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Design optimization with genetic algorithms: How does steel mass increase if offshore wind monopiles are designed for a longer service life?

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Abstract. Knowledge about the scaling of steel mass of monopiles is needed to decide for which service life an offshore wind farm should be planned. A computer-aided method to optimize monopiles for different fatigue lifetimes was developed. The optimization was performed with a genetic algorithm. Fatigue constraints were evaluated with aero-hydro-elastic load simulations in the time-domain. Importance sampling was applied to reduce the required number of load cases to 120 (only 7% of total amount of load cases). The optimization was tested for an 8 MW offshore wind turbine. Results prove that the developed method using importance sampling is suitable to gain fast and accurate optimization results. Only 5% more steel is needed to raise the fatigue lifetime from 25 to 35 years for a design without inspections. The increase of steel mass flattens out towards longer fatigue lifetimes since the structure becomes stiffer and less prone to wave excitation. This is valuable input to decide on the ideal service lifetime and maintenance strategies.

Keywords: offshore wind turbine; monopile; genetic algorithm; optimization; importance sampling; fatigue lifetime; maintenance; design fatigue factor

1. Introduction

Offshore wind energy has developed rapidly in the past two decades - from small near shore wind farms up to large turbines in deeper water today. Monopiles are still the most installed support structure type covering more than 75% of the offshore wind market in 2016 [1]. In the past years, offshore wind turbines were typically designed for 20-25 years. Today, the wind industry aims to design new offshore wind farms for a longer service life to lower the levelized cost of energy. The design lifetime should be chosen considering various technical and economic aspects, such as scaling of structural dimensions, maintenance concepts, and financing. It should ideally be set in an early project phase already since it has large influence on other project decisions. This creates the need for fast methods to evaluate how the primary steel mass of monopiles scales for different fatigue lifetimes.

The design of monopiles is complex and time-consuming. Non-linearities in aero- and hydrodynamic loading require computational expensive time-domain simulations. The fatigue limit state is often the design-driver for monopiles with larger diameter [2]. A large number of



environmental and operational conditions have to be addressed according to design standards [3]. In current practise, design optimization relies on the designer's expertise and is often performed manually. This approach is inconvenient to decide on the ideal design lifetime. Computer-aided optimization can be used to explore a larger design space and find the best solution efficiently.

Several researchers in the field of offshore wind energy work on computer-aided optimization. Muskulus and Schafhirt [4] reviewed the state-of-art of design optimization of offshore wind support structures. They highlight that it is difficult to apply analytical methods based on gradient calculations to optimize the structure of dynamic systems with fatigue constraints. As alternative, several methods for simulation-based optimization are applicable – one popular tool is the genetic algorithm [4]. Genetic algorithms have been studied for structural optimization of wind turbine towers [5], jackets [6],[7], and monopiles [8]. Gentils et al [8] model monopile, tower, and transition piece of an offshore wind turbine with 3D finite elements. A severe shortcoming of their work is the highly simplified load analysis: quasi-static analysis and separation of aero-and hydrodynamic loads neglects important dynamics and interaction effects, such as aerodynamic damping. To make computer-aided optimization suitable for application by the offshore wind industry, it is essential that the load and structural analysis is in line with state-of-art design methodologies. Unfortunately, due to time and computational restrictions it is not feasible to perform design optimization with the recognized simulation setup for offshore wind monopiles: aero-hydro-elastic time-domain simulations of several thousand load cases.

The objective of this research is to develop smart methods to reduce the number of required load simulations, while keeping the complexity of load and structural analysis at industrial standard. This study implements a genetic algorithm for optimization of monopile substructures for offshore wind turbines. Importance sampling was applied to reduce the number of load cases. Aero-hydro-elastic time-domain simulations were performed for the reduced load case sets to evaluate fatigue lifetimes of all welds. The optimization is limited to the fatigue limit state currently. Ultimate and serviceability limit states were only partly addressed through buckling and frequency constraints.

The remainder of this paper is organized as follows. Section 2 gives an overview of genetic algorithms and its application in this paper. The method to reduce the number of load cases is described in Section 3. A case study of an 8 MW offshore wind turbine is introduced in Section 4. Results are discussed in Section 5 and concluded in Section 6.

2. Genetic algorithm

Genetic algorithms are search procedures for solving mathematical optimization problems. They are inspired by nature's evolutionary process. The goal of an optimization is to minimize an objective function. It quantifies how well a set of design variables fulfils an optimization problem within given constraints. In order to find the global optima, the genetic algorithm starts with a set of individuals grouped into one generation. Each individual is a specific combination of the design variables – one monopile design – which is a potential solution to the optimization problem. In a *first step*, the fitness of each individual is evaluated. The fitness specifies how well the individual fulfils the objective function. In *step 2*, the individuals are bred into a new generation. The selection of individuals for breeding is triggered by their fitness. The algorithm enters now an iterative procedure with step 1 (fitness evaluation) and step 2 (breeding) until a convergence criterion is reached.

2.1 Objective function

The overall goal of optimizing monopile designs should be to minimize the levelized cost of energy. This is not a trivial task since numerous variables influence costs of support structure designs. In addition, the interaction with other project decisions is large. The mass of the primary steel is often taken as cost indicator. This does indeed make up a major portion of the costs since material and (partly also) manufacturing costs scale per ton. On the other hand, other parameters may significantly change the cost situation. These are for example [9]:

- Cone sections are more expensive to manufacture than sections with constant diameter.
- A large degree of automatization of handling and welding lowers manufacturing costs.
- Design changes in tower versus design changes in monopile and transition piece often have a reciprocal effect influencing costs of the other element.
- Shortage of transport and installation vessels suitable for the designed structure increases costs.
- Maintenance costs are driven by design choices. The lower the design fatigue factor (DFF) is, the higher are the number of required inspections during the service life [10]. The DFF is a safety value multiplied with the cumulative fatigue damage of the structure. According to [10], inspections for fatigue cracks should be performed in line with Equation 1. Int is the required inspection interval and T_{life} is the calculated fatigue lifetime.

$$Int = T_{life} \frac{DFF}{3} \quad (1)$$

The objective function is defined here as minimization of steel mass of the monopile m_{MP} in line with Equation 2. Designs of tower and transition piece are assumed to be given. Implementing other cost aspects mentioned above into the objective function is desirable but out of scope of this study.

$$f = \min(m_{MP}) \quad (2)$$

2.2 Design variables

Monopiles are cylindrical structures. They are manufactured out of rolled steel plates which are connected with longitudinal welds to one segment. The segments are then connected with circumferential welds. The geometry of the structure is defined by outer diameters at top (or bottom) of each section, wall thicknesses, length of sections, cone angle, and soil penetration depth. This leads to $4n+1$ design variables with n being the number of sections.

We have simplified the monopile geometry into three segments as shown in Figure 1. Each segment is defined through a common geometry but contains multiple sections connected by circumferential welds: Segment 1 and 3 have a constant diameter, segment 2 is a cone. The length of segment 1 is set by the length of the splash zone and the overlap with the transition piece. The length of the cone section (segment 2) is also fixed for simplification. The outer diameter of section 1 is determined by the bottom diameter of the tower. This also sets the upper outer diameter of section 2. The number of circumferential welds is fixed to 24. Five design variables are optimized, namely *cone angle of section 2*, *length of section 3*, and *wall thicknesses of all sections*. All remaining parameters are calculated from this set of variables.

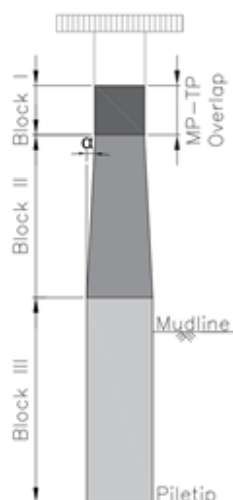


Figure 1. Model of monopile used in optimization. It consists of three sections which have common geometry (block I-III). Each segment contains multiple sections connected by circumferential welds.

Table 1. Constraints of design variables.

Design variable	Unit	Lower bound	Upper bound
Cone angle 2	[°]	2.5	3.0
Length section 3	[m]	30	50
Wall thickness 1-3	[mm]	55	133

2.3 Constraints

Constraints ensure that the optimized design is technically feasible and fulfils requirements. The fitness of an individual is penalized if its configuration violates constraints. The design variables are restricted with an upper and lower bound according to Table 1. Diameter, length and cone angles can be manufactured with any chosen value within the bounds and are thus optimized as continuous variables. Rolled steel plates are typically available with thicknesses specified in catalogues depending on the manufacturer. Therefore, wall thicknesses are optimized as discrete variable.

The fatigue limit state is represented with the constraint that the fatigue damage of no weld is allowed to exceed 1 for a given lifetime. Weldability requires that the wall thickness between neighbouring sections do not differ more than 10%. This constraint couples different design variables which is easily addressed in a genetic algorithm but difficult to consider in other optimization methods. The first natural frequency is restricted to an operational range between $1P$ and $3P$ with P being the blade crossing frequency. The factor $f_1 > 1$ clears the lower frequency bound from the nominal speed of the turbine representing $1P$. The factor $f_2 < 1$ ensures a reasonable distance to $3P$ at rotational speeds from cut-in. Buckling is prohibited by ensuring that diameter over wall thickness ratios do not exceed 120. These functional constraints are summarized in Table 2.

Table 2. Functional constraints of monopile optimization.

Constraint	Parameter	Lower bound	Upper bound
Fatigue limit state	Fatigue damage	--	1.0
Weldability	Wall thickness change	--	10%
Resonance	First natural frequency	$f_1 \cdot 1P$	$f_2 \cdot 3P$
Buckling	Diameter / wall thickness	--	120

2.4 Settings of genetic algorithm

The genetic algorithm is implemented in MATLAB[®] by use of the Global Optimization Toolbox [11]. A mixed-integer genetic algorithm is chosen so that available wall thicknesses can be pre-set. Each generation contains 15 individuals. Individuals of the first generations are randomly generated from a uniform distribution for each of the design variables. New generations are formed out of elite children, crossover children, and mutation children [11]. The crossover probability is 0.8 and the mutation probability is 0.2. One elite child (individual with best fitness) survives to the next generation.

2.5 Convergence criteria

Convergence criteria define conditions under which the optimization terminates. These can be, for instance: the fitness of the best individual is not increasing more than a specified tolerance over a number of generations, a maximum number of generations, or a time limit is reached [12]. In this study, the tolerance for convergence is 10^{-3} (approximately 1 t) which shall not improve over 20 generations. The maximum number of generations is 45.

3. Reduction of design load cases with importance sampling

The standard IEC-61400-3 [3] specifies design load cases (DLC) which must be considered for design of offshore wind turbines. DLCs compile conditions for power production, idling, start-up and shut-down, faults, and temporary events, such as transport and installation [3]. An offshore site implies a large number of environmental conditions (e.g. wind speed, wave height and period, current, etc.) that may occur in any combination. The scatter of environmental conditions causes that thousands of simulations are necessary to properly address all DLCs. The computational time needed may be several hours depending on computational resources. This is infeasible for computer-aided

optimization as the following estimate shows: assume that the computation of all load cases takes three hours, 25 generation are needed until convergence and each of it has 15 individuals – this takes 47 days to compute. It is necessary to reduce the computation time while keeping high accuracy. Instead of analysing all load cases, aero-hydro-elastic simulations are run for a reduced set of load cases only.

Importance sampling is applied to reduce the number of load cases and estimate the total fatigue damage [13]. Importance sampling is a variance reduction method which uses a priori information about the problem that needs to be solved. The classical technique approximates a result from an original distribution by random sampling from an alternative (sampling) distribution [13]. This is often applied for Monte Carlo simulations. In this paper, a sampling distribution is set up which utilizes that some load cases contribute more to the cumulative fatigue damage than others and thereby dominate the total fatigue damage. This significantly reduces the error of the fatigue damage estimate obtained by only simulating a small number of load cases (instead of all).

The methodology consists of two steps (cf. Section 3.1 and 3.2):

1. *Creation of a reduced set of load cases:* A number of designs must be evaluated with aero-hydro-elastic simulations for all load cases in order to calibrate the sampling distribution and correction factors for the optimization. The sampling distribution is applied to determine which load cases should be included in the reduced set.
2. *Estimation of total fatigue damage:* For all new designs, aero-hydro-elastic simulations are only performed for the reduced set of load cases. The total fatigue damage is estimated from there by transforming the evaluation of the sampling distribution back to the original distribution.

3.1 Reduced set of load cases

In order to calibrate the sampling distribution, a number of designs are randomly created from the design variables. The designs are selected so that the design variables fulfil all constraints stated in Table 1 and the resonance constraint of Table 2. For each design, aero-hydro-elastic simulations in the time-domain are computed for all fatigue load cases (complete design basis). Rainflow counting is performed on the stress time series of each load case to determine stress ranges and corresponding number of cycles. The fatigue damage caused by every load case is evaluated through Miner's rule of linear damage accumulation [14]. The number of cycles that the material can withstand is obtained from the SN-curve applicable for the considered welding detail [15]. The importance of load cases differs for every location of the structure. Fatigue cracks typically initiate at welds due to small welding defects and local stress concentration [15]. For each weld, a number of hot spots around the circumference should be evaluated.

The sampling distribution is set up as the cumulative density function (CDF) of the fatigue damages from all load cases. CDFs for fatigue damage differ for each design and each of the hot spots. The mean damage value over all designs and all hot spots is taken for each load case to form a sampling distribution representative for the entire monopile. The reduced load case set is randomly drawn from this sampling distribution. This ensures that load cases with larger damage contribution are selected more likely.

3.2 Estimation of total fatigue damage

The standard method to calculate the total fatigue damage D of a specific hot spot as a result of different load cases is stated in Equation 3. D is the sum of fatigue damages caused by each load case D^{LC} . l is the number of load cases. D^{LC} is obtained from rainflow counting on the stress time series of the simulated load case, application of Miner's rule and scaling with the number of hours this load case is expected to occur during the design life.

$$D = \sum_{i=1}^l D_i^{LC} \quad (3)$$

Equation 3 results in large errors of the total fatigue damage estimate if it is directly applied to results from the reduced set of load cases. The estimation significantly improves by transforming the results back to the full load case set with help of the sampling distribution. Equation 4 provides the formula to estimate the total fatigue damage D_{est} . n is the number of load cases of the reduced set, g is the sampling distribution for the considered hot spot (i.e. the CDF of fatigue damages from all load cases), and D^{LC} is the fatigue damage per load case.

Equation 4 must be calculated individually for each hot spot. It gives an unbiased estimate which may be an over- or underestimation of the true fatigue damage. In order to obtain conservative results, D_{est} is multiplied with a correction factor β_k as shown in Equation 5 and 6. The factor β_k is calibrated individually for every hot spot k according to Equation 6. μ_k is a normalised mean value from damage estimates of the specific hot spot considered and σ_k is a normalized standard deviation. Both values are calculated prior to the optimization with the genetic algorithm from the set of designs which undergo the full fatigue analysis with all load cases (i.e. the ones for calibration of the sampling function). For each of the designs, fatigue damages were estimated with a reduced load case set. The resulting value is then divided by the true fatigue damage (all load cases). The mean and standard deviation of these normalised values yield μ_k and σ_k for each hot spot. s is a safety factor between one and three depending on the level of conservatism desired (one is used for the optimization later).

$$D_{est} = \frac{1}{n} \sum_{i=1}^n \frac{D_i^{LC}}{g_i} \quad (4)$$

$$D_{cons} = \beta_k \cdot D_{est} \quad (5)$$

$$\beta_k = \mu_k + s \cdot \sigma_k \quad (6)$$

4. Case study

The developed optimization method was applied for a monopile of an 8 MW offshore wind turbine. The monopile was optimized while transition piece, tower, and turbine remained unchanged. The turbine was placed in a typical offshore environment with medium water depth. DLC 1.2 (power production) and DLC 6.4 (idling) were considered in this study [3]. A design basis was used to translate the DLCs into 1700 load cases with wind conditions, sea states, and directionality representative for typical sites in the North Sea.

Aero-hydro-elastic simulations in the time-domain were performed for every load case with the software LACflex and ROSAP. Both are in-house tools of Ramboll used for design of support structures for offshore wind turbines. Wind turbine and tower were modelled in LACflex, while transition piece and monopile were modelled in ROSAP. LACflex is an aero-elastic software based on the solver FLEX 5 [16]. ROSAP is a structural analysis software specialized on hydrodynamic loading. The monopile was reduced to a Craig-Bampton superelement which was integrated into LACflex. The superelement included the structural response to hydrodynamic loading. LACflex performed aero-elastic analysis of the turbine supported by the superelement. The resulting structural responses at tower bottom are then input for structural analysis of the detailed model of the transition piece and monopile in ROSAP [17],[18]. Output of the analysis are fatigue damages at 12 radial positions for each of the 24 circumferential welds of the monopile (for every load case).

5. Results and discussion

5.1 Results on load case reduction

Aero-hydro-elastic simulations of all load cases were performed for 41 designs randomly created from the design variables (cf. Section 3.1). Figure 2 (left) presents how much each load case contributes to the overall fatigue damage at one hot spot of the monopile. The damage contributions are averaged over the 41 designs. The load cases left from the red line belong to DLC 1.2 (turbine

operates), while the load cases on the right belong to DLC 6.4 (turbine idles). Some of the load cases contribute little, while others are more dominant. Idling causes an important amount of damage due hydrodynamic excitation and the lack of aerodynamic damping [19]. CDFs of fatigue damages from all load cases are shown in Figure 2 (right). Three functions are plotted: the CDF of one hot spot (blue line), the CDF as mean over all radial positions at one circumferential weld (black line), and the CDF as mean over all hot spots (red line). The differences between the three CDFs are minor. The larger the slope of the CDF, the more contributes this load case to the cumulative fatigue damage. We chose to use 120 load cases for the genetic algorithm since this resulted in an acceptable time of 2-3 days until convergence. The reduced set of load cases was sampled from the CDF of all hot spots.

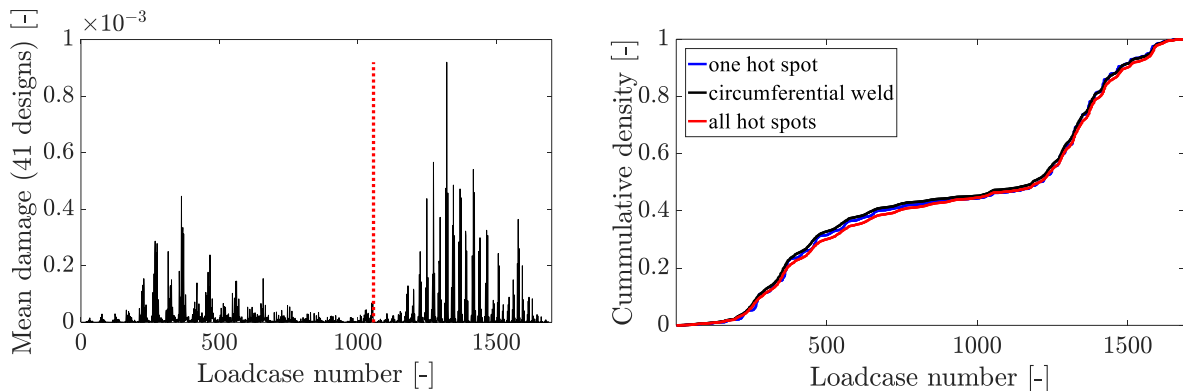


Figure 2. Contribution of load cases to cumulative fatigue damage of a monopile. The values are averaged over 41 randomly created designs. *Left:* Fatigue damage per load case for one hot spot of the monopile. Load cases left of the red line belong to DLC 1.2 (operation), the others belong to the DLC 6.4 (idling). *Right:* Cumulative density function of fatigue damage for one hot spot (blue line), mean over all radial positions of one circumferential weld (black line), and mean over all hot spots (red line).

Figure 3 presents how well the fatigue damage of a design can be estimated with importance sampling by simulating 120 load cases only. Fatigue damages of all hot spots (24 circumferential welds times 12 radial positions) were estimated with Equation 5. The correction factor for the left plot is one standard deviation ($s=1$), and three standard deviations for the right plot ($s=3$). Both plots compare the estimation with 120 load cases to the cumulative fatigue damage obtained from simulating all load cases. The percentages are positive if the estimation is below the true value (under-estimation). Negative percentages are over-estimations of the fatigue damage (conservative). The estimation errors are below 20%.

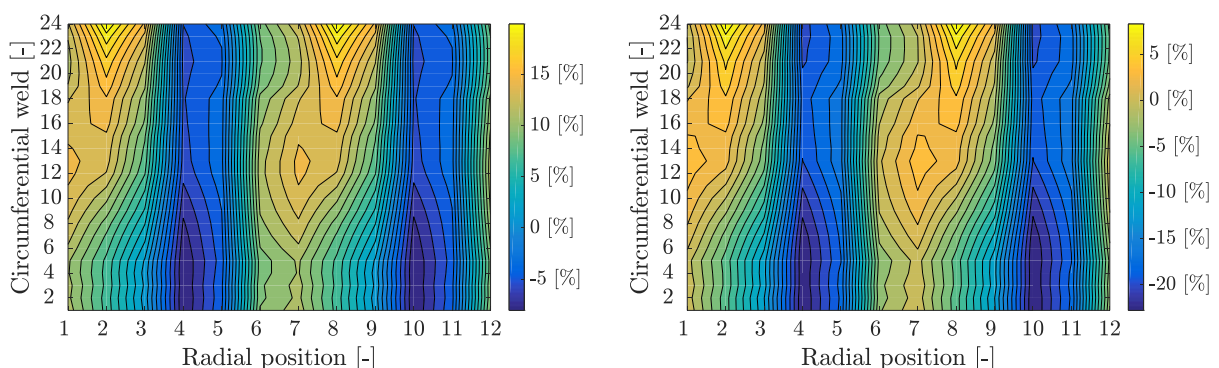


Figure 3. Fatigue damage results obtained from importance sampling with 120 load cases compared with simulations of all load cases. Positive values are underestimation of the fatigue damage; for negative values importance sampling estimated higher fatigue damages than the true value. Results are plotted for all circumferential welds and radial positions. The *left* figure includes a correction factor of one standard deviation. The *right* figure includes a correction factor of three standard deviations.

The estimation seems to be fairly consistent along the monopile structure in the vertical direction. In the horizontal direction (around the circumference) differences are standing out: some areas are always overestimated (around radial position 4 and 10), while other areas are underestimated (around radial position 1 and 7). This is linked to the directionality of the wind-wave climate. For this case study, the maximum fatigue damage occurs mostly at radial position 4, 9, or 10 which are estimated conservatively.

5.2 Results of genetic algorithm

The evolution of the monopile mass during the optimization is presented in Figure 4. The mass is normalized to the converged result. The plot shows two runs of the genetic algorithm with the goal to optimize for a design lifetime of 25 years with a DFF of 1. Both runs result in a similar value after convergence. The first run converged after 33, the second one after 37 generations. The convergence criteria about fitness increase became effective, i.e. the mass did not improve more than approximately 1 t within 20 generations.

For each generation, masses of the best and worst individual are plotted in Figure 4. The mass of the best individual is often constant over a number of generations indicating that no further improvement has been achieved during these iterations. Mass decrease occurs if mutation and crossover result in a better design than the previously best one.

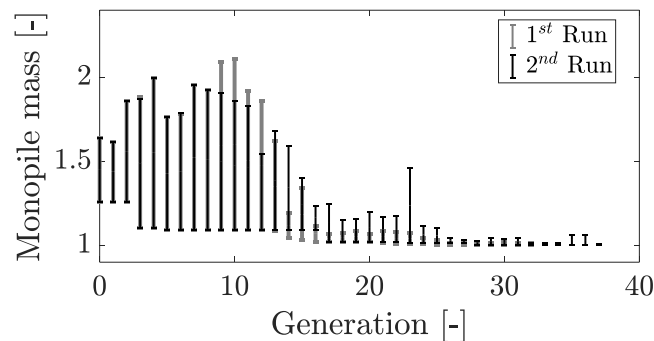


Figure 4. The evolution of the monopile mass during two optimizations with the genetic algorithm. The monopile is optimized for a design lifetime of 25 years with design fatigue factor 1. The mass of the best and worst monopile is plotted, normalized to the converged results.

5.3 Results on increase of steel mass for a longer service life

The optimization was performed for four design lifetimes: 25, 50, 75, and 100 years with a DFF of one. This can be transformed into design lives with a DFF of two or three according to Table 3. Each optimization was performed twice to ensure that the genetic algorithm converged to a representative optimum.

Aero-hydro-elastic simulations with the complete set of load cases were performed for the optimized designs in order to compute their true fatigue life. The true fatigue lives obtained during the four optimizations are shown in Table 4. The targeted design lives are matched well.

Table 3. Transformation of design lifetime with different design fatigue factors (DFF).

Optimization	Design life with DFF = 1	Design life with DFF = 2	Design life with DFF= 3
I	25	12.5	8.3
II	50	25	16.7
III	75	37.5	25
IV	100	50	33.3

Table 4. Targeted and obtained design lives during the optimization. The relative difference between the obtained and target design life (as reference value) is given in brackets.

Optimization	Design life, target	Design life, obtained Optimization run 1	Design life, obtained Optimization run 2
I	25	26.7 (7%)	26.4 (6%)
II	50	49.1 (2%)	49.1 (2%)
III	75	76.3 (2%)	74.1 (1%)
IV	100	106.2 (6%)	106.2 (6%)

Figure 5 (left) presents the increase of steel mass if monopiles are designed for longer design lifetimes. The increase of mass is not linear but flattens out towards longer design lifetimes. Designs with longer lifetimes become stiffer in order to reduce the stresses caused in the material by cyclic loading. This stiffening shifts the first natural frequency of the designs further away from the wave excitation frequencies as shown in Figure 5 (right). Less dynamic amplification reduces fatigue loading and in consequence also the relative steel mass required to withstand these loads.

Results from the optimization allow decisions on the ideal design lifetime as well as maintenance strategy. This is visualized in Figure 5 (left) with the markings A and B as example:

- A: For 25 years design life, a reduction of the DFF from three to two saves 7% of steel mass.
- B: An increase of the design life from 25 to 35 years costs 5% more steel mass (DFF of three).

5.4 Limitations

The structure of a monopile was simplified into five design variables. Results of the optimizations show that the increase of required steel is modest making longer lifetimes economically interesting. It has to be verified if these trends remain once more design variables are introduced. At current stage, an experienced manual designer would achieve a lower monopile mass if he considers more design variables. Further limitations are that only the monopile is optimized. Ideally, the entire wind turbine assembly - or at least the support structure (monopile, transition piece, and tower) - should be optimized simultaneously. The additional mass required for transition piece and tower being designed for a longer service life is not considered here.

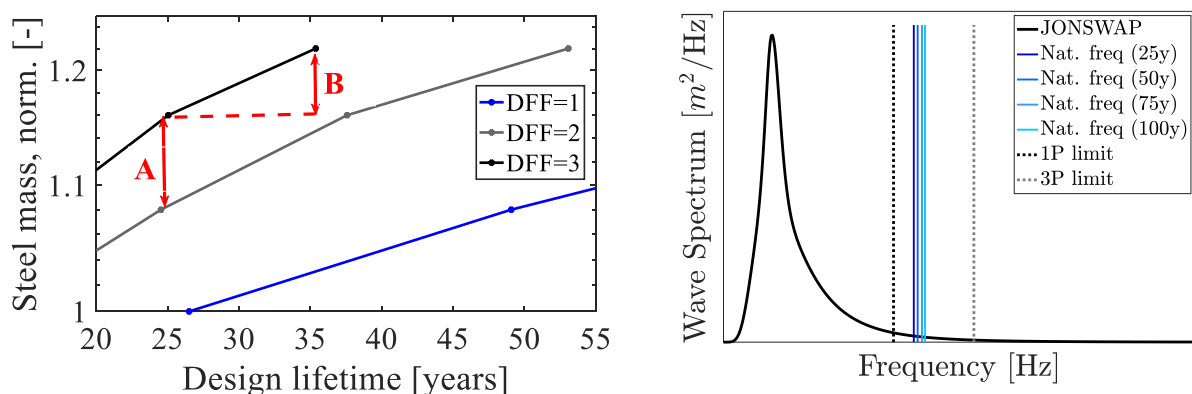


Figure 5. *Left:* The increase of steel mass for longer design lifetime of the monopile. Curves are plotted for different design fatigue factors. The designs were optimized with the genetic algorithm. *Right:* The first natural frequencies of the optimized designs are plotted in addition to JONSWAP wave spectra and 1P and 3P of the wind turbine.

6. Conclusion and Outlook

This paper presented a novel methodology for computer-aided design optimization of monopiles using a genetic algorithm. The method successfully applied aero-hydro-elastic load simulations and structural analysis in the time-domain following state-of-art of the wind industry. Computational time was reduced with importance sampling which proved to be suitable to estimate fatigue damages after simulating 120 load cases only (i.e. 7% of total amount of load cases). Results from a case study with an 8 MW offshore wind turbine showed that estimation errors were below 20%. The targeted design lives were met well during the optimization. The mass of the monopile increased by only 5% for a 10 year longer design life without inspections (DFF=3).

Knowledge about the increase of steel mass is valuable to lower the cost of wind energy. Operators can now make informed decisions on design lifetimes of their project and maintenance strategies. Future work should include:

- Increase the number of design variables. This requires further work on the genetic algorithm to still converge within a reasonable time.
- Simultaneous optimization of transition piece and tower together with the monopile.
- Detailed assessment of other limit states (ultimate limit state, serviceability limit state).
- Enhancement of the objective by designing a cost indicator that not only represents the monopile mass but also other cost drivers (e.g. ease of manufacturing).
- Design of a decision model to decide on ideal design lifetimes and maintenance strategies.

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