Study on Genetic Algorithms and Constraint Handling Techniques Applied to the Optimization of Jacket Structures for Offshore Wind Turbines

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Abstract. Recently, steel jackets have been an attractive alternative as support structures for Offshore Wind Turbines (OWT), supporting the production of wind energy. Design of offshore jackets require complex analysis due to the dynamic environmental loads and the frequencies from the turbine operation. So, it is important to address coupled models where the interactions between the jacket and the turbine are considered. The jacket weight also represents an important measure since a lighter structure has a lower cost and a potential of higher efficiency. The main objective of this work is to study optimization techniques based on Evolutionary Algorithms (EA) to minimize the weight of jackets for OWT, considering a coupled model. The structure model used in this work was based on that developed in the OC4 (Offshore Code Comparison Collaboration Continuation) project. A Genetic Algorithm (GA) was applied as the optimization algorithm. Two constraint handling techniques were compared in the problem. Preliminary results present feasible solutions which decreased the weight and natural frequencies.

Keywords: Structural optimization, offshore jackets, Offshore Wind Turbines, Genetic Algorithm, Constraint Handling Techniques.

1 Introduction

The OWTs have the advantage of being placed in locations of steadier and faster winds, which results in a higher energy generation, according to Savsani *et al.* [1]. Wind energy is a renewable energy source and it is rapidly growing. The GWEC (Global Wind Energy Council) [2] data shows that in 2008 the new installed capacity worldwide was 26.9GW and grew to 93GW in 2020. The offshore contribution is not as significant as the onshore yet as its 2020 installed capacity was 6.1GW compared to the 86.9GW of onshore. However, the offshore installed capacity has grown 1425% since 2008, while the onshore has grown 227.92%. This demonstrates an intrinsic potential that requires attention and developments.

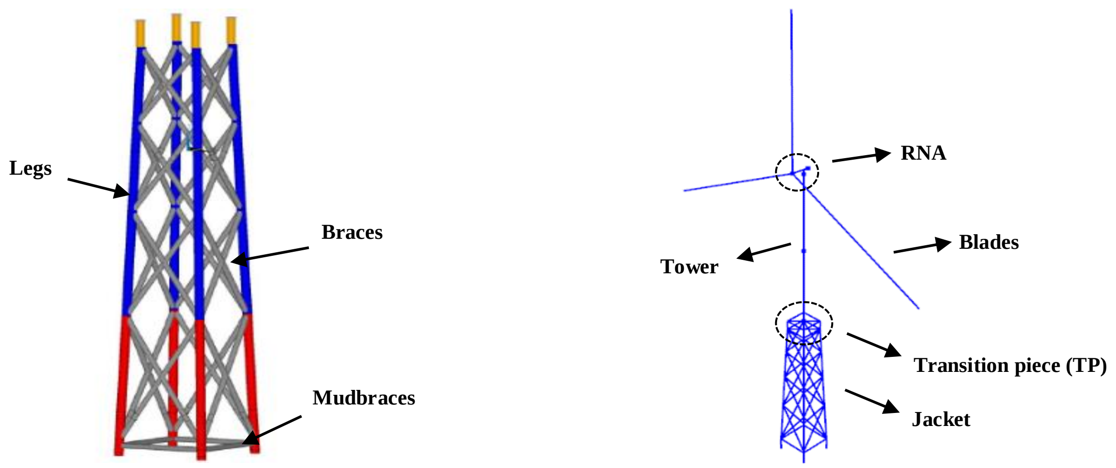
The OWTs are usually installed with bottom fixed support structures such as monopiles, tripods, gravity structures and jackets, as seen in Savsani *et al.* [1]. It is reported that the support structures for OWT represents nearly the cost of 17% of the entire system (support structure and OWT), according to Chew *et al.* [3]. This cost is usually analyzed in optimization problems as the consideration of the support structure weight. Then, a jacket with lower weight would be related to a lower cost and may also present higher efficiency due to a better utilization of its structural capabilities. This optimal usage is the configuration desired for the jacket design.

Thus, an optimization procedure is adopted. The optimization is applied to the OC4 (Offshore Code Comparison Collaboration Continuation) project model to get the jacket's best design. The optimization objective is to minimize the jacket weight by its sizing. Design variables are the diameters and thickness of the jacket elements and the constraints refers to local buckling and free vibrations. A GA, as stated in Goldberg [4], is adopted and two constraint handling techniques are compared: the Tournament Selection Method (TSM), described in Deb [5], and the Multiple Constraint Ranking (MCR), described in Garcia *et al.* [6]. The algorithm results are shown regarding weight and the jacket's element dimensions.

2 OC4 Structure

The OWT and jacket considered in this work were those used in the OC4 project model described in Vorpahl *et al.* [7]. The model is based on the UpWind reference jacket described in Vemula *et al.* [8] and the NREL (National Renewable Energy Laboratory) 5-MW Wind Turbine described in Jonkman *et al.* [9]. This structure was addressed by the Finite Element Method through the software ANSYS® [10] and the Python library known as PyAnsys developed in Kaszynski [11]. The coupled model uses elements with six degrees of freedom and point masses. It was designed with 283 elements and 220 nodes.

The model used in the OC4 project was designed for a depth of 50m of water. The jacket has a length of 70.15m, the tower has 68m and each blade has 61.5m of length. The modeled jacket has four legs, four levels of X braces and mudbraces right above the seafloor, as shown in Fig. 1. The lower parts of the legs, the red elements in Fig. 1(a), are connected to foundation piles and clamped in the seafloor. The jacket has 108 elements divided into four groups identified in different colors in Fig. 1(a): braces (group 1 - gray), lower parts of the legs (group 2 - red), intermediate parts of the legs (group 3 - blue) and upper parts of the legs (group 4 - yellow). Each group has different values for cross-sectional dimensions. The jacket elements within the depths from -40m to -2m are modeled with an external additional thickness in order to reproduce marine growth. The free flooded jacket's legs of the OC4 project model, as seen in Vorpahl *et al.* [7], were not modeled yet.



(a) Jacket layout. Adapted from Vorpahl *et al.* [7]

(b) OC4 project model modeled on ANSYS® [10]

Figure 1. Jacket and OWT details

The Finite Element model is presented in Fig. 1(b). The transition piece (TP) was modeled with 17 rigid elements with distributed masses and the layout presented in Couceiro *et al.* [12]. The tower considered tubular elements and point masses to represent installed equipment. The rotor nacelle assembly (RNA) was modeled with point masses and rigid elements without mass. Regarding the three blades, they were modeled by 49 elements.

The OWT is a more sensible structure to dynamic effects than the oil and gas platform associated with jackets, due to the cyclic loads such as current, waves and wind, in addition to the aerodynamic effects. The turbine produces excitation frequencies that may affect the coupled structure and result in the effect of resonance. These frequencies are the rotational frequency of the rotor (1P) and the blade-passing frequency through the tower (3P), according to Couceiro *et al.* [12]. They are associated with the rotor speed, which in most turbines, remains within an operational range of values, as stated in Souza [13]. Couceiro *et al.* [12] also reports that a 10% margin is applied to their boundaries values in order to ensure safety conditions.

Figure 2 shows the excitation frequencies related to the NREL 5-MW Wind Turbine presented in Jonkman *et al.* [9]. The rotational frequency of the rotor (1P) has the upper limit of 0.22Hz and the blade-passing frequency (3P) has a lower limit of 0.31Hz. The region between these values is known as soft-stiff and it is the recommended range for the lower natural frequencies of the coupled structure. The soft-soft and stiff-stiff regions result in flexible and over-stiffed structures, that may be easily excited by wind and wave forces or cause a high cost respectively.

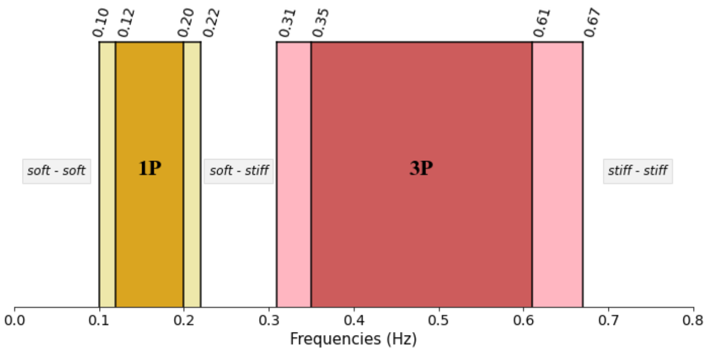


Figure 2. Operational frequencies of the NREL 5-MW Wind Turbine. Adapted from Couceiro *et al.* [12]

3 Optimization Problem

The optimization problem considered in this work is defined by eq. (1). The optimization of the jacket for the NREL 5-MW Wind Turbine is a mono-objective constrained optimization. The problem is subjected to nine constraints $g_j(x), j = 1, 2, \dots, 9$ that are related to the analysis of free vibrations and local buckling. Eight variables are adopted in the problem such as diameters (D_k) and thickness (t_k) of the four jacket groups of elements.

$$\begin{cases} minimize\ f(x) = \sum_{i=1}^{n} \rho_i\, A_i\, l_i \\ subjected\ to\ g_1(x) = \dfrac{\omega_1}{0.22} - 1 \geq 0 \\ g_2(x) = 1 - \dfrac{\omega_1}{0.31} \geq 0 \\ g_3(x) = \dfrac{\omega_2}{0.22} - 1 \geq 0 \\ g_4(x) = 1 - \dfrac{\omega_2}{0.31} \geq 0 \\ g_5(x) = \dfrac{\omega_3}{0.605} - 1 \geq 0 \\ g_j(x) = 1 - \dfrac{D_k/t_k}{76.909} \geq 0, for \begin{array}{ll} j = 6\ and\ k = 1, & j = 8\ and\ k = 3 \\ j = 7\ and\ k = 2, & j = 9\ and\ k = 4 \end{array} \\ 0.5 \leq D_k \leq 1.83, k = 1,2 \\ 0.0032 \leq t_k \leq 0.065, k = 1, 2 \\ 0.5 \leq D_3 \leq D_2 \\ 0.0032 \leq t_3 \leq t_2 \\ 0.5 \leq D_4 \leq D_3 \\ 0.0032 \leq t_4 \leq t_3 \end{cases} \tag{1}$$

where the objective function $f(x)$ is the jacket weight. The weight of an element i is defined by its density ρ_i, cross-sectional area A_i and its length l_i. The best solution for the optimization would refer to an individual whose objective function has the lowest value among the feasible solutions. Thus, it results in a lighter structure and therefore a lower cost.

Between the nine constraints, five are related to frequencies, $g_1(x)$ to $g_5(x)$, in which the natural frequencies ω_1, ω_2 and ω_3 of the coupled structure are compared with the limit values of the excitation frequencies presented in Fig. 2. The ω_3 value is compared to the 3P frequency upper limit without the 10% margin. The last four constraints are represented by $g_j(x)\ j \in \{6, 7, 8, 9\}$. They refer to the local buckling analysis and are checked for each jacket group, with pairs of D and t, by eq. (2) from Det Norske Veritas - DNV [14]. The steel S275 with $f_y = 275$MPa is adopted, as in Couceiro *et al.* [12].

$$D/t \leq 90\left(\sqrt{\frac{235}{f_y}}\right)^2 \tag{2}$$

The eight optimization variables are defined as the diameters and thickness of the four jacket groups shown on Fig. 1(a). Their boundaries values are shown in eq. (1) regarding dimensions in meters (m). The lower boundaries are adopted as in Couceiro *et al.* [12]. Some upper boundaries are taken according to EN 10220 from the European Committee for Standardization - CEN [15]. The jacket's foundation pile has a diameter of 2.082m that represents a limit as it has a connection to lower level leg elements. Then, an immediately below value of 1.83m is adopted and the maximum thickness of 0.065m is also selected from EN 10220, CEN [15]. The groups 3 and 4 upper boundaries are based on the values of groups 2 and 3 respectively. This approach is used to define leg groups in lower levels with cross-sectional areas equal or greater than subsequent groups in upper levels.

4 Genetic Algorithm

In this work the GA is adopted as the optimization algorithm. It was originally developed in Holland [16] and is a metaheuristic inspired by the process of natural selection and evolutionary concepts. The GA searches the optimal solution in the problem's search space by a population of points that represents the individuals on the evolutionary process. Each individual represents a potential solution for the optimization problem and is described by its chromosome and genes, as presented in Goldberg [4]. Chromosome is a data structure such as a vector of real numbers, composed by the genes that are the variables which describe a solution according to the optimization problem domain.

A fitness value is also related to each individual. It is a measure of the individual quality, defined by the optimization's objective function. The fitness guides the optimization to the optimum solution as a fitter individual has more chances of surviving and reproducing.

According to Lacerda and Carvalho [17], a standard GA initializes a random population of individuals with the user defined size. All genes are set based on the variables boundaries in the optimization problem. Next, the individuals are evaluated to determine their fitness and then a loop begins: individuals are selected to an intermediate population, in which the crossover and mutation operators are applied to produce new individuals. Then, they are evaluated and selected to arrange a new population. These last steps occur until a stop criterion is achieved.

For the selection operation, the GA developed in this work uses the Tournament Selection Method. It chooses two solutions in the population and compares them according to their fitness value. The one with the higher fitness is selected to the intermediate population. The crossover operator adopted was the $BLX - \alpha$ for having been applied in a wide range of successful research, according to Lacerda and Carvalho [17]. In the $BLX - \alpha$ crossover is generated a single child c_1 from the two parents p_1 and p_2 by the combination of its genes as shown in eq. (3). The β value is defined randomly in $(-\alpha, 1 + \alpha)$ for each gene. In this work, $\alpha = 0{,}5$. For the mutation operator, the Uniform approach was used in this work. It consists of a random change in each gene of an individual according to variable boundaries of the optimization problem. The crossover and mutation are subject to probabilities of 0.9 and 0.02, respectively, to determine its application to the pair of individuals and specific gene respectively.

$$f_1 = p_1 + \beta(p_2 - p_1) \tag{3}$$

Other important features of the GA are the elitism, the stop criterion and the constraint handling technique (in the case of constrained optimization problem). The elitism is an approach in which the best individuals of the population are kept for the next generation. According to Lacerda and Carvalho [17], this procedure may result in better performance and faster convergence. In this work, elitism was considered in some executions of the GA, keeping only one individual in the population. For the stop criterion, it was adopted the maximum number of 1040 evaluations of the individuals. Two constraint handling techniques were evaluated in this work, they are described in the next section.

5 Constraint Handling Methods

The GA was proposed to solve unconstrained optimization problems, except the lateral limits of the design variables. To solve constrained optimization problems, it is necessary to include a constraint handling method between the GA operations. Different alternatives have been proposed in the literature as seen in Mezura-Montes and Coello [18]. In a constrained optimization problem, an individual that does not violate any of the constraints is known as feasible and represents a possible solution to the problem. If one or more constraints are violated, the individual is known as infeasible to the problem. Thus, the feasible solutions are preferable in the search of the optimal solution. However, despite being impractical solutions, the infeasible individuals may have important genes to the population evolution. In this work two methods were applied to the GA, the TSM and the MCR.

5.1 Tournament Selection Method – TSM

The TSM was developed in Deb [5], based on the selection operator, in particular the Tournament method. The TSM compares two individuals from the population according to three rules: (1) if one individual is feasible and the other is infeasible, the feasible one is selected; (2) if both individuals are feasible, that with better objective function value is selected; (3) if both are infeasible, that with least violation is selected. These criteria result in a comparison in which a feasible solution is preferred over an infeasible one.

5.2 Multiple Constraint Ranking – MCR

The MCR is the second constraint handling technique adopted in this work. It was presented in Garcia *et al.* [6]. The MCR is described as a method capable of handling constraints with different units and magnitudes to avoid a dominance by some of them. The technique addresses multiple rankings of the individuals based on their objective function value (R_f), number of violated constraints (R_{Nv}) and the constraints violations (R_{ϕ}^{i}, where $i = 1,2, \ldots, m$ and m is the number of constraints in the optimization problem). Each individual has its position in each ranking defined by the sum of 1 and the number of individuals that dominate it (individuals that have previous positions in the respective ranking). Finally, the fitness function $F(x)$ of each individual is defined by eq. (4).

$$F(x) = \begin{cases} R_{Nv} + \sum_{i=1}^{m} R_{\phi}^{j} & if\ only\ infeasible\ individuals \\ R_f + R_{Nv} + \sum_{i=1}^{m} R_{\phi}^{j} & otherwise. \end{cases} \tag{4}$$

6 Results

Four different GA configurations were evaluated for the optimization of the jacket weight. The changes between them were based on the constraint handling technique and the elitism. Two GA configurations without elitism used the TSM and MCR respectively. They are named TSM and MCR respectively. The last two GA configurations were considered with both constraint handling techniques, however with an elitism of one individual. These are named to as TSM + Elit and MCR + Elit respectively.

For each GA configuration, 20 independent runs were performed, applying the same algorithm's parameters. The GA parameters used were a population size of 80 individuals, crossover probability of 0.9 and a mutation probability of 0.02. The statistics of the best solutions obtained in every runs were evaluated.

The weight results in the runs of the optimization problem are shown in Tab.1. Column Best in Tab. 1 presents the lowest weight obtained for the jacket in 20 runs. Column Worst refers to the higher jacket weight in 20 runs. Other statistics on these values presented in Tab. 1 are the Mean, Median, standard deviation (sd) and feasibility rate (FR). The FR is the ratio between the number of runs that found a feasible individual and the total runs.

Table 1. Statistics of the jacket weight for the best solutions of 20 runs of the GA configurations

Case	Best	Worst	Median	Mean	sd	FR (%)
TSM	294.081	435.634	332.146	338.857	30.746	100
MCR	293.893	403.108	327.254	336.595	33.166	100
TSM + Elit	284.163	329.046	309.879	310.690	11.576	100
MCR + Elit	286.266	363.320	311.375	313.161	18.768	100

From Tab. 1, it is possible to compare both constraint handling techniques and the application of elitism. Comparing the configurations, TSM and MCR, it is noted that the first one achieved the worst solution with

+8.07% difference from the same metric related to the MCR and lowest sd. The median and mean values are lower for MCR and the best solutions have a small difference of -0.06% when comparing the MCR to TSM. The MCR may be considered as the best configuration between those without elitism due to lower values in more statistics.

Regarding the cases in which the elitism was adopted, a different situation is seen in Tab. 1: the TSM + Elit has the best solution with a difference of -0.73% compared to MCR + Elit, and has the lower median, mean and sd values. The MCR + Elit has the worst solution with a +10.42% weight difference for TSM + Elit. It is also shown that the use of elitism is a positive approach for the GA. The two configurations with elitism outperformed those without it, considering all metrics in Tab. 1.

Comparing Tab. 1 values with the OC4 jacket weight of 673.87t it is seen that all achieved results were lower. For the configurations TSM and MCR, the differences of best solutions to the OC4 project are of -56.36% and of -56.39%. Regarding the configurations TSM + Elit and MCR + Elit, the differences are of -57.83% and -57.52%.

The dimensions and areas of the jacket's elements are compared in Tab.2. The best solutions achieved by the TSM + Elit and MCR + Elit are shown in respect to the four groups. The colors used in Tab. 2 are the same in Fig. 1(a) referring to each group. The area differences are set according to the OC4 project values and all of them resulted in reductions up to -84%. Some dimensions and areas obtained with TSM + Elit and MCR + Elit have close values. As it was defined in the optimization problem, the areas decreased from group 2 to group 4.

Table 2. Cross-sectional data of the group elements for best solutions

Group	OC4			TSM + Elit				MCR + Elit			
	D (m)	t (mm)	A (m^2)	D (m)	t (mm)	A (m^2)	Dif. (%)	D (m)	t (mm)	A (m^2)	Dif. (%)
1	0.8	20	0.049	0.54	7.66	0.013	-73.9	0.51	7.05	0.011	-77.5
2	1.2	50	0.181	1.36	21.70	0.091	-49.4	0.84	28.02	0.072	-60.3
3	1.2	35	0.128	0.62	18.41	0.034	-73.1	0.57	18.27	0.032	-75.2
4	1.2	40	0.146	0.56	13.62	0.023	-84.1	0.54	17.52	0.029	-80.4

The first three natural frequencies for the coupled model are shown in Tab. 3. The first and second mode of vibrations have their frequencies close to the upper boundary of 0.31Hz for the OC4 model. However, the optimized structures have shown a significant reduction in this value achieving natural frequencies closer to the lowest boundary of 0.22Hz. The third mode also shows decreased value in the natural frequency although not as significant as the others two.

Table 3. Comparison of the first three natural frequencies of the coupled model

Modo	OC4	TSM	MCR	TSM + Elit	MCR + Elit
1	0.3175	0.231	0.222	0.230	0.220
2	0.3182	0.231	0.222	0.231	0.221
3	0.6171	0.610	0.610	0.610	0.609

7 Conclusions

The optimization problem of a jacket for an Offshore Wind Turbine was studied in this work. The jacket was optimized regarding the element's dimensions, aiming to minimize its weight, applying constraints related to frequencies and local buckling limits. The considered coupled structure was based on the OC4 project model and modeled by the Finite Element Method with the software ANSYS.

The results achieved a significant weight reduction in comparison to the reference OC4 project model. The Genetic Algorithm (GA) and the constraint handling methods adopted, Tournament Selection Method (TSM) from Deb [5] and the Multiple Constraint Ranking (MCR) from Garcia *et al.* [6], were successful in all configurations analyzed. Both TSM and MCR achieved similar performances with the GA. The GA configurations with elitism produced better solutions than those without it, which resulted in the lighter jacket design.

As future works, the GA can be investigated with the application of parameters variations and other constraint handling techniques. Other optimization algorithms such as the Differential Evolution (DE) and Particle Swarm

Optimization (PSO) can also be investigated. Future works and next steps of the research also may include the further development of the structure model, addition of environment loads, Ultimate Limits State and fatigue analysis, a shape and/or topology optimization, besides a multiobjective optimization can also be considered.

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