of the support structure, while for the spar base height the minimum draft of the floating system is decisively. As cost-efficient ballast materials, sand with different water contents ($\rho \in [1.281 \text{ kg/m}^3, 2.082 \text{ kg/m}^3]$ [28]), concrete ($\rho \in [1.750 \text{ kg/m}^3, 2.400 \text{ kg/m}^3]$ [29]), and rocks (up to $\rho = 2.600 \text{ kg/m}^3$ [30]) are considered. This leads to the following allowable value ranges for the deterministic design variables:

- $x_1 \in [6.5 \text{ m}, 9.4 \text{ m}]$ (original: 9.4 m),
- $x_2 \in [8.0 \text{ m}, 108.0 \text{ m}]$ (original: 108.0 m),
- $x_3 \in [1,281 \text{ kg/m}^3, 2,600 \text{ kg/m}^3]$ (original: 1,907 kg/m$^3$).

These limitations are addressed by means of the inequalities constraints $g_1$ to $g_9$, outlined in Section 2.8.

2.3. The objective functions

Focusing on the global dynamic FWT system performance and at the same time aiming to avoid an oversized design due to an over-conservative approach, the horizontal nacelle acceleration ($\ddot{\theta}_{\text{nacelle}}$) and total system inclination angle ($\theta_s$) shall approach but not exceed a maximum allowable value, which is set in each case according to common values [25,31–35], while the dynamic translational motion ($s_{\text{dyn,transl}}$) is to be minimized due to the restricted allowable motion of the power cable. Thus, the objective functions are defined as given in Eqs. (2) to (4), while the non-exceedance of maximum allowable values are addressed by means of the inequalities constraints $g_7$ to $g_9$ (Section 2.8).

$$f_1(\text{system}(X)) = \frac{|\ddot{\theta}_{\text{nacelle}} - 1.962 \text{ m/s}^2|}{1.962 \text{ m/s}^2}$$

$$f_2(\text{system}(X)) = |\theta_s - 10.0\degree|$$

$$f_3(\text{system}(X)) = s_{\text{dyn,transl}}$$

2.4. The limit states

In the final reliability assessment, LSs have to be considered. Thus, two parameters, which might become critical for the considered optimization objectives (Section 2.3) and are as well judged in other studies [31,36–38] as important parameters for LS analyses, are selected and discussed in the following.

2.4.1. Bending stress at the tower base

The tower base fore–aft and side–side bending moments depend highly on the thrust force, as well as on the degree of damping in fore–aft and side–side motion, and are influenced by the floater motion. The overall bending moment experienced at the tower base is derived as the combined fore–aft and side–side tower base bending moment ($M_{\text{TB}}$). Relating this to the cross-sectional area at the tower base with diameter $D_{\text{TB}}$ (6.5 m) and wall thickness $t_{\text{TB}}$ (0.027 m) according to Eq. (5), the combined tower base bending stress ($\sigma_{\text{TB}}$) is obtained.

$$\sigma_{\text{TB}} = \frac{32}{\pi} \frac{D_{\text{TB}}}{(D_{\text{TB}} - 2t_{\text{TB}})^4} M_{\text{TB}}$$

For this bending stress at the tower base, the LS is defined as follows:

- the common construction steel is S355 with a minimum yield stress of 355.00 MPa [39,40],
- a partial safety factor of 1.35 is applied according to standards and guidelines [41–44],
- the resulting limit for the allowable stress amounts to 262.96 MPa.

This limit defines both the LS for the reliability assessment and the ultimate tower base bending stress.
The investigated load cases are: nature of the LSs, 54 environmental conditions from operational DLCs focusing on the maximum global system performance and the ultimate when choosing the critical DLC to be used within the RBDO. Due to LS parameters, selected and specified in Section 2.4, are considered only certain critical load cases are investigated in system and design effort and comprehensiveness of load analyses. Thus, commonly including design optimization, forces a compromise between computational effort and comprehensiveness of load analyses. Thus, commonly only certain critical load cases are investigated in system and design analyses [36–38,49].

For designing a FWT system, standards and technical specifications by IEC (International Electrotechnical Commission), DNV (Det Norske Veritas), and DNV GL (Det Norske Veritas and Germanischer Lloyd) recommend a set of design load cases (DLCs) for various environmental conditions and turbine operational states to be considered. However, the highly iterative character of the development of a system design, including design optimization, forces a compromise between computational effort and comprehensiveness of load analyses. Thus, commonly only certain critical load cases are investigated in system and design analyses [36–38,49].

Not all environmental loading conditions and operating modes are design driving for the specified optimization problem. Thus, the objectives, which are defined and described in Section 2.3, as well as the LS parameters, selected and specified in Section 2.4, are considered when choosing the critical DLC to be used within the RBDO. Due to the focus on the maximum global system performance and the ultimate nature of the LSs, 54 environmental conditions from operational DLCs for ultimate analyses are selected from IEC standard 61400-3-1 [42]. The investigated load cases are:

- 18 conditions for DLC 1.1 around rated wind speed (10.0 m/s, 11.4 m/s, 13.0 m/s) with normal turbulent wind conditions, normal irregular sea state, and normal current conditions, as the largest system inclination and mean translational motion, as well as tower base bending stress and stress in the upwind mooring lines are expected to be driven by the highest thrust force occurring at rated wind speed;
- 18 conditions for DLC 1.3 below, at, and above rated wind speed (8.0 m/s, 11.4 m/s, 25.0 m/s) with extreme turbulent wind, but normal irregular sea state and normal current conditions, as for a wind-dominated site the largest nacelle acceleration and dynamic translational motion are expected to be driven by the high fluctuations in the wind loading; and
- 18 conditions for DLC 1.6 below, at, and above rated wind speed (8.0 m/s, 11.4 m/s, 25.0 m/s) with normal turbulent wind conditions and normal current conditions, but severe irregular waves, as for a wave-dominated site the largest nacelle acceleration and dynamic translational motion are expected to be driven by the high fluctuations in the wave loading.

In each DLC three yaw misalignment angles (−8°, 0°, 8°) and two discrete seed numbers (each for wind and waves) per yaw misalignment angle are considered. This leads, combined with the three different wind speeds addressed in each DLC, to the mentioned 18 conditions per DLC.

Fully-coupled system simulations in time-domain are performed with the specified reference FWT (Section 2.1) for these environmental conditions. The evaluated system parameters are on the one hand the optimization objectives defined in Section 2.3, as well as a fourth constrained performance parameter – the mean translational motion (\(s_{\text{mean,trans}}\)) – and on the other hand the LS parameters specified in Section 2.4.

From the set of 54 environmental conditions, the three DLC settings that turn out to be most critical to some of the evaluated system parameters are presented in Table 1. The criticality of each case for each parameter of interest is expressed in terms of the position of the specific case within all 54 simulated conditions.

Further assessment, rating horizontal nacelle acceleration and total inclination angle as the two most important performance parameters and noticing that the highest mooring line stress achieved in all simulated cases is way below the specified LS (less than one third of it) while the tower base bending stress reaches a much closer value to the corresponding LS (almost 80% of it), yields the selection of DLC 1.6

- at 11.4 m/s wind speed,
- with seed number 8 for the normal turbulence model,
- yaw misalignment angle of −8°,
- severe sea state (SSS) with 50 years recurrence period, and
- irregular waves of 10.4 m significant wave height, 14.7 s peak period, and seed number 14

as design driving and most critical load case for the considered optimization objectives and LSs given in Sections 2.3 and 2.4.

### 2.6. The stochastic variables

As the considered FWT is just a reference system, which is not operating at or designed for an explicit offshore site – only the water depth is prescribed, however, no information on annual distributions of wind and waves is available – the environmental parameters, used within the DLC setup (Section 2.5) based on equations and relations provided in standards, are selected as uncertain parameters in this study, which are then accounted for in the reliability analysis. Specifically the mean value of the turbulent wind speed (11.4 m/s in the selected critical DLC), as well as the significant wave height of the irregular waves in the severe sea state (10.4 m in the selected critical DLC), are taken.

To define a stochastic variable, its type of distribution and statistical coefficients have to be specified. This is done in Sections 2.6.1 and 2.6.2 for the two selected uncertain parameters.

#### 2.6.1. Statistical properties for the wind speed

For the wind speed \(V\) (long-term n-minute average speed), a Weibull distribution can be assumed, according to the classification notes 30.6 by DNV [50]. The Weibull distribution parameters are derived from data at an offshore site, which shall represent realistic site conditions for the considered FWT system, as well as a mean wind speed of 11.4 m as stated in the DLC (Section 2.5). Considering the locations of the
\( N = \frac{365^2 \times 24^4}{3^2 \times \pi} = 2.920 \) (8)

Based on this, the distribution parameters and statistical coefficients for the stochastic variable \( H_s \) are derived and presented in Table 3.

The mean value is by about 9.6\% larger than the significant wave height specified in the selected critical DLC (Section 2.5), but still close enough for such an extreme event, so that these site distribution values are utilized for the stochastic variable \( H_s \).

2.7. The reliability criteria

Various standards, technical specifications, and classification notes by IEC, DNV, DNV GL, and ISO (International Organization for Standardization) are reviewed regarding the target value for the reliability index (\( \beta \)) to be considered. While IEC [41–43] recommends a nominal annual failure probability of 5E-4, corresponding to \( \beta = 3.291 \), and refers to ISO 2394 [52], which defines the allowable probability of failure in dependency on the amount of the relative cost of safety measure and the magnitude of the consequences of failure, DNV [39,50] and DNV GL [53] recommend for the same reference period of one year a nominal failure probability of 1E-4, corresponding to \( \beta = 3.719 \), which is even tightened in case of unacceptable consequences of failure to a failure probability of 1E-5, corresponding to \( \beta = 4.265 \).

In the considered case of a single FWT system under normal operating condition in a severe sea state – as specified in Section 2.5 – and, hence, being unmanned, the consequences of failure are likely neither related to human injuries nor to impacts to other structures or the environment and most probably have mainly financial repercussions, for which reason the target safety level is set to a maximum allowable failure probability of 1E-4 or a minimum required reliability index of \( \beta = 4.265 \), respectively.

This has to be fulfilled for all four LS parameters – bending stress at the tower base, as well as stresses in ML1, ML2, and ML3 – defined in Section 2.4, while accounting for the uncertainties in the environmental conditions, specified through the two stochastic variables \( V \) and \( H_i \) stated in Section 2.6.

2.8. The constraints

The specified optimization problem comes with no \( n = 0 \) equality constraint \( \left( a_i \right) \) and 18 \( \left( n = 18 \right) \) inequalities constraints \( g_i \). The first ten constraints are corresponding to the inequalities constraints already prevailing in the DDO application example [25]. These are Eqs. (9) to (14) for the allowable value ranges of the design variables specified in Section 2.2, Eqs. (15) to (17) for defining the direction from which the objective functions on the global system performance parameters mentioned in Section 2.3 shall be approached, as well as

| Table 1 |
| --- |
| Criticality of specific DLC settings for evaluated system parameters. |
| | DLC 1.1 @ 11.4 m/s (seed 10) | DLC 1.6 @ 11.4 m/s (seed 8) | DLC 1.6 @ 11.4 m/s (seed 11) |
| Parameter | Value | Value | Value |
| \( \alpha_{\text{rot, yaw}} \) | Position 33 | 3 | 1 |
| Value | 0.706 m/s | 2.324 m/s | 2.334 m/s |
| \( t_{\text{rot}} \) | Position 21 | 1 | 5 |
| Value | 4.4° | 5.1° | 4.8° |
| \( s_{\text{yaw, yaw}} \) | Position 16 | 26 | 40 |
| Value | 7.6 m | 7.1 m | 5.7 m |
| \( s_{\text{wind, yaw}} \) | Position 5 | 10 | 9 |
| Value | 20.7 m | 20.5 m | 20.5 m |
| \( \sigma_{\text{TB}} \) | Position 35 | 127.61 MPa | 204.74 MPa | 202.14 MPa |
| Value | 1 | 47 | 46 |
| \( \sigma_{\text{ML1}} \) | Position 33 | 113.89 MPa | 108.39 MPa | 108.57 MPa |
| Value | 2 | 32 | 13 |
| \( \sigma_{\text{ML2}} \) | Position 2 | 207.35 MPa | 194.70 MPa | 201.74 MPa |
| Value | 12 |
| \( \sigma_{\text{ML3}} \) | Position 1 | 210.36 MPa | 202.25 MPa | 193.68 MPa |
| Value | 210.36 MPa | 202.25 MPa | 193.68 MPa |

| Table 2 |
| --- |
| Statistical coefficients of the stochastic variable wind speed. |
| Parameter | Value |
| Weibull scale factor | 12.8 m/s |
| Weibull shape factor | 2.659 |
| Mean wind speed | 11.4 m/s |
| Standard deviation | 4.6 m/s |
| Least square error of fit | 4.86 – 4 m²/s² |

| Table 3 |
| --- |
| Statistical coefficients of the stochastic variable significant wave height. |
| Parameter | Value |
| Weibull scale factor | 2.290 m |
| Weibull shape factor | 1.385 |
| Weibull location parameter | 0.594 m |
| Reference period of extreme event | 3 h |
| Mean significant wave height for SSS | 11.4 m |
| Standard deviation | 1.1 m |

Hywind demonstrator (west of Karmøy) and the Hywind Scotland pilot park (east of Peterhead), the database [51] for the northern North Sea and central North Sea areas is investigated. Here it strikes that at grid point 14715 in the northern North Sea the mean wind speed in month December matches exactly the required value of 11.4 m/s. To the available data on percentage exceedance, a two-parameter Weibull distribution is fitted. The obtained parameters and statistical coefficients are summarized in Table 2.

2.6.2. Statistical properties for the significant wave height

For the significant wave height \( H_s \), the classification notes 30.6 by DNV [50] prescribe a three-parameter Weibull distribution. Such a three-parameter Weibull distribution is derived in [50] from scatter data in the North Sea — hence, the similar region considered already in Section 2.6.1. As, however, the sea state considered in the selected DLC (Section 2.5) is severe, an extrapolation to such an extreme significant wave height is required. In an application example in the classification notes 30.6 [50], an extreme three-hour event is considered. Following the same approach, the cumulative density function for the significant wave height in SSS \( (F_{\text{SSS}}(H_s)) \) is derived according to Eq. (7) from the common cumulative density function \( (F(H_s)) \) with accounting for the reference period of the extreme event by means of \( N \), as expressed in Eq. (8) for a three-hour extreme event.

\[
F_{\text{SSS}}(H_s) = \left[F(H_s) \right]^N
\] (7)

\[
N = \frac{365^2 \times 24^4}{3^2 \times \pi} = 2.920
\] (8)
Eq. (18) for another global system performance parameter — the mean translational motion, which shall not exceed 20% of the water depth.\footnote{This limit is based on consultation with technology developers.}

\begin{alignat}{2}
g_1(x_1) & = 6.5 \, m - x_1 & \quad & (9) \\
g_2(x_1) & = x_1 - 9.4 \, m & \quad & (10) \\
g_3(x_2) & = 8.0 \, m - x_2 & \quad & (11) \\
g_4(x_2) & = x_2 - 108.0 \, m & \quad & (12) \\
g_5(x_3) & = 1.281 \, kg/m^3 - x_3 & \quad & (13) \\
g_6(x_3) & = x_3 - 2.600 \, kg/m^3 & \quad & (14) \\
g_7(\text{system}(X)) & = a_{\text{hor, nacelle}} - 1.962 \, m/s^2 & \quad & (15) \\
g_8(\text{system}(X)) & = \omega_{n} - 10.0^\circ & \quad & (16) \\
g_9(\text{system}(X)) & = -\delta_{\text{dyn,transl}} & \quad & (17) \\
g_{10}(\text{system}(X)) & = \sigma_{\text{mean,transl}} - 64.0 \, m & \quad & (18)
\end{alignat}

Up to now, the optimization problem defined through the three design variables $x_1$ to $x_3$ (Section 2.2), the three objective functions $f_1$ to $f_3$ (Section 2.3), and the above listed ten inequalities constraints $g_1$ to $g_{10}$ is already significantly constrained, but describes just a DDO problem. Thus, for stating a RBDO problem, the reliability criteria for the four LS parameters given in Section 2.4, with considering environmental uncertainties by means of the two stochastic variables specified in Section 2.6, have to be added. Defining them through additional objective functions would put much more restrictions on the optimization problem. This would not necessarily inhibit the convergence of the algorithm, but would significantly slow it down. Due to computational limitations, the reliability criteria are integrated as constraints for the lower limit — the minimum required reliability of the system LS parameters. These constraints entail Eqs. (19) to (22) for limiting the lowest allowable value for the reliability index obtained for the tower base bending stress, as well as the stress in each mooring line. The evaluation of the reliability index itself is described in detail in Section 2.2.2.

\begin{alignat}{2}
g_{11}(\text{system}(X)) & = 3.719 - \beta_{\text{TB}} & \quad & (19) \\
g_{12}(\text{system}(X)) & = 3.719 - \beta_{\text{ML,1}} & \quad & (20) \\
g_{13}(\text{system}(X)) & = 3.719 - \beta_{\text{ML,2}} & \quad & (21) \\
g_{14}(\text{system}(X)) & = 3.719 - \beta_{\text{ML,3}} & \quad & (22)
\end{alignat}

Furthermore, as already indicated in Section 2.4, the maximum values for the tower base bending stress and the stresses in the three mooring lines are limited to not exceed the corresponding ultimate stress values. These limitations add four more inequalities constraints, as given in Eqs. (23) to (26).

\begin{alignat}{2}
g_{15}(\text{system}(X)) & = \sigma_{\text{TB}} - 262.96 \, MPa & \quad & (23) \\
g_{16}(\text{system}(X)) & = \sigma_{\text{ML,1}} - 770.26 \, MPa & \quad & (24) \\
g_{17}(\text{system}(X)) & = \sigma_{\text{ML,2}} - 770.26 \, MPa & \quad & (25) \\
g_{18}(\text{system}(X)) & = \sigma_{\text{ML,3}} - 770.26 \, MPa & \quad & (26)
\end{alignat}

3. Numerical implementation

The realization of the RBDO problem defined in Section 2 utilizes, on the one hand, a Python–Modelica framework – introduced in Section 3.1 – for executing automatically fully-coupled system simulations with the FWT, as well as performing automatically the optimization task. On the other hand, two levels of preprocessing – (1) for elaborating the approach and boundary conditions for the reliability assessment of one specific system, based on response surface method and stochastic variables (Section 3.2), and (2) for generating various response surfaces for different designs in the optimization design space (Section 3.3) – are required before addressing finally the iterative RBDO process, described in Section 3.4. The subsequent postprocessing of the results is covered in Sections 4.2 and 4.3. A flowchart of these modular steps is presented in Fig. 2.

3.1. Python–Modelica framework

The numerical implementation of the RBDO problem, including the preprocessing as well as the final process, is based on the Python–Modelica framework \cite{54,55}, developed at Fraunhofer IWES (Institute for Wind Energy Systems). This framework consists – as presented in Fig. 3 – of a modeling environment to model the specific FWT system, a simulation tool for performing fully-coupled system simulations with the created model, and a programming framework, by which means system simulations and iterative optimization tasks are performed automatically.

Utilizing this Python–Modelica framework, the wind turbine system is modeled by means of MoWiT (Modelica library for Wind Turbines), developed at Fraunhofer IWES \cite{56-58}. This component-based library uses the object-oriented and equation-based modeling language Modelica\textsuperscript{3} and allows for fully-coupled aero-hydro-servo-elastic wind turbine system simulations, which are executed in Dymola\textsuperscript{4} (Dynamic Modeling Laboratory) – the corresponding simulation tool in the Python–Modelica framework – in time-domain. The processing of the system model (including interface setup, parameter redefinition, and simulation settings definition), the task management for organization of all tasks and available processors, as well as the automatic execution of the simulations – either independent system simulations with different settings and parameter values or various system simulations with settings and variable values depending on the specified optimization problem or also including preprocessing generations of turbulent wind time series by means of TurbSim \cite{59} – are carried out by the programming framework coded in Python.

In a preceding study \cite{60}, the utilized reference FWT from OC3 phase IV (Section 2.1) is already implemented in MoWiT and verified against several other numerical codes and tools. Based on this, the

\footnote{https://www.modelica.org/ (Accessed: 23 March 2020).}
\footnote{http://www.dymola.com/ (Accessed: 23 March 2020).}
Python–Modelica framework has been successfully applied to a number of design optimization tasks on FWT systems [25,61,62]. In this work now, it is extended by adding the reliability assessment method to cover as well RBDO tasks.

3.2. Preprocessing level one

Ahead of performing any RBDO task on the FWT, some preparatory investigations, simulations, and studies are required. At first, the approach and boundary conditions for the reliability assessment of one specific system have to be elaborated. This comprises the specification of the environmental conditions in terms of a DLC, under which the system is investigated, as well as the LSs, which are to be considered in the reliability assessment; the choice and definition of uncertain parameters, which are then handled as stochastic variables with specific statistical properties; the selection of a specific reliability analysis method to be followed to determine the reliability index for each LS; and, finally, the investigation of the plausibility of the settings and results, as well as their closeness to reality. The flowchart of these preprocessing level one steps is presented in Fig. 4. This approach has similarities regarding its structure with other studies on reliability assessments of complex renewable energy systems [17,63,64]; however, the decisions on the DLC and LSs are primarily driven by the optimization objectives of the RBDO problem and the selection of the reliability analysis method already takes account of the final application within the iterative RBDO process.

3.2.1. Determination of DLCs, LSs, and stochastic variables

The reliability assessment of the FWT system to be optimized is done for a specific DLC, focusing on certain LSs, and considering uncertainties through stochastic variables. The limit states are selected based on the defined objective functions (Section 2.3) and specified in Section 2.4. The selection procedure for choosing a critical environmental condition is presented in Section 2.5. For this, fully-coupled system simulations are required, as already mentioned. These are performed automatically and in parallel utilizing the Python–Modelica framework introduced in Section 3.1. As the evaluation of the system response in a DLC is based on ten-minute time series, each DLC simulation is run for 800 s, which allows for sufficient (200 s) presimulation time, in which any initial transients have already decayed. The final postprocessing, in which the maximum occurring values for the parameters of interest (system performance and LSs) are extracted from the time series, is, hence, always based on the last 600 s.

Based on the found critical DLC, the stochastic variables $V$ and $H_i$ and their statistical properties are defined in Section 2.6. As not all possible combinations of the stochastically distributed wind speed and significant wave height can be elaborated in the subsequent reliability assessment, sample points for which the reliability analysis shall be performed have to be specified. As the wind speed follows a non-normal distribution (Section 2.6.1), five sample points of the stochastic variable are taken from the 5th to 95th percentile range and, additionally, directly the mean value, as the distribution is not symmetric. All selected sample points for the stochastic variable $V$ are presented in Table 4.

For the significant wave height, which is as well non-normal distributed (Section 2.6.2), the sample points are again composed by five values taken from the 5th to 95th percentile range, as well as the mean value. The corresponding peak period $T_p$ is determined – as done in the DLC specification – according to Eq. (27) with the gravitational constant $g$. This uses the upper bound of the peak period range specified in the IEC standard 61400-3 [65] in order to realize a peak-shape parameter which is as close as possible to one. This, namely, reflects a Pierson–Moskowitz spectrum, which follows the concept of a fully developed sea — what is the condition at such a far offshore and deep
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Table 4
| Sample points of the stochastic variable wind speed | Wind speed |
|---------------------------------------------------|------------|
| 5th percentile                                   | 4.2 m/s    |
| 25th percentile                                   | 8.0 m/s    |
| 50th percentile                                   | 11.2 m/s   |
| mean value                                        | 11.4 m/s   |
| 75th percentile                                   | 14.5 m/s   |
| 95th percentile                                   | 19.4 m/s   |

Table 5
| Sample points of the stochastic variable significant wave height | Significant wave height | Peak period |
|------------------------------------------------------------------|-------------------------|------------|
| 5th percentile                                                   | 9.8 m                   | 14.3 s     |
| 25th percentile                                                  | 10.5 m                  | 14.8 s     |
| 50th percentile                                                  | 11.2 m                  | 15.3 s     |
| mean value                                                       | 11.4 m                  | 15.4 s     |
| 75th percentile                                                  | 12.0 m                  | 15.8 s     |
| 95th percentile                                                  | 13.5 m                  | 16.8 s     |

The selected sample points for the stochastic variable \( H_i \) and the corresponding peak periods are summarized in Table 5.

3.2.2. Evaluation of reliability index

The reference FWT system (Section 2.1) is simulated according to the determined critical DLC (Section 2.5), however, replacing the values for wind speed and significant wave height (as well as peak period) by any combination of the selected sample points of the two stochastic variables (Section 3.2.1). Thus, a total of 36 simulations (each of 800 s simulation length) are performed and the system responses related to the specified LSs (Section 2.4) are extracted from the last 600 s (excluding any transients within the first 200 s of the simulation) — similarly as done in the DLC simulations (Section 3.2.1). Through the 36 values for each LS parameter, a response surface is developed by means of a quadratic regression analysis based on the least squares method (LSM) [17,64,66,67]. The quadratic regression model of the considered case, with

- a \( 36 \times 4 \) matrix \( Y \), containing the values for each LS parameter at all simulated stochastic variables combinations,
- a \( 36 \times 5 \) matrix \( X \) of \([1 \ V^2 \ H_i \ H_i^2]\) for each of the 36 simulated combinations,
- a \( 5 \times 4 \) matrix \( A \), containing the regression coefficients \([a_0 \ a_1 \ a_2 \ a_3 \ a_4]\) for each LS parameter, and
- the \( 36 \times 4 \) error matrix \( E \),

is expressed in Eq. (28).

\[
Y = XA + E \quad (28)
\]

The regression coefficients for each LS parameter, contained in the matrix \( A \), are derived following Eq. (29).

\[
A = (X^\top \cdot X)^{-1} \cdot X^\top \cdot Y \quad (29)
\]

The stochastic response surface method is commonly used as basis for analytical – using FORM or SORM – or stochastic – using MCS or other sampling methods – reliability analyses for determining the reliability index [16]. FORM and SORM come with a similar affordable computational effort independent on the resulting failure probability, while MCS becomes more and more computationally expensive when aiming to accurately cover larger and larger probabilities of failure. However, as the failing convergence of the iterative calculations within the HL–RF (Hasofer–Lind–Rackwitz–Fiessler) method applied within FORM is a widely discussed issue that appears for specific conditions, such as nonlinear LS functions or complicated phenomena [68–72], as well as the herein considered RBDO problem, in this study, it is decided to directly use MCS in combination with the stochastic response surface method. Applying the response surfaces, which are already derived, means that no more system simulations are required. Just more computational effort for the MCS – namely, evaluating Eq. (28) for a certain number \( r \) of random samples of \( V \) and \( H_i \) – is needed, depending on the order of magnitude of \( r \). Based on a rule of thumb, \( r \) should be one or two orders of magnitude higher than the probability of failure that shall be covered accurately enough. As the limit for an acceptable reliability index is 3.719, as derived in Section 2.7, which corresponds to a probability of failure of 1E−4, \( r \) is set equal to 1E+6, which sufficiently captures the limit for an acceptable reliability index (including as well some higher values) and at the same time comes with a reasonable computational effort, as Eq. (28) can be evaluated for 1E+6 different \( X \)-matrices in just about half a minute on a conventional computer.

Thus, each 1E+6 random values for wind speed and significant wave height are generated, based on their distribution type and statistical coefficients given in Tables 2 and 3, respectively. Performing the MCS by solving Eq. (28) with a now 1E+6 \( \times 5 \) \( X \)-matrix, covering the random set of the stochastic variables, and counting all events \( j \), in which the specified limit for the LS parameter (Section 2.4) is exceeded, the reliability index \( \beta \) for each LS parameter is derived according to Eq. (30), with the inverse of the normal cumulative density function \( \phi^{-1} \).

\[
\beta = \phi^{-1} \left(1 - \frac{l}{r}\right) \quad (30)
\]

This yields infinite (meaning zero failure events) for all LS parameters, which is because of the very safe distance between the obtained maximum values for the LS parameters in the system simulations and the allowable limits specified in Section 2.4. This is already noticeable in the initial DLC simulations presented in Table 1 and gets more clear when comparing the limit values with the maximum values obtained from the 36 simulations for the sample points of the stochastic variables, as presented in Table 6.

A reduction of the allowable maximum values to for example 225.00 MPa for \( \sigma_{TB} \) and 230.00 MPa for \( \sigma_{ML3} \) proves with reliability index values between 2.74 and 4.47 the approach and sufficient order of magnitude of \( r \). Even if the stress in the mooring lines is expected not to become critical to the specified limit when changing the FWT design during the subsequent RBDO (Section 3.4), the bending stress at the tower base could become critical to the reliability index limit, as larger stresses are expected for higher system inclination angles. The considered DLC and specified statistical properties of the stochastic variables are, hence, judged as realistic and appropriate for the defined application example.

3.3. Preprocessing level two

Integrating reliability assessment into design optimization, which is of iterative nature, requires some additional investigations on how the reliability index for each single system design appearing within
an optimization algorithm can be determined in an efficient manner. Performing 36 simulations for the sample points of the stochastic variables – as done in Section 3.2.2 with the original FWT system – but now with each individual design obtained in an iterative RBDO process, would make the total number of simulations and the required computational effort skyrocket and, hence, is definitely not the most efficient way to assess the reliability of each of these FWT system designs. Thus, in this work, response surfaces – on which basis the reliability index can be determined, as already presented in Fig. 4 and described in Section 3.2.2 – are generated for a limited number of floating system designs lying within the optimization design space. The obtained regression coefficient sets each define a system-specific response surface, which relates the response parameters of each of these specific floater geometries to the input environmental parameters, using the same random set of environmental conditions as determined and applied in the level one preprocessing (Section 3.2). These regression coefficient sets build the basis for an interpolation approach, used later on during the iterative optimization algorithm in order to determine the regression coefficients – and based on these perform the reliability assessment – of each single system design appearing within the optimization algorithm. The steps for generating various response surfaces in the optimization design space are presented in Fig. 5 and described in more detail in Sections 3.3.1 and 3.3.2. Furthermore, the derivation and quality assessment of the interpolation approach, which serves as time- and computationally efficient method for the reliability assessment within the iterative RBDO, are detailed in Section 3.3.3.

3.3.1. Definition of discrete floater geometries in the design space

During the RBDO, the FWT system designs can vary within the allowable value ranges of the design variables, as specified in Section 2.2. Within this optimization design space, for each optimization variable five discrete values, evenly spaced in the corresponding allowable value range, are selected, as well as the original system parameter value if not yet included. This leads to five values for the spar base diameter, five values for the spar base height, and six values for the ballast density, as presented in black in Table 7. Thus, combining all discrete values for the optimization variables with each other, 150 system geometries are selected.

3.3.2. Generation of response surfaces

For each of the 150 system geometries, specified in Section 3.3.1, simulations for all 36 combinations of the sample points of the stochastic variables (Section 3.2.1) for the selected critical DLC condition (Section 2.5) are performed and the maximum values for the specified LS parameters (Section 2.4) extracted from the time series (again between 200 s and 800 s). Following the approach described in Section 3.2.2, response surfaces and the corresponding regression coefficients are derived for each system geometry. As, however, not all combinations of the discrete optimization variables yield stable FWT designs with a positive metacentric height, it is not striking that some simulations fail due to bad system performance and do not complete the total 800 s simulation time. These failing designs are excluded and the regression coefficients are just set to \( \text{NaN} \) (Not a Number).

Analyzing the results, it is noted that none of the FWT systems with a spar base height of either 8.0 m or 33.0 m is stable and still for spar base heights of 58.0 m and 83.0 m several system simulations fail when combined with low spar base diameters and low ballast densities. Thus, two more discrete values for the spar base height are added, presented in red in Table 7, recombined with the other two design variables, simulated, and evaluated. This way, the separation area between stable and failing FWT system designs is narrowed down and a total of 72 successfully simulated designs are obtained, while 138 show unstable behavior due to a negative metacentric height.

Overall, 210 system geometries are considered and a total of 7,760 simulations are performed. Utilizing the Python–Modelica framework, introduced in Section 3.1, this takes about 185 h on an AMD Ryzen Threadripper 2990WX 32-Core Processor with 64-bit system and using all of its 64 virtual processors for parallel execution of the simulations.

In order to prove that the quadratic regression analysis with \( X = \{V, V^2, H, H^2\} \) is sufficient, the responses \( Y \) are re-computed based on the determined regression coefficients (Eq. (28)) and compared – by means of the coefficient of determination \( R^2 \) – with the maximum values obtained directly from the system simulations. This comparison can only be done for the 72 successfully simulated system geometries. For all those corresponding 288 LS parameter results, except for three, \( R^2 \) values of at least 0.96 (mostly even above 0.99) are obtained. This proves that the selected quadratic regression analysis approach is sufficient for the considered system and problem.

3.3.3. Interpolation of response surfaces for arbitrary floater geometries in the design space

During the optimization, the design variables can take on any value within the allowable value ranges in any combination with each other. The system geometries for which response surfaces are generated, however, are just 210 discrete combinations of five \( (k_p) \), six \( (k_s) \), and

### Table 7

| Spar base diameter \( D \) [m] | 6.5 | 7.225 | 7.95 | 8.675 | 9.4 |
|-------------------------------|-----|-------|------|-------|-----|
| Spar base height \( H \) [m]   | 8.0 | 33.0  | 45.5 | 58.0  | 70.5 |
| Ballast density \( \rho \) [kg/m\(^3\)] | 83.0 | 108.0 |

Fig. 5. Preprocessing level two flowchart for generating response surfaces in the optimization design space.
In the next step, the position of design $x$ with respect to its eight neighbors is determined in terms of factors $f_D$, $f_H$, and $f_P$ as fraction of the distances between the surrounding neighbors, as given in Eqs. (35) to (37).

$$f_D = \frac{D - D_{\text{left}}}{D_D}$$

$$f_H = \frac{H - H_{\text{left}}}{D_H}$$

$$f_P = \frac{\rho_s - \rho_s^\text{left}}{D_P}$$

Based on these, weights $w_P$ are calculated for the neighboring points $P_i$ to $P_k$ based on the closeness of the neighbors to design $x$. The weights are determined according to Eq. (38) for the numbering of the neighbors indicated in Fig. 6.

$$w_{P_i} = (1 - f_D)(1 - f_H)(1 - f_P)$$

The weights are used to interpolate the regression coefficients of each neighboring point $A_i$, following Eq. (39), to obtain the regression coefficients $A_x$ for defining the response surface of design $x$. Within this calculation it is checked whether the regression coefficients of any neighbor is NaN to ensure that only numeric values are added up. In case that all eight neighbors fail in the system simulations, a zero vector is assigned to the regression coefficients of design $x$, which is later on (Section 3.4.2) utilized for excluding such designs from the set of potential satisfying solutions.

$$A_x = \sum_{P_i} w_{P_i} A_{P_i}$$

To verify the accuracy of the applied interpolation approach, 32 control points are defined, for which – in each case – the 36 system simulations for the sample points of the stochastic variables are performed. A couple of these control points are selected to lie in between the discrete values of one design variable, while matching a specified discrete value of the other two design variables, and some further are completely between the grid points defined by the discrete values of the design variables. A summary of the selected control design geometries is presented in Table 8.

For these 32 control points, from which just one system design fails during the simulations, the regression coefficients are calculated based on the above presented interpolation approach. First, again the coefficient of determination is computed for the simulation results and the quadratic regression analysis results (Eq. (28)). The 124 LS parameter results corresponding to the 31 successful control design geometries score higher than 0.99, except for two with a minimum $R^2$ of 0.97. Due to these very high values for the coefficient of determination, the comparison of the interpolated results with the values obtained directly from the simulations yields similar values to the comparison of the interpolated results with the quadratic regression analysis results. This yields for just six out of 124 LS parameter results a $R^2$ value below 0.9, however, of minimum 0.84. The affected designs lie on the margins of the design space or the separation area between stable and failing PWT system designs, for which the interpolation is less accurate – but still very good – due to some NaN values, which are excluded from the regression coefficients calculation. Overall, the presented interpolation approach proves to be of very high precision and, thus, can be applied for determining the regression coefficients of the individual system designs appearing within the highly iterative optimization approach.
3.4. RBDO process

Based on the preprocessing done in Sections 3.2 and 3.3, now the actual task can be addressed. The RBDO is performed with the reference FWT system described in Section 2.1 for the optimization problem (design variables, objective functions, and optimization constraints) specified in Section 2 and implying the selected LSs, stochastic variables, and reliability criteria. In addition to the optimization problem, also an optimizer needs to be chosen (Section 3.4.1) and the iterative RBDO algorithm has to be defined (Section 3.4.2), incorporating the reliability assessment based on the beforehand derived response surfaces.

Thus, NSGAII requires the population size – meaning the number of individuals per generation – and, as stop criterion, the total number of simulations or alternatively a convergence tolerance as input. In the DDO approach 36 individuals and a total of 2,011 simulations are considered and show good convergence [25]. As, however, the present RBDO task is much more complex and heavily constrained, the total number of simulations is significantly increased and set equal to 10,000. The number of individuals in each generation is as well enlarged and set equal to 60, based on the available processors on the utilized computational machine (an AMD Ryzen Threadripper 2990WX 32-Core Processor with 64-bit system and 64 virtual processors), so that parallel simulation of the individuals in one generation is feasible.

3.4.2. Specification of the iterative RBDO algorithm

The iterative optimization algorithm of NSGAII, integrated into the Python–Modelica framework, works as follows (Fig. 7):

0. The start population (individuals of generation 0) are selected purely based on the specified allowable value ranges for the design variables, given in the inequalities constraints $g_1$ to $g_6$ (Eqs. (9) to (14)).

1. Each individual wind turbine system model is simulated for the specified critical DLC (Section 2.5) for a period of 800 s, using Rkfx4 (Runge–Kutta fixed-step and 4th order method) as solver with fixed integrator step-size of 0.01 s, and the system parameters are written in an .csv-file with an output interval length of 0.05 s.

2. From the last 600 s (discarding any transients in the first 200 s) of the time series, the maximum values for the system performance parameters $\sigma_{\text{torque}}$, $\sigma_{\text{torque,transient}}$, $\sigma_{\text{transl}}$ and the LS parameters $\gamma_{\text{w1}}$, $\gamma_{\text{w2}}$, $\gamma_{\text{w3}}$ are extracted and used for evaluating the objective functions $f_1$ to $f_5$ (Eqs. (2) to (4)), as well as the inequalities constraints $g_7$ to $g_{10}$ (Eqs. (15) to (18)) and $g_{15}$ to $g_{18}$ (Eqs. (23) to (26)). For $g_{11}$ to $g_{14}$, first, the

---

Table 8

| Design combinations | $H$ [m] | $D$ [m] | $\rho$ [kg/m$^3$] |
|---------------------|---------|---------|------------------|
| 1.                   | 108.0 m | 6.8625  | 8.2              |
| 2.                   | 83.0 m  | 7.5875  | 9.3              |
| 3.                   | 9.4 m   | 51.75   | 106.0            |
| 4.                   | 8.675 m | 57.0    | 95.5             |
| 5.                   | 9.4 m   | 64.25   | 2,435.125        |

Further combinations:

- $D=8.675$ m and $\rho=2,600$ kg/m$^3$
- $H=83.0$ m
- $\rho=1,445.875$ kg/m$^3$
- $1,850$ kg/m$^3$
- $1,923.75$ kg/m$^3$
- $2,000$ kg/m$^3$
- $2,435.125$ kg/m$^3$

- $D=8.675$ m and $\rho=1,907$ kg/m$^3$
- $H=108.0$ m
- $\rho=2,600$ kg/m$^3$
- $1,300$ kg/m$^3$
- $1,758.875$ kg/m$^3$
- $1,907$ kg/m$^3$
- $2,200$ kg/m$^3$
- $2,435.125$ kg/m$^3$

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5. https://platypus.readthedocs.io/en/latest/ (Accessed: 1 April 2020).
regression coefficients for the specific individual design and the four LS parameters are determined according to the interpolation approach (Section 3.3.3), based on which afterwards the reliability indices are calculated by means of MCS (Section 3.2.2) and then substituted in the corresponding inequalities constraints (Eqs. (19) to (22)).

3. A new set of individuals for the next generation is created by the optimizer, based on the fitness (performance with respect to objective functions and inequalities constraints) of the individuals in the current generation and again in accordance with the allowable value ranges for the design variables.

4. Steps 1. to 4. are iterated until the specified maximum number of simulations (10,000) is reached.

As already addressed in Section 3.3, some FWT system geometries might fail and not complete the total simulation time. For these unstable system designs, the evaluation of the objective functions and inequalities constraints (step 2.) has to be addressed in a different way. As such poorly performing individuals shall not be considered by the optimizer for any further recombination, the values for the system performance parameters and LS parameters for evaluating Eqs. (2) to (4), (15) to (18), and (23) to (26) are set to the following undesirable values:

- $a_{hor, nacelle} = 2 \cdot 1.962 \text{ m}^2 = 3.924 \text{ m}^2$
- $b_{tot} = 2 \cdot 10.0^\circ = 20.0^\circ$
- $s_{dyn, transl} = -1 \text{ m}$
- $s_{mean, transl} = 2 \cdot 64.0 \text{ m} = 128.0 \text{ m}$
- $\sigma_{TH} = 2 \cdot 262.96 \text{ MPa} = 525.93 \text{ MPa}$
- $\sigma_{ML1} = 2 \cdot 770.26 \text{ MPa} = 1,540.53 \text{ MPa}$
- $\sigma_{ML2} = 2 \cdot 770.26 \text{ MPa} = 1,540.53 \text{ MPa}$
- $\sigma_{ML3} = 2 \cdot 770.26 \text{ MPa} = 1,540.53 \text{ MPa}$

For the calculation of the reliability index, MCS based on the interpolated regression coefficients is as well not performed in case of an incomplete time series. In this case, $\beta = 0$ is set for all LS parameters for the failing system design. This is an undesirable value for the reliability index and ensures that the corresponding inequalities constraints (Eqs. (19) to (22)) are violated. Setting all regression coefficients to zero if all eight neighboring designs fail in the system simulations, as mentioned in Section 3.3.3, leads to the same result.

Another particularity – when evaluating the reliability criterion – has to be addressed, namely the case that MCS yields infinite for the reliability index, what already happens in the evaluation of the reliability index of the original design of the reference FWT system (Section 3.2.2). This is an indicator that the maximum value occurring in the time series of the LS parameter is much below the specified limit value and, hence, the corresponding reliability index value cannot be captured by the chosen amount of random samples ($r = 1 \times 10^6$). As Eqs. (19) to (22) can only be evaluated with a real number, in these cases, where MCS yields infinite for the reliability index, $\beta = 2 \cdot 3.719 = 7.438$ is set instead, ensuring full compliance with the inequalities constraints $g_{11}$ to $g_{14}$.

4. Results

During the execution of the RBDO, the simulations need to be interrupted two times due to system shutdown and grid disconnection. To continue the highly time-consuming iterative RBDO instead of restarting the optimization algorithm, the last fully simulated generation is used as start population of the next run, utilizing the operator InjectedPopulation from Platypus. The effective time for all 10,000 simulations, excluding the duplicated generations at the point of continuation, amounts about 695 h. Individuals of generation 0 up to including generation 171 are created, while in the last generations not all 60 individuals are yet created.

4.1. Progression within the iterative RBDO process

The design variables of all individuals created and simulated within the RBDO are presented in Fig. 8. This shows that at the beginning, the optimizer utilizes the entire design space, defined through the
allowable value ranges of the design variables as specified in the inequalities constraints in Eqs. (9) to (14), to select individuals. This large spread, however, diminishes in the further generations — very fast for the spar base height, a bit slower for the spar base diameter, and after around 20 to 30 generations also for the ballast density. It is interesting to see that, for the spar base height and ballast density, the individuals in the end tend to cluster around the original value of the reference FWT system, while the spar base diameter approaches a much lower value compared to the original one.

Similarly, Figs. 9 to 11 present the resulting values of all individuals for the inequalities constraints $g_7$ to $g_{18}$. The critical performance parameters are clearly the horizontal nacelle acceleration and total inclination angle, while both dynamic and mean translational motion values always — apart from some failing individuals in generations 0 and 1 — comply with the constraints, as visible in Fig. 9. Looking at the reliability criteria (Fig. 10) and the maximum allowable stresses (Fig. 11), it becomes clear that both constraints are connected, as they all depend on the maximum stress values obtained. Thus, in both cases, the stress in the mooring lines is highly safe, what is already perceived in Section 3.2.2, while the tower base bending stress exceeds for some individuals the maximum allowable target.

Finally, the development of the objective functions throughout the iterative RBDO process is presented in Fig. 12. The largest spread in the results is as well perceived in the first generations. For the horizontal nacelle acceleration objective ($f_1$), the value is significantly reduced compared to the objective function result of the original reference FWT system. Most of the individuals as well score better in the total inclination angle objective ($f_2$) than the original design. Only the resulting value for the dynamic translational motion objective is slightly increased compared to the original floating system.

4.2. Selection of the optimized FWT system design solution

To select the optimized FWT system design solution from the 10,000 simulated individuals, first, the individuals that violate one or more constraints have to be excluded from the further analyses. These individuals that comply with all constraints at the same time are indicated in the development plots (Figs. 8 to 12) by darker-colored crosses. In the first generations no individual meets all requirements, but from generation 13 on some individuals can fulfill them. These are just a few at the beginning, but become more and more, especially from generation 140 on.

From these individuals that comply with all constraints, the optimum solution is selected following a similar approach as applied in the DDO example [25].
1. The utopia – theoretically best possible performing system design – is defined through the minimum value for each objective function, occurring within the individuals that meet all the requirements.

2. The distance of each individual that complies with all constraints to utopia is determined, taking the square root of the sum of squares of the differences between the individual’s objective function value and the utopia’s one. Here it has to be noted that the difference between the dynamic translation objective function values is normalized by the utopia objective function value to allow comparable weightings of all three objective functions, as the horizontal nacelle acceleration and total inclination angle objective functions are already normalized in Eqs. (2) and (3), respectively.

3. The individual with the smallest resulting distance to utopia is selected as the optimized FWT system design solution and is indicated in all presented development plots (Figs. 8 to 12) by means of a yellow filled circle.

This design solution is individual 58 of generation 133. A schematic drawing of this RBDO-based optimized design shape is presented in Fig. 13 in red, together with the original OC3 phase IV reference FWT indicated in black. The key figures of the optimized design solution in comparison to the original reference FWT system are set out in Table 9. While spar base height and ballast density are similar to the original system design, the spar base diameter is significantly reduced, what is already reflected by Fig. 8. The horizontal nacelle acceleration of the original floating system exceeds the specified limit and is now in...
the optimized design solution below but close to it, while the total inclination angle, which is for the original design just less than half of the defined maximum allowable value, is for the optimized FWT system as well close but below the limit. The reliability index for all LSS is in both the original and the optimized designs beyond twice the specified minimum required value. The underlying reliability analysis based on the stochastic environmental parameters and MCS is illustrated in Fig. 14 by means of the obtained histograms for each of the specified four LS parameters and the corresponding maximum allowable values. Finally, while increasing just slightly the considered stresses, the overall structural mass of the floating spar-buoy can be reduced by almost 20% and the ballast mass by around 44%.

4.3. Final checks with the optimized FWT system design solution

Finally, the full DLC set investigated in Section 2.5 is simulated and analyzed analogically with the selected optimized FWT system design solution. Comparing the results from the 54 DLC simulations with the original reference FWT system (Section 2.5), yields the following conclusions:

- **\( \sigma_{\text{hor,nacelle}} \)**
  - For the original FWT system there are already two more critical environmental conditions; for the optimized design solution now there are three other DLCs yielding a bit higher maximum horizontal nacelle acceleration. Two of them are exceeding with 1.990 m/s² and 1.965 m/s² marginally the specified upper limit. As, however, even up to 0.3 times the gravitational acceleration (corresponding to 2.943 m/s²) are in some applications considered as allowable maximum horizontal nacelle acceleration [25, 31, 34], these values are judged as uncritical.
  - **\( t_{\text{tot}} \)**
    - There is a significant shift in the order of criticality of the DLCs. The considered DLC, which is most critical for the original FWT system, is for the optimized solution just on position 25. There are in total 13 other environmental conditions – mostly from DLC 1.1 and DLC 1.3 at either 11.4 m/s or 13.0 m/s wind speed – that yield maximum total inclination angle values above the specified limit (10°), with a highest value of 10.8°. Thus, the consequence would be that the optimized FWT system has to stop operation for these environmental conditions if the limit is strict. This might affect the overall power output; however, the highest total inclination angle occurring does not lead to an overall instability of the floating system.
  - **\( \sigma_{\text{dyn,trans}} \)**
    - The considered critical DLC, which is already just on position 26 for the original system design, is now for the optimized solution just on position 41, but yields a similar value. The highest value obtained for the maximum dynamic translational motion is with 14.2 m for just one case a bit larger compared to the original FWT system, while the remaining numbers are of a similar order of magnitude as before.
  - **\( \sigma_{\text{mean,trans}} \)**
    - There is no significant change in the order of criticality of the considered critical DLC compared to the other 53 environmental conditions. For all cases, the mean translational motion is increased compared to the original FWT system, however, is with a highest value of 28.1 m still way below the maximum allowable value of 64.0 m.
  - **\( \sigma_{\text{arb}} \)**
    - There is a shift in the order of criticality of the DLCs, as now the considered critical DLC is no longer yielding the highest tower base bendering stress, but is just on the sixth position. The highest value for \( \sigma_{\text{arb}} \) is with 236.24 MPa about 8.22 MPa higher than for the applied critical DLC but still 26.72 MPa below the maximum allowable stress value. Thus, this shift is neither critical for the maximum allowable stress value nor for the minimum required reliability index.
  - **\( \sigma_{\text{ML3}} \)**
    - There is no significant change in the order of criticality of the considered critical DLC compared to the other 53 environmental conditions. The highest stresses in the mooring lines obtained are as well of the same order of magnitude compared to the original system simulations and, thus, are still way below the maximum allowable value, resulting in reliability indices way beyond the minimum required value.

To approve again the applied interpolation approach for determining the regression coefficients and on their basis the reliability index, also all stochastic environmental conditions specified in Section 2.6 are
simulated with the optimized FWT system design solution. The simulation and analysis results show a high accuracy of the interpolation approach. The coefficient of determination is with $R^2 = 0.98$ for the tower base bending stress the lowest (but still very high), while $R^2$ is above 0.99 for the stresses in the mooring lines.

5. Discussion

The presented results of the RBDO approach already show a clear tendency, as well as significant improvements with respect to the optimization objectives and constraints, even if full convergence is not yet reached with the simulated 10,000 individuals. Imposing in the analysis this stop criterion of 10,000 simulations, however, is mainly due to practical limitations, as due to limited availability of computational infrastructure. As towards the end more and more individuals, which are additionally of similar shape, comply with all constraints, the achieved solution can be judged as already significantly improved compared to the original design and expected to be close to the final real optimum obtained when performing more simulations.

Comparison of the RBDO-based optimized FWT system design solution with the optimum design obtained by means of the DDO approach ($D = 7.0 \, m$, $H = 106.8 \, m$, $\rho = 2.583 \, kg/m^3$, $a_{\text{hit,accel}} = 1.910 \, m/s^2$, $\theta_{\text{tol}} = 9.9^\circ$, $a_{\text{dyn,trans}} = 7.7 \, m$) [25], as indicated additionally in green in Fig. 13, makes clear that inclusion of reliability criteria prevents from a slightly higher reduction in the outer dimensions of the spar-buoy, while the system performance parameters are less critical. This is reasonable as, for example, a larger total inclination angle of the floating system would result into higher bending stresses in the tower base, which itself would reduce the corresponding reliability index.

The shifts in the order of criticality of the DLCs, experienced and presented in Section 4.3, emphasize the relevance of careful selection of one or some environmental conditions to be considered within the design optimization, as well as well thought out specification of the targets and limits in the objective functions and constraints. The single critical DLC chosen in this work is sufficient for the purpose of this study to illustrate the realization of RBDO with a FWT system and the applicability of the Python–Modelica framework to such a complex optimization problem. Since this proves to be successful, it can be proceeded in future work to inclusion of more DLCs. However, a trade-off between compliance with all environmental conditions and computational efficiency of the highly time-consuming RBDO process is required. A potential approach could be to use just a few (or only one) critical DLC(s) but to apply safety factors to the targets in the objective functions and constraints. The practicality of this strategy is already underlined by the obtained results: the case that a higher limit for the horizontal nacelle acceleration – than specified in this study – is as well common practice, provides already a good example for specifying a reasonable target value, while a small exceedance of this – in maybe other environmental conditions – not directly leads to a really critical value. This could then be correspondingly applied to the total inclination angle limit.

The inclusion of reliability criteria by means of quadratic regression and MCS proves to work; however, there are still alternatives and potential improvements to be discussed and recommended for future work.

- First, utilization of the MCS method limits the covered range of reliability index values or requires unreasonable high computational resources. For the specified limit of $\beta = 3.719$ the MCS with $r = 1E+6$ random samples is both sufficient and acceptable with respect to the computational effort. For higher flexibility, an alternative or modified HL–RF method could be more suitable. This, however, implies that the existing HL–RF method is customized for the applied regression model and considered complex FWT system, so that convergence of the iterative calculations within the HL–RF method is ensured and FORM can be applied for the reliability index calculation.

- Furthermore, the method to implement reliability criteria can be diverse. The applied open end solution, with just having a lower limit for the reliability index, can be substantiated by the fact that the satisfied objectives – approaching the maximum allowable system performance values – will lead to an already limited $\beta$ value. The results of the RBDO emphasize this tendency, as for the tower base bending stress a large number of individuals fail to comply with the corresponding reliability constraint. Some individuals exhibit slightly higher values for the reliability index than required, while others’ reliability index can no longer be captured by the chosen amount of random samples in the MCS. Thus, having additionally an upper limit could be more realistic. This could be, for example a probability of failure of $1E-6$, corresponding to $\beta = 4.753$, which is not extremely over-conservative as a failure probability of $1E-6$ is also a common value. However, in this case $r$ in the MCS would have to be adjusted accordingly to capture as well this higher reliability index, which on the other hand would require more computational capacity — as already
discussed before. Constraining the reliability index from both sides might as well have the drawback that – if the reliability criteria are not the dominant constraints – $\beta$ might not lie within the allowable value ranges. For actually realizing RBDO, the reliability criteria should directly be implemented as objective functions. The constraints for the lower limit would then still be required, while the additional specification of an upper limit is not mandatory and maybe a bit redundant. Changing from the realized reliability-constrained design optimization to RBDO, would put much more restrictions on the optimization problem and, hence, its realization is – after the success of this study – just a matter of computational resources.

Furthermore, for a structural reliability analysis, not only uncertainties in the environmental loading but also in the system strength need to be considered, which can be added in future work for more realistic optimization applications and studies. For this application – to show the functionality of coupling optimization with reliability assessment of FWT systems – the presented approach is fully sufficient. More constraints would only require more computational capacity, as more individuals per generation have to be considered and overall more simulations need to be performed.

Indeed, the presented RBDO example requires considerable computational time; however, a fully optimized floating support structure design for an offshore wind turbine can be obtained, having the reliability aspect directly integrated and considered in the design optimization. By means of the presented approach, the computational time of the optimization procedure itself is not increased. The main task for future work and improvements is the enhancement of the code to achieve better computational performance and in the end real-time capability for simulating floating wind turbine systems.

6. Conclusions

In this paper, a proven methodology for RBDO of FWT systems is developed, presented, and applied to the spar-buoy FWT from OC3 phase IV. The study enhances a DDO, which targets a less over-dimensioned floating structure by aiming for a global system performance within the defined limits for safe operation, by incorporating reliability criteria and accounting for environmental uncertainties. The presented methodology of integrating the reliability aspect into the design optimization comprises: (1) the reference system definition and specification of corresponding relevant LSs, environmental conditions, stochastic variables, and reliability criteria; (2) the subsequent definition of the RBDO problem comprising design variables, objective functions, and optimization constraints; (3) the utilization of a Python–Modelica framework for performing automatically fully-coupled system simulations, as well as the optimization task; (4) a level one preprocessing to elaborate an appropriate reliability assessment approach, which utilizes MCS based on quadratic regression analysis; (5) a subsequent level two preprocessing to develop and approve an interpolation approach for deriving the regression coefficients for any floater geometry based on pre-generated response surfaces for a set of discrete floater geometries within the optimization design space; (6) the definition of the RBDO process including the selection of an optimizer; (7) and the final application of the RBDO with subsequent postprocessing of the results. Both the selected reliability assessment approach and the developed interpolation approach are of high accuracy, represented by high values for the coefficient of determination. The iterative RBDO itself is not more computationally intensive than the DDO; however, much more iterations are required due to the significantly stronger constrained optimization problem. This is as well underlined by the much slower convergence rate of the RBDO results. Nevertheless, a clear tendency is already visible in the simulation results and an improved floater geometry is obtained that meets all specified constraints – including the reliability criteria – and performs well for the selected and most of the other considered environmental conditions, while it needs just around 80% of the original floater’s steel mass, as well as around 44% less ballast mass. Thus, this study demonstrates that reliability assessment and design optimization of FWT systems can be combined, but it as well emphasizes the high complexity of such tasks – leaving some improvements regarding the considered environmental conditions, as well as the manner in which the reliability criterion is incorporated as outlook for future work. Nonetheless, the developed methodology is deemed to have great potential for solving various complex problems, due to the robustness and modularity of the presented framework.

CRediT authorship contribution statement

Mareike Leimeister: Conceptualization, Data curation, Methodology, Software, Validation, Formal analysis, Investigation, Project administration, Visualization, Writing - original draft, Writing - review & editing. Athanasios Kolios: Conceptualization, Methodology, Supervision, Writing - review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was partially supported by grant EP/L016303/1 for Cranfield University, University of Oxford and University of Strathclyde, Centre for Doctoral Training in Renewable Energy Marine Structures - REMS (http://www.remscdt.ac.uk/) from the UK Engineering and Physical Sciences Research Council (EPSRC) and the German Fraunhofer Institute for Wind Energy Systems (Fraunhofer IWES).

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