

# Multi-Objective Optimization of Mooring Systems for Offshore Renewable Energy

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**Abstract**—This paper presents a method for the optimization of mooring systems in offshore renewable energy systems. This methodology considers the location of anchors as well as the length, material, and diameter of the mooring lines in order to simultaneously minimize the tension in the lines, the cost of the mooring system, and the fatigue damage in the system. By considering these three objectives using a multi-objective approach rather than reduction to a single objective optimization problem allows a Pareto hull of solutions to be obtained representing a range of solutions which balance the three objectives. From this, a system designer can select the design which appropriately balances the trade-off between the competing objectives. In this work, a set of mooring designs that represent efficient solutions for the constraints are found and presented considering the OC4 DeepCWind semi-submersible at Wave Hub. This reliability-based design optimization approach will be applicable to other offshore technology subsystems allowing reliability to be considered in a multi-objective optimization from the design phase.

**Index Terms**—offshore renewable energy; multi-objective genetic algorithm; reliability-based design optimization; mooring system design

## I. INTRODUCTION

With the growth of the renewable energy sector, optimization has been increasingly applied to both explore new novel designs and to existing designs in order to ensure that the designs are as efficient as possible. The present work explores the extension and application of a newly developed optimization framework for mooring systems using a multi-objective genetic algorithm (MOGA) [1]. This work builds on existing optimization work in the renewable energy field [2] making use of a genetic algorithm (GA) to aid in the design process.

Mooring systems for floating offshore renewable energy devices serve a vital function in ensuring that the device can stay on station and operate for the duration of the project lifetime. Current design methodologies, however, do not make use of formal optimization approaches, but rather use an iterative process to revise a design until specific design criteria are met [3]. By including an automated multi-objective optimization algorithm such as the nondominated sorting genetic algorithm II (NSGA-II) it is possible to characterize how changes in the mooring design can affect the competing objectives that

a system designer must consider [4]. In particular, given the challenge for offshore renewable energy developers to find the fine balance between capital expenditure and operational cost in the quest to minimize the lifetime cost of energy, the design of offshore renewable energy devices and their subsystems therefore lends itself to the use of multi-objective optimization approaches in order to identify these trade-offs. Through use of a such a design methodology, compromises between the competing objectives can be better described for decision makers and a wider range of design alternatives can be explored compared to the standard design methodologies.

The optimization routine implemented here seeks to minimize the material cost of the mooring system, the tension in the mooring lines, and the cumulative fatigue damage over the lifetime of the project. These have been selected to further develop the methodology and demonstrate where optimization can be deployed in the design process for offshore renewable energy devices. The present work explores the extension of the methodology exploring the inclusion of fatigue damage as an explicit objective allowing the system designers to better describe the impact the design variables has on the fatigue characteristics. Further objectives can be explored in the future depending on the criteria of interest to the mooring system designer and decision makers. To assess the suitability of a given mooring design, the optimization routine makes use of Orcina's OrcaFlex software.

This paper presents the developed methodology and using the Wave Hub site in Cornwall, United Kingdom, a case study is explored demonstrating the capabilities of this approach for the optimization of the mooring system for the OC4 semi-submersible [5] designed for use with floating offshore wind turbines highlighting how this methodology can aid in decision making and justify engineering design decisions.

## II. METHODS

The approach taken in this study to optimize the mooring configuration for an offshore renewable energy platform expands on the method outlined in Pillai et al. [1] in which a multi-objective genetic algorithm (MOGA) is integrated with OrcaFlex, an industry standard finite element analysis tool for mooring systems [6]. By integrating the optimizer and OrcaFlex in this way, the mooring systems proposed

during the optimization process are evaluated using a validated industry standard software package in order to assess the performance of this mooring design. Each proposed mooring design is therefore evaluated using a standard approach thereby reducing the uncertainties associated with the results. In the original development of this methodology, the optimization algorithm, an implementation of the nondominated sorting genetic algorithm II (NSGA-II) by Deb and Pratap [7], sought to minimize the tension in the mooring system and the material cost. Following the initial development it has been decided to include the fatigue damage on the mooring system as an objective allowing this to be considered in the design process and thereby highlighting the trade-offs between all three objectives to aid in the decision making process during the design stage.

### A. Multi-Objective Genetic Algorithm

GAs represent a family of bio-inspired population based meta-heuristic optimization algorithms that borrow ideas from evolution as observed in biological systems and operate analogously to biological evolution [8]. GAs are commonly deployed as they represent a family of generic algorithms which can be applied to a wide range of problems of varying degrees of complexity. As such, GAs have frequently been applied to complex engineering design problems with good quality solutions often being found [9, 10]. Given the GA's heuristic nature, there is no guarantee that the true global optima is located, but in general high quality solutions are identified in reasonable time-scales.

In a GA, several solutions are considered simultaneously it is assumed that by combining good existing solutions, new solutions can be evolved leading to improvements. Keeping with the analogy to evolution, in a GA, the candidate solutions are thought of as individuals in a population. Individuals that have a higher fitness or quality are assigned a higher probability of reproducing and undergo the evolutionary process by which new candidate solutions are generated. The principal steps of a GA involve the *evaluation* of the fitness for each individual (mooring system) in the population; the *selection* of individuals to reproduce; the genetic operators *crossover* and *mutation*; and the *replacement* of the newly generated candidate solutions, individuals, into the population. The principle genetic operators by which new candidate solutions are generated are *crossover* in which existing solutions are recombined to create new solutions and *mutation* in which the individual is slightly altered in order to introduce a stochastic element. This stochastic element is included to avoid premature convergence to a local optima and promote exploration of the search space. For the present implementation, the evaluation function is made up of three separate objectives which are computed during the OrcaFlex simulations for that given mooring configuration.

In a traditional GA, the selection of individuals to reproduce is done based on the fitness value of the individuals or their relative fitness. As multi-objective optimization no longer has a single metric which describes the quality of a solution,

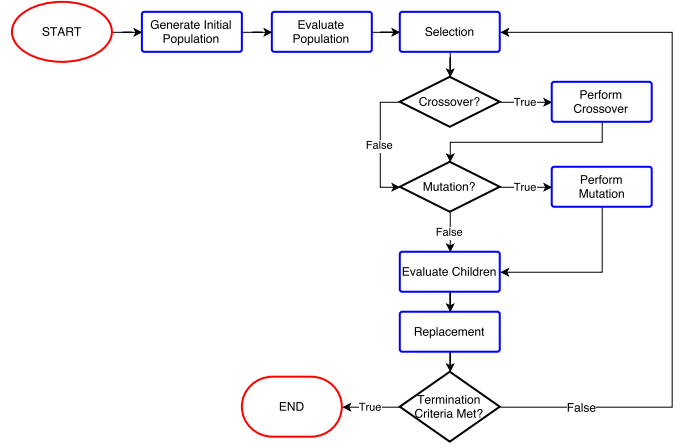


Fig. 1. Flowchart of a standard genetic algorithm

these selection methods are not applicable. For a true multi-objective problem that aims to keep the nuance of the problem, the probability of an individual being selected now needs to be related to how it compares on all objectives to other individuals. This introduces the concept of *dominance*, defined by Deb [4] as:

**Definition 1.** A solution,  $x^{(1)}$ , is said to dominate the other solution,  $x^{(2)}$ , if both conditions 1 and 2 are true:

- 1) The solution  $x^{(1)}$  is no worse than  $x^{(2)}$  in all objectives, or  $f_j(x^{(1)}) \not\triangleright f_j(x^{(2)})$  for all  $j = 1, 2, \dots, M$ .
- 2) The solution  $x^{(1)}$  is strictly better than  $x^{(2)}$  in at least one objective, or  $f_j(x^{(1)}) \triangleleft f_j(x^{(2)})$  for at least one  $j \in \{1, 2, \dots, M\}$ .

where  $f_j$  is the objective function for objective  $j$  of the  $M$  objectives;  $\triangleleft$  is used to denote that a solution is better than another for a specific objective; and  $\triangleright$  is used to denote that a solution is worse than another for a specific objective.

NSGA-II operates by sorting the individuals of the population based on dominance and identifying solutions which are nondominated. The selection operator of NSGA-II selects individuals based on dominance in a standard tournament selection method and in the event of equal dominance in the tournament (i.e. the individuals in tournament are nondominating), the *crowding distance*, a measure of the search space surrounding a solution that is unoccupied by other solutions of the population, is used as a tie-break [4]. This helps to ensure that diversity is maintained in the GA. NSGA-II also uses a replacement method which ensures the survival of the best individuals and therefore not only has diversity preservation, but implicit elitism.

Compared to single-objective optimization, rather than identifying a single optimal solution, multi-objective optimization algorithms such as NSGA-II seek to identify the Pareto front of nondominated solutions. The entire population at the end of the execution of the MOGA is therefore needed in order to define this front and characterize the trade-offs between the competing objectives. It is important to note that though

multi-objective optimization can be addressed by integrating the different objectives and reducing the problem to a single-objective optimization problem. Approaching the problem through this approach can still identify high quality solutions with respect to the various objective functions, however, it does not allow the compromise between the objectives to be characterized.

The present implementation of NSGA-II uses the parameters described in table I.

TABLE I  
GENETIC ALGORITHM PARAMETERS

Parameter	Value
Population Size	100
Maximum Number of Generations	50
Crossover Operator	Uniform
Mutation Operator	Gaussian
Probability of Crossover (Individual)	0.50
Probability of Crossover (Attribute)	0.50
Probability of Mutation (Individual)	0.20
Probability of Mutation (Attribute)	0.05

### B. Mooring Design

The design of mooring systems is of vital importance for offshore renewable energy devices as the mooring system must not only ensure that the device can stay on station and survive the environmental conditions for the duration of its lifetime, but it must also elicit the correct response as required by the renewable energy device [11, 12].

The engineering design process of mooring systems typically takes an iterative design approach starting from a design advised from past experience in the sector. Through the iterations, the mooring design is altered until a set of design criteria are met. For offshore renewable energy devices these criteria can include the cost; the ability to station keep; the integration with the power take-off system; the connection to the seabed; the installation and decommissioning process; the site suitability; and the fatigue damage [12]. Increasingly, fatigue in mooring systems has been highlighted as a design criteria that should be included.

By replacing the iterative design approach with an optimization approach, a wider range of mooring designs can be explored thereby identifying novel site and device specific designs. As the mooring system responds differently depending on the applied loading conditions, it is necessary to evaluate the response and the relevant mooring line tension cycles for each of the wave conditions that occur at the site under consideration.

### C. Model Structure

Using the OrcFxAPl Python API provided by Orcina Ltd. [6], the developed Python optimizer is linked to OrcaFlex allowing the mooring configurations proposed by the optimizer to be evaluated using OrcaFlex. The results of a simulation are accessible through this Python API allowing the optimization routine to both select the model inputs, and process the outputs

as required. Figure 2 shows the general flow of the optimizer's evaluation function indicating how the optimizer and OrcaFlex interact through the optimization process. In order to account for the range of wave loading which the mooring system is expected to experience, each sea state given in a wave scatter plot for the site is simulated in OrcaFlex, performing a time-series analysis of the response of the platform and the tension in the mooring lines.

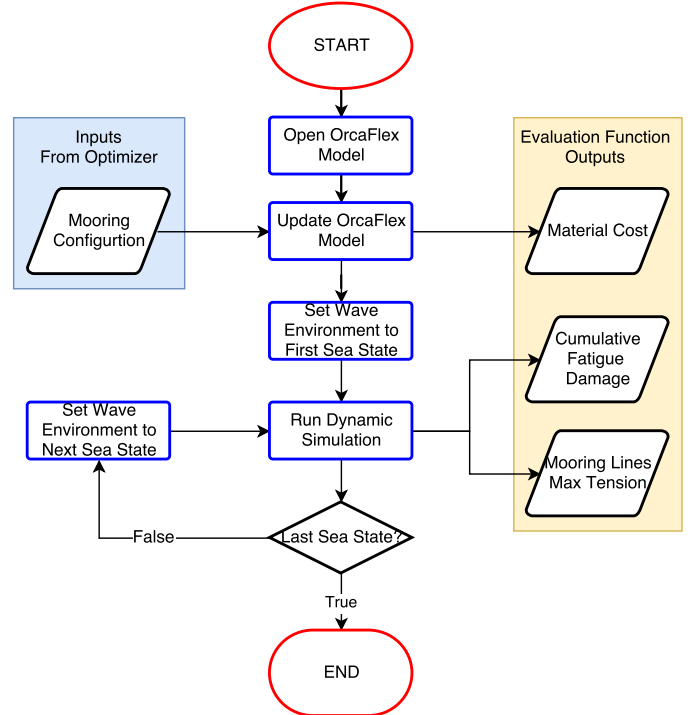


Fig. 2. Flowchart of evaluation process for a candidate solution

In the present study, the optimizer seeks to minimize the tensions, material cost, and the fatigue damage of the proposed mooring system. To achieve this aim, the following decision variables are considered for each of the three mooring lines:

- the horizontal distance between the platform and the anchor [meters];
- the angle between the platform and the anchor [degrees];
- the length of each section of the mooring line [meters];
- the material of each section of the mooring line [chain/polyester]; and
- the diameter of each section of the mooring line [millimetre].

As NSGA-II is implemented, the final solutions proposed by the optimizer should highlight the trade-offs that must be made between these three objectives allowing the system designer to determine the model philosophies to explore in greater detail.

For the present study, the number of lines are kept constant, the anchors are kept within a 1000m radius of the floating platform, and the anchors are kept within a  $\pm 15^\circ$  of their original angle defined in the OrcaFlex model relative to the floating body. Further constraints are introduced in order to ensure that only chain was in contact with the seabed through

the simulations and that the minimum breaking load (MBL) of the mooring line types was not exceeded in any of the dynamic simulations. No constraints are applied on the length of the mooring lines allowing both taut and catenary mooring systems to be proposed by the optimizer. In order to explore the feasibility of this methodology including fatigue damage as an objective, the mooring lines were each limited to have a maximum of three different sections.

1) *Material cost of mooring system*: The material cost of the mooring lines is taken as a sum over the mooring system of the unit cost of each line type taken from manufacturer provided cost data multiplied to the length of each of the defined line types deployed in the mooring system. In this way, this metric does not include any consideration of the anchors, and in fact the OrcaFlex simulations are also not used in computing this objective. This objective is given by:

$$\min f_1(x) = \sum_{l \in \mathbb{L}} \sum_i c_i \cdot x_{l,i} \quad (1)$$

$$\forall i \in \{2, 4, 6, \dots, N_l - 1\}$$

where  $x$  is the vector of decision variables,  $c_i$  is the unit cost of the line segment  $i$ ,  $N_l$  is the number of variables associated with line  $l$ , and  $\mathbb{L}$  is the set of mooring lines. Given the structure of the decision vector for the present problem, for each line, the first two variables (indexed from 0) define the position of the anchor and the subsequent pairs of variables describe the length of each line section and the line type used. The variables describing the line type are therefore located at indexes 2, 4, 6, ...,  $N_l - 1$ .

2) *Evaluation of peak tensions*: The peak tensions are evaluated using all of the OrcaFlex simulations for the mooring system thereby considering all of the sea states at the site. For this objective, the maximum tension experienced along the length of each line across all the simulations is stored. The objective function seeks to minimize the sum of these tensions over all of the lines thereby minimizing the tension experienced by the system. As this objective is evaluated without considering the relative occurrence of each sea state, the tensions are not time weighted, but instead the sum of the absolute peak tensions is minimized.

$$\min f_2(x) = \sum_{l \in \mathbb{L}} \max(t_{l,a}) \quad (2)$$

$$\forall s \in \mathbb{S}; \forall \{0 < a \leq L_l\}$$

where  $t_{l,a}$  is the tension in line  $l$  at position  $a$  along its length  $L_l$ , and  $s$  is a sea state within  $\mathbb{S}$ , the set of sea states experienced at the site.

3) *Fatigue damage evaluation*: The final of the objectives explored in this optimization problem is the fatigue damage. This is assessed by using the time-series tension data from each OrcaFlex simulation and using the rainflow counting method to establish the applied tension half-cycles. These tension half-cycles are then used in conjunction with the fatigue

properties of the mooring line material and the Palmgren-Miner rule to estimate the cumulative damage [13, 14].

$$\min f_3(x) = \max \left( \sum_{s \in \mathbb{S}} (d(x_l, s, a) \cdot p_s) \right) \quad (3)$$

$$\forall l \in \mathbb{L}; \forall \{0 < a \leq L_l\}$$

where  $d(x_l, s, a)$  is the damage experienced by line  $l$  at position  $a$  along the line during sea state  $s$  and  $p_s$  is the occurrence rate of sea state  $s$  from the scatter table. Since each OrcaFlex simulation is executed for the same length of time, the damage is scaled by the occurrence of the individual sea state in order to assess the cumulative damage of the mooring system over the desired period.

### III. WAVE HUB CASE STUDY

#### A. Case Study Description

The present study continues the previous work of the authors [1] and explores the deployment of the OC4 DeepCwind semi-submersible at Wave Hub. The OC4 semi-submersible described in detail in Robertson et al. [5] is a platform designed for use with a 5 MW offshore wind turbine. The original platform was proposed for deployment in depths up to 200 m. The DeepCwind semi-submersible is pictured in figure 3. This semi-submersible is composed of a main column connected to the wind turbine and three offset columns which are connected to this main column. The original design of the platform called for three mooring lines each of which is connected to one of the three offset columns. The present study assumes that the fairleads are kept the same as originally defined.

Wave Hub is a renewable energy test site located 33 km northwest of Hayle in 55 m mean water depth [15]. For this study, the wave scatter table shown in table II was used to define the wave conditions to be run for each of the proposed mooring systems. For each mooring design proposed by the optimizer a 600 s simulation was run for each sea state in OrcaFlex with the three objectives evaluated as shown in fig. 2.

TABLE II  
WAVE SCATTER TABLE FOR WAVE HUB SITE [15]

		Wave Period, $T_z$ [s]				
		4	6	8	10	12
Sig. wave height, $H_s$ [m]	6.5	0	0	9	0	0
	5.5	0	0	62	27	0
	4.5	0	9	114	27	0
	3.5	0	280	298	27	0
	2.5	96	1253	298	27	0
	1.5	1813	1945	298	35	9
	0.5	1436	693	18	0	0

As the optimization approach makes use of predefined line types in the OrcaFlex model, a portion of the DTOcean Database [16] is provided to the optimizer allowing it to select from ten line types, six chains and four polyester ropes between 24 mm and 200 mm diameters, for each line segment

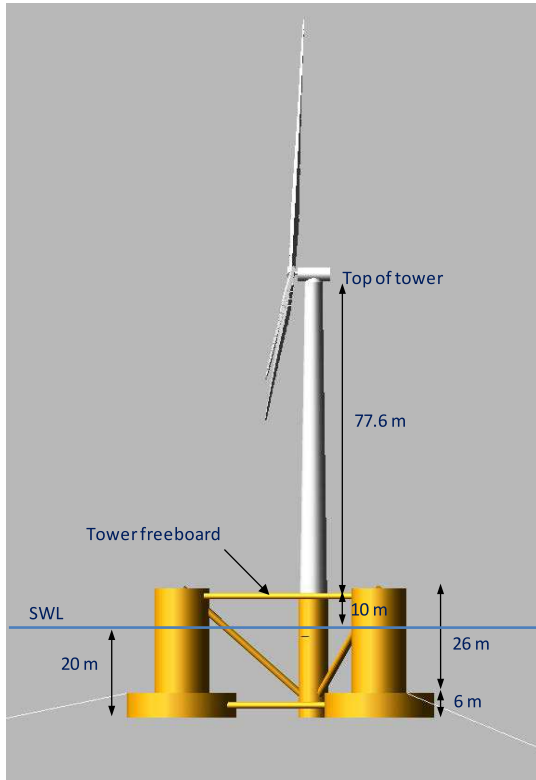


Fig. 3. DeepCwind floating wind system used as part of the Offshore Code Comparison Collaboration Continuation (OC4) project [5].

of each mooring line. This component database includes not only the dimensions, MBL, and stiffness of each possible line type, but also the unit material cost of each component. To complement this, fatigue curves published in Banfield et al. [17] and DNV [18] are used in order to compute the fatigue damage as a result of the tension cycles during the dynamic simulations. The Gerber Parabola is used to account for any mean stress effects [13].

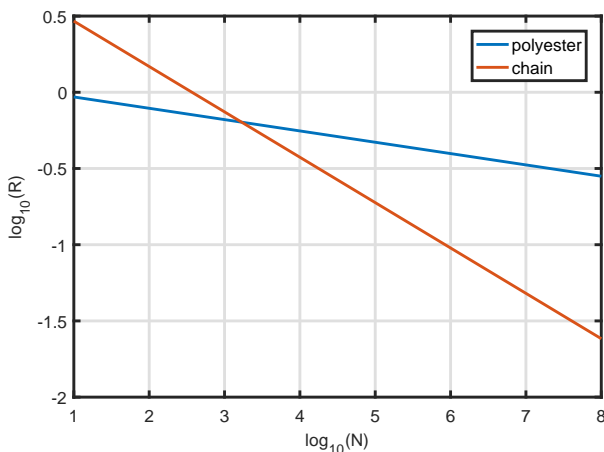


Fig. 4. Fatigue curve for polyester mooring ropes and chains used to compute the fatigue damage. Where  $N$  is the number of cycles and  $R$  is the ratio of the tension range to the absolute breaking strength of the material. Data from [17, 18].

## B. Results

Executing the GA as described leads to the optimization results shown in fig. 5 in which a range of solutions to the optimization problem are shown. This figure shows the nondominated solutions found by the optimizer and not the full range of solutions explored. Each of these nondominated solutions strikes a different balance between the three competing objectives. As these are nondominated solutions rather than the full range of solutions explored, these all represent equally good solutions from the optimization perspective and it is up to the system designer to decide where along this Pareto hull they wish to be. From this figure it can be seen that the three objectives are competing, and the choice of design philosophy depends on the relative importance of the different objectives to the system designer. It should be noted at this stage that these results come from a heuristic approach and therefore there is no guarantee that the true optima (i.e. the true Pareto hull) is found. The solutions presented may therefore be further improved through improvements to the optimizer and allowing a larger population run for more generations.

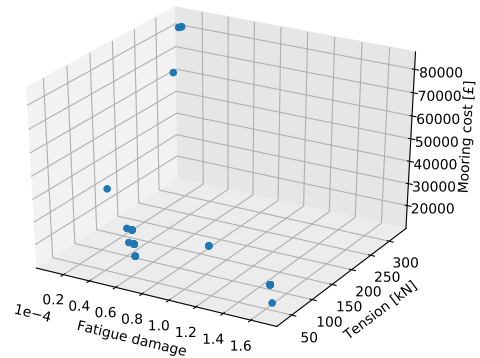


Fig. 5. Nondominated solutions shown relative to the objective functions.

The range of solutions in the whole population including dominated solutions which are not shown in fig. 5 have cumulative fatigue damages in the range of  $1.02 \times 10^{-5}$  to  $1.67 \times 10^{-4}$ , peak tensions in the range of 35 kN to 720 kN, and mooring costs between £18,147 and £807,717.

In multi-objective optimization spanning more than two objectives there exists a challenge in representing the Pareto hull in such a way as to allow the trade-offs to be clearly visualized. In fact, the present results shown in fig. 5 lack sufficient points to create a surface plot of the Pareto hull. As this is quite common in complex MOGA problems where the population size is not sufficiently large to easily visualize the hull, a common approach for tri-objective problems is therefore to analyse the projections of the Pareto hull on two of the objective dimensions [19]. Figures 6 and 7 show two-dimensional approximation sets of the Pareto hull showing the trade-off curves for two objectives at a time. From this,



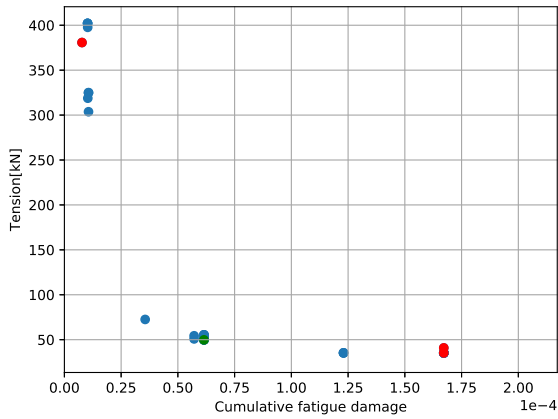


Fig. 6. Approximation set of Pareto hull showing the trade-off between mooring line tension and the cumulative fatigue damage; red points represent extreme solutions and green point represents a compromise solution.

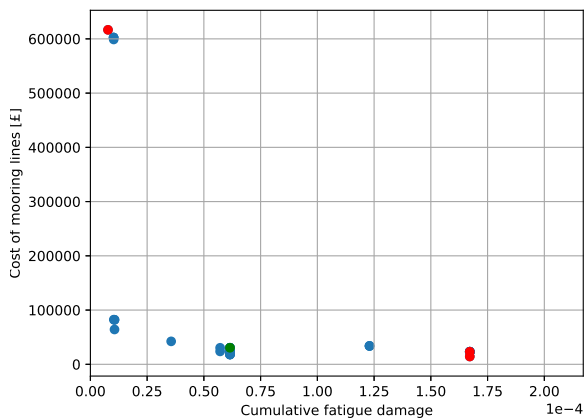


Fig. 7. Approximation set of Pareto hull showing the trade-off between the mooring system cost and the cumulative fatigue damage; red points represent extreme solutions and green point represents a compromise solution.

the design trade-offs between cost/tension can be seen against the fatigue damage, highlighting how a system designer could identify designs of interest for further investigation. Highlighted on these figures are three solutions marked in red which indicate the extreme values of the Pareto hull which minimize a single objective. Tables III to V describe these extreme solutions.

The result described in table III minimizes the fatigue loading by increasing the length of the heavily loaded line, line 2, utilizing a long catenary chain in order to allow the fatigue damage to be reduced. This, however, comes at a cost as by utilizing a larger diameter chain, the peak tension increases as a result of the weight of the chain. This solution also utilizes a polyester-chain construction on line 3 which further increases the costs of this mooring solution compared to similar lengths of chain.

TABLE III  
NUMERICAL RESULT - MINIMUM FATIGUE DAMAGE

Line	Anchor distance [m]	Anchor direction [°]	Line length [m]	Line type
1	231.53	232.62	259.45	32 mm chain
2	908.80	350.49	928.50	152 mm chain
3	150.34	110.71	24.38	192 mm polyester
3			37.85	52 mm polyester
3			99.94	84 mm chain

TABLE IV  
NUMERICAL RESULT - MINIMUM TENSION

Line	Anchor distance [m]	Anchor direction [°]	Line length [m]	Line type
1	231.53	232.62	259.45	32 mm chain
2	62.14	6.60	75.11	24 mm chain
3	156.68	132.61	152.27	24 mm chain
3			21.28	105 mm chain

Exploring the other extremes, minimizing either the peak tension or the cost of the system as shown in tables IV and V forgo the use of polyester lines in favour of all chain constructions as these lead to a reduction of cost and the tension. Compared to the minimum cost case, the minimum tension case makes use of longer catenary mooring lines resulting in both higher costs and lower tensions.

TABLE V  
NUMERICAL RESULT - MINIMUM MATERIAL COST

Line	Anchor distance [m]	Anchor direction [°]	Line length [m]	Line type
1	59.07	254.90	41.69	24 mm chain
1			31.31	32 mm chain
2	62.14	6.60	75.11	24 mm chain
3	56.68	138.72	52.29	24 mm chain
3			21.28	52 mm chain

As the three extremes represent the consideration of only a single objective, they do not represent realistic solutions for the system designer as they don't balance the three objectives, but rather look at only a single objective. Therefore, the result shown in table VI may be of greater interest. This solution is also a nondominated solution, however, is taken from a more central position along the Pareto hull thereby representing a compromise between the three objectives.

#### IV. CONCLUSION

The extension of a multi-objective optimization framework for the design of mooring systems for offshore renewable energy devices has been presented. Building on the previous work of the authors, this framework now includes the consideration of the cumulative fatigue damage on the mooring system due to the wave loading thereby allowing the system designers to characterize how this competes with traditional

TABLE VI  
NUMERICAL RESULT - A POTENTIAL COMPROMISE

Line	Anchor distance [m]	Anchor direction [°]	Line length [m]	Line type
1	231.53	234.11	259.45	32 mm chain
2	76.84	353.00	8.93	84 mm chain
2			71.65	32 mm chain
2			13.65	105 mm chain
3	156.68	132.61	152.27	24 mm chain
3			21.28	105 mm chain

design criteria. By developing an optimization routine that considers the peak tensions in the mooring system, the cumulative fatigue damage, and the material cost of the mooring system the balance between these competing objectives can be explored leading to better informed decisions with respect to the mooring design.

The present application of this methodology to the deployment of the OC4 semi-submersible platform for use with floating offshore wind turbines has been analysed for deployment at the Wave Hub site off the Cornish coast in the UK. Through exploration of the solutions highlighted by this methodology the system designers and site developers can better identify mooring system design philosophies which are of interest and can potentially aid in the cost reduction sought by offshore renewable energy developers.

From the perspective of a device or site developer, the true Pareto hull is sought in order to identify the full range of applicable designs. Due to limited tuning of the implemented genetic algorithm, there remains work to be done in selection of the crossover and mutation probabilities which could further improve the convergence properties of the genetic algorithm resulting in a better defined Pareto hull.

Ongoing work by the authors is exploring further parameter tuning of the genetic algorithm in order to better define the Pareto front as well as the extension of the methodology to include not only the wave loading, but also the current and wind loading conditions. Along with this, future work will explore the application of the methodology to a range of sites in order to illustrate the benefits of site specific mooring design approaches.

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