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Layout design of wave energy parks by a genetic algorithm

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Abstract

If wave energy systems are to become a viable option competitive with more mature renewable energy sources, the systems must be optimized with respect to maximal electricity production and minimized costs. The number of parameters involved in large-scale wave energy systems is typically too large for traditional optimization methods to be feasible, and the solution space may contain many local minima. Here, an optimization tool for application in wave energy design based on a genetic algorithm is presented. The internal parameters of single point-absorbing wave energy converters (buoy radius, draft and generator damping) are optimized and the results validated against parameters sweep optimization. Further, since the individual devices in a park affect each other by scattered and radiated waves propagating in all directions, the tool is used to find the optimal spatial layout of parks. Arrays with different number of devices are studied and similar optimal layouts appear in all cases, which allows extrapolation of the results to even larger parks. The results show that the tool is effective in finding layouts that avoid destructive interactions and get a q -factor slightly above 1.

Keywords: Wave energy arrays, genetic algorithm, optimization, WEC, hydrodynamic interaction.

1 INTRODUCTION

Wave energy is a clean and renewable energy source that has the potential of contributing to 10% of the world's electricity consumption [1], or as much as 17% in some countries such as UK [2]. However, in order to become economically feasible, the efficiency of the wave energy technology must improve. To produce electricity in the MW range, wave energy converters (WECs) must usually be deployed in large arrays, or parks. In particular, this is true for small point absorber devices.

The WECs will interact hydrodynamically by scattered and radiated waves, which may affect the total power production positively or destructively, and the total performance of the park will be affected by many different parameters, for example the number of devices, their separation distance and individual dimensions, the geometry of the park and the wave climate. The increase in power production and reduction in power fluctuations as functions of the number of devices in a park was studied by [3–5] and [6] and the effect on the park performance of the separating distance between devices has been studied by [7, 8] and [9]. The global geometry can have a large effect on the output power and the fluctuations in an array. [10] showed that certain array layouts can increase the power with 5% or lead to a decrease of up to 30%.

Most studies on designing optimal wave energy parks have been based on comparisons of a few different configurations [11, 12]. A more systematic approach is to use an optimization scheme such as a genetic algorithm (GA). Genetic algorithms originate from theory of evolution studies, but have since been applied in a variety of areas, ranging from string theory [13] to pharmaceutical research [14]. The algorithm mimics the process of natural selection and incorporates inheritance, mutation and selection among states in the solution space to find global minima of stated problems.

A few works on array layout optimization using a genetic algorithm approach have been presented by [10, 15–17] and [18]. They deal with the problem of optimization of arrays of point-absorber WECs in terms of spatial layout or of power take off characteristics. [15] and [16] used two optimization methods: parabolic intersection and genetic algorithm. By means of these two approaches the spatial configuration of 5 identical devices upon power output of the array was optimized with different kind of tuning of the devices. In their study, the MATLAB GA and Direct Search Toolbox was used. Another model to determine array configurations, where the evaluation function contained power output and costs, was presented by [17], with binary and continuous GA. Both optimizations of power take off characteristics, given a fixed layout, and of array layout of 10 identical WECs, given fixed power take off coefficients, were included in the work by [10].

The mentioned works all shed important insight into optimal configurations of wave energy parks, but approximations and model differences imply that no generic conclusions can be drawn on optimal wave energy parks.

The objective of this study is to develop and use a new optimization tool for arrays of point absorber wave energy converters which can be used as a reliable and fast pre-deployment evaluation method, where the motion and power of each device is computed in the time domain and the input is irregular waves.

Differently from the previous studies, the present work first studies full optimization of the design variables of a single point absorber device, i.e. the simultaneous search of the best geometry of the floater and the best PTO setting for a given sea states. Secondly, the comparison with a parameter sweep (PS) optimization of the single device, has allowed validation of the GA method and evaluation of its accuracy. Furthermore, regarding the array layout optimization, two different GA models have been created from scratch: discrete and continuous variables optimization of arrays up to a customizable number of fully hydrodynamically interacting WECs. A comparison between these two approaches has been carried out. The influence of the variation in the number of devices (from 4 to 14 WECs) within the same constrained space has been also addressed. The power production of the devices is calculated in the time domain and no resonance condition is assumed as in [17]. The crossover method implemented is different from [15] but similar to the one in [17], as described in more detail in section 2.

The semi-analytical hydrodynamic model used to compute the interactions among the devices is suitable for axisymmetric cylindrical floaters and it has been used here with point absorbers buoys. However, the genetic algorithm layout optimization routine implemented can potentially be applied to arrays of different devices (in geometry and working principle), provided that a suitable interactions model is included.

The paper is organized as follows: the genetic algorithm model and parameters setting are outlined in section 2. The description includes the different variations for a single WEC and for the array. In section 3, results of the optimization are presented, and further discussed in section 4. Conclusions are drawn in section 5.

2 METHOD

2.1 Genetic algorithm

Evolutionary algorithms are specific metaheuristic optimization algorithms which base their procedure and nomenclature on the theory of biological microevolution of living being. The genetic algorithm is one of these methods, developed by [19]; the optimization is performed by implementing and iterating a "genetic evolution" over a set of solutions, until sufficiently good results are obtained. These methods rely on an intelligent search of a large but finite solution space using statistical methods and can deal with discrete variables and non-continuous cost functions [20]. In fact, in optimization problems of energy converters arrays, a large parameter space is involved (making parameter sweep infeasible) and the shape of the cost function is not known and probably multi-peaked [15]. Therefore, a genetic algorithm method is well suited for the problem.

In this study three slightly different GAs were developed and implemented in the MATLAB programming language. The algorithms were coded from scratch based on the theory described in [20], and are described in details later in this section. In this paper we deal with the following optimization cases:

- Single device: optimization of the internal hydrodynamic parameters such as buoy radius, draft and generator damping coefficient of a single point absorber WEC of the type developed at Uppsala University [21].
- Array code A: optimization of the spatial coordinates of an array of identical devices where the possible coordinates (solutions) are random positions on a fixed regular grid.
- Array code B: optimization of the spatial coordinates of an array of identical devices where the possible coordinates (solutions) are continuous random numbers.

The single WEC genetic algorithm tool aims to find the optimal value of the radius (R) and draft (d) of the buoy and the damping coefficient (γ) of the generator, considering the point-absorber WEC similar to the one developed at Uppsala University (Fig. 1). It consists of a linear generator located at the seabed and a floating buoy at the surface, connected by a connection line. The linear generator is composed by a moving part (translator) with permanent magnets and a static part (stator) with coil windings. As the incoming waves reach the WEC, the buoy and the translator move upwards (wave crest) and downwards (wave trough). The relative movement between the permanent magnets and the coils induces electricity. Further details about the converter can be found in [21].

For a given sea state, the single WEC GA method allows to find the size of the buoy and the PTO setting which gives the highest theoretical power production. The array optimization aims to find a layout geometry for a number of identical (in geometry and generator damping coefficient) WECs which improves the total power production.

Fig. 1: Uppsala University wave energy converter concept. The dotted line indicate the mean surface water level (m.s.w.l.).

Parameters settings The genetic algorithm routine is based on the arbitrary choice of some parameters which can influence the achievement of convergence and the output results. Nomenclature is inspired by evolutionary theory. Here, parameters, terminology and notation used in the paper are presented.

The optimization process starts with the random creation of the first *population*, which is a set of a fixed number ($nPop$) of *chromosomes*. According to the variables involved in the optimization process, each chromosome contains a certain number ($Nvar$) of *genes* ($nGene$). Each *gene* represents a variable that will be optimized in the process. In the single WEC genetic algorithm the number of different genes ($nGene$) in every chromosome is three: R , d , γ , while for the array codes A and B the number of different genes ($nGene$) is equal to one (namely the couple of coordinates $[x_i, y_i]$, where i is the i -th device in the park). Therefore, in code A and B, there will be $Nb \cdot nGene$ genes ($Nvar$) in every chromosome, where Nb is the number of WECs in the array (see Fig. 4).

Initial population The first *population* (or first set of chromosomes) is generated by uniform random sampling. It represents the first set of solutions from which the algorithm will start its optimization routine.

In the single WEC genetic algorithm a set of discrete possible values for R , d and γ were defined as the first sampling pool. The first population is therefore a set of possible combinations of R , d and γ , each set representing a parameter configuration of a WEC.

Regarding the array code the initial population contains, as well, a certain number of solutions which are geometrical layouts. Therefore, each chromosome contains the coordinates of the WECs that form a specific configuration.

In the array code A, the devices are allowed to take their coordinates over a fixed gridded ocean area: coordinates values are uniformly sampled at random from the possible positions according to the ocean area limits ($Area$) and the minimum separation distance allowed along the x and y axis (dx , dy). When the sampling produces the same couple of coordinates in the same chromosome, the algorithm is forced to re-sample, thus avoiding WECs to be placed at the same spot.

In the array code B the process is the same as in code A, but the sampling is done using continuous values within the ocean area limits; a minimum distance among the devices is set in advance and sampling is re-performed if this limit is violated.

Evaluation As a first step, the first population is evaluated by associating every chromosome with a fitness value calculated by the evaluation function operator. This fitness or objective cost function is defined as the negative value of the power production of the single WEC or of the park. The genetic algorithm optimization is coupled with an analytical fast multiple scattering method for the calculation of the hydrodynamic parameters of the fully hydrodynamically coupled WECs. The hydrodynamic model has been presented, validated and used to study parks with over hundred devices by [22]. The input to the model consists of 20 min time series of unidirectional irregular waves measured off-shore at the Lysekil research test site at the west coast of Sweden. After computation of the hydrodynamic parameters (added mass, radiation damping and excitation force), the dynamics of the WECs is determined in the time domain by inverse Fourier transform. With the vertical position $z_i(t)$ of the buoy, the instantaneous power absorption of the WEC i is given as $P_i(t) = \gamma \cdot \dot{z}_i(t)^2$, while

Fig. 2: Example plot of evaluation values for an array of 9 devices with 12 members of the *population* and 50 iterations. A higher power production is obtained as the number of iterations increases.

the power output of the full park will be the sum of all Nb WECs:

$$P_{\text{tot}}(t) = \sum_{i=1}^{Nb} P_i(t). \quad (1)$$

The 20 min time series, characterized by a specific significant wave height H_s and energy period T_e , was iterated three times to have 60 minutes of input waves into the model. Then, the final fitness value is the time-average of the instantaneous power over this time window.

Ranking After evaluation, the GA routine requires that the population is ranked in descending order, from the best chromosome (higher fitness value/power production) to the worst (lower fitness value/power production).

Fig. 2 shows an example of how the fitness value of the ranked populations evolves with the iterations. Population 1 represents the best one for every iteration and the trend of the fitness value (negative value of the absorbed power) is descending, as expected. As the iterations proceed, the best solution improves (getting a lower value) and is kept until a better one is found.

Convergence As the genetic algorithm proceeds, some criteria are needed to stop the search at some point. The number of iterations that evolve depends on whether an acceptable solution is reached or a set number of iterations is exceeded [20]. Therefore, the following convergence criteria were implemented in the method and checked at every iteration:

- 1) a maximum number of iterations ($MaxIt$) is reached;
- 2) all the chromosomes in the actual population are the same;
- 3) the solution ceases to improve after a certain number (I) of iterations.

If one of these conditions is fulfilled, the algorithm stops and the first chromosome of the ranked population is taken as final optimal solution. It is to be noted that in some simulations the condition 3) was not implemented, in order to let the code evolve until the fixed maximum number of iteration decided (more details in Table 1).

Reproduction If convergence is not reached, the genetic algorithm moves forward towards *reproduction*. It consists of the following operations: *natural selection*, *pairing*, *mating – crossover*, *elitism*, and *mutation*.

- a. *Natural selection*: This operator selects the upper percentage (*selection rate*) of individuals in the ranked population that will survive and continue to the next generation.

Fig. 3: Chromosome and single point crossover representation for the single WEC (a), array layout optimization code A (b) and array layout optimization code B (c). The blue and red genes are swapped, while the highlighted genes are the blended ones.

- b. *Pairing*: The selected part of the population chromosomes represents the new *parents*; odd and even rows are paired from top to bottom to generate a new part of the population called *offspring*.
- c. *Mating – crossover*: The crossover operator exchanges genetic material between two parent chromosomes during reproduction, so that potentially positive distinctive genes from both individuals will be inherited by every child. This procedure is performed in a slightly different way according to the optimization problem (see Fig. 3), but always with a single point crossover.

In the single WEC optimization code one gene is uniformly randomly chosen as “crossover point” and then swapped between the two parents chromosomes (Fig. 3a).

In array code A a random selected gene divides the chromosome into two parts that are consequently swapped between the two parents individuals (Fig. 3b).

In array code B almost the same procedure as in code A is implemented, but the “crossover point” is also supposed to blend. The blending process produces two new variables from the combination of the two corresponding parents’ genes as follows [20]:

$$\begin{aligned} x_{B1}, y_{B1} &= [x_{\alpha 1}, y_{\alpha 1}] - \beta([x_{\alpha 1}, y_{\alpha 1}] - [x_{\alpha 2}, y_{\alpha 2}]) \\ x_{B2}, y_{B2} &= [x_{\alpha 2}, y_{\alpha 2}] + \beta([x_{\alpha 1}, y_{\alpha 1}] - [x_{\alpha 2}, y_{\alpha 2}]) \end{aligned} \quad (2)$$

where B represents the blended variable, α refers to the α -th random gene chosen as crossover point, 1 is the variable in the mother’s chromosome and 2 in the father’s chromosome, and β is a random coefficient between 0 and 1. Both α and β are reset randomly for every mating couple of chromosomes. The offspring will inherit the new blended variable and the following part of the chromosome swapped between mother and father (Fig. 3c).

In the array codes offsprings are checked for possible WECs being in the same position within the same chromosome; in array code B minimum distances requirement between WECs is also checked; the process is iterated if those conditions are not fulfilled.

- d. *Elitism and Mutation*: *Mutation* introduces new genetic material in the population by randomly changing a chosen percentage of variables (i.e. genes). This ensures that other regions in the solution space will be explored, without the algorithm potentially being stuck in a local minimum. *Elitism* protects the first upper set (*elitism rate*) of the ranked individuals from potentially negative mutations, in order to preserve the best solutions unaltered in the following generation. Again, overlapping coordinates and minimum distances requirements are checked by the algorithm.

New Population The combination of the first selected population (parents) and the new generated offsprings, after mutation, constitutes the new population that will be evaluated in the next *generation* or *iteration*.

The general scheme of the GA procedure is outlined in Fig. 4.

2.2 Simulations settings

As previously mentioned, the user can customize the parameters inside the GA tool. Here, the choice of the values used in this study will be outlined.

Fig. 4: Scheme of the GA procedure; highlighted with colors different chromosomes for the three type of codes: single device chromosome (blue), array layout optimization code A and B (red).

Table 1: Nomenclature and genetic algorithm parameters settings used for different simulations.

Symbol	Parameter's description	1 WEC	Array A-B
Nb	Number of WECs	1	4, 5, 7, 9, 14
nPop	Initial population size (number of chromosomes)	16	12
nGene	Number of different genes	3	1
Nvar	Number of genes in every chromosome	3	Nb-nGene
MaxIt	Maximum number of iteration/generation	100	250, 500
selection rate	Fraction of nPop that is selected for mating	0.5	0.5
mutation rate	% of population to be mutated	0.2	0.2
elitism rate	Number of solutions kept unaltered in the next generation	1	3
I	Iteration needed to converge if solution doesn't improve	25	—
dx, dy	Separation distance in the x and y directions	—	10 m
Area	Ocean area available for deployment	—	50x50 m ² , 80x80 m ²

In the single device GA optimization the following range of parameters are chosen: $R = 1 : 0.5 : 5$ m, $d = 0.2 : 0.05 : 0.4$ m and $\gamma = 15 : 1 : 2000$ kNs/m. The maximum number of iterations that the GA can perform is set to 100 and I number of iterations is 25. The mutation rate is 20%. With these settings, 20 different simulations have been performed, after which the results were validated against parameter sweep of the variables (i.e. computation of the power output for every combination of radius, draft and γ coefficient possible). The results of the validation are shown in Fig. 5.

Regarding the array layout optimization code, simulations were performed considering arrays of 4, 5, 7, 9 and 14 devices; each WEC has the same design characteristics: $R = 3$ m, $d = 0.45$ m and $\gamma = 140$ kNs/m. In array code A, devices are allowed to take coordinates on a gridded available ocean area of 2500 m² (or 6400 m² for some simulations); the dimension of a cell of the grid is 10 m in both the x and y directions; as a consequence, the minimum separation distance between the center of two WECs is fixed at 10 m. In the array code B, devices can take every coordinates within the ocean area, but 10 m minimum distance constraint between the devices is implemented.

In all simulations the input to the hydrodynamic model is time series of irregular waves with significant wave height $H_s = 1.53$ m and energy period $T_e = 5.01$ s. In the array optimizations, the irregular waves are unidirectional and moving from west to east along the x axis.

Table 1 shows notation and parameters values considered in the simulations, which were performed on a desktop PC with 15 parallel Intel(R) Xeon(R) 2.40 GHz processors and 32 GB RAM.

3 RESULTS

3.1 Parameter optimization of the single device

Fig. 5 shows the results obtained from the single device optimization tool from 20 simulation runs. The surfaces represent the power output calculated by the parameter sweep, while the diamonds represent the solutions found by the genetic algorithm. As can be seen from the figure, the agreement is very good: less than 0.2% difference in the final average power output calculated by the two methods was obtained in all 20 simulations. Exact value of the optimal radius and optimal draft was found by the GA 100% of the times, while the optimal GA γ value has at most 8% difference with the PS value. The reason of this difference is most likely connected to the number of iterations that the tool was allowed to perform.

Fig. 5: Genetic algorithm optimal solutions vs parameter sweep values and optimum. Surfaces show the PS results for a given fixed (optimal) value of the draft (a), the radius (b) and the γ coefficient (d). Diamonds represent GA solutions. (c) and (e) show a zoom of the GA results (diamonds) with parameter sweep optimum (crosses) [18].

The computational time between the PS and GA methods has also been evaluated: one run of PS with the previous mentioned parameter space took 87.2 min, while 85% of the GA runs took less than 10 min to reach convergence. Moreover, most of the runs reached convergence of type 3, meaning that the actual solution was in reality found within a I number of iterations (in this case 25) before maximum number of iterations (100), so the computational time was shorter than 10 min.

3.2 Multiple WECs layout optimization

Fig. 6 shows the results for the array layout optimization for different park sizes (4, 5, 7, 9 and 14 WECs), after 250 GA iterations. The best results obtained (in terms of power output) are plotted both for code A and B in the first and second column, while the worst configurations obtained are plotted in columns three and four.

The best solution from code A for parks of 4 and 5 WECs is, as expected, the perfect alignment of the buoys with the incident wave front, so that no WEC is shadowed by another. The same results was obtained for a simulation of 4 devices in a double size ocean area, i.e. 100 x 100 m; therefore the ocean area, if big enough, is not influencing the results and the spacing among the WECs. In fact, it is interesting to notice that the separation distance is 10 m (i.e. dy) and not bigger, even if this latter can be achieved. This means that this particular distance of separation produces a positive interaction, given the specific buoy's geometry.

When the ocean area becomes a limiting factor, so that buoys cannot align themselves with the incoming waves, results suggests that the biggest power output is reached by adding to a "complete line" a supplemental front line with buoys located every second spot. This is valid, for example, for the 7 and 9 buoys parks. When the number of WECs increases further, the solution results in a sequence of 2 filled lines perpendicular to the wave direction.

The continuous code results (shown in column 2) show the same trends: 4 and 5 WECs tend to align in a single row. Similarities between the gridded and continuous code results are not as clear for the bigger parks; since the solution space is much larger than before, the tool needs a much larger number of iterations to get the same results as the gridded. But even though two perfect lines are not distinguishable, it is visible that WECs are not completely spread out over the ocean area (as one may expect to have less destructive interaction), but

Fig. 6: Results of the GA code. Best solutions from gridded (code A) and continuous (code B) GA are shown on the first and second column respectively, while the corresponding worst configurations obtained are shown in column three and four.

Fig. 7: q -factor of the different arrays shown in Fig. 6. Red lines represent best solutions, blue lines worst solutions, both with gridded GA code (code A) and continuous GA code (code B). (Lines are drawn as a guide for the eye and don't represent a linear interpolation between the results.)

instead they occupy a quite narrow (in the x-direction) and long (in the y-direction) area; moreover, also the separation distance is rather small. The 14 WECs solution is more spread, which is related to the few number of iterations performed. The size of the solution space increases rapidly with the park size: by increasing the number of devices in the park, the complexity of the problem increases drastically.

The worst layouts shown in Fig. 6 clearly present a lot of shadowing effect and spreading of the devices in the x-direction, both with code A (gridded) and code B (continuous). In all cases, more than half of the buoys in the parks are shadowed.

Fig. 7 shows, for every layout of Fig. 6, the *interaction factor* (q -factor), defined as:

$$q = \frac{P_{tot}}{\sum_{i=1}^{Nb} P_i^{IS}} \quad (3)$$

P_{tot} represents the total power of the array, while P_i^{IS} is the power of the i -th device in isolation. For parks up to 9 WECs, a configuration with positive interaction gain (i.e. power production > power production of the same amount of WECs in isolation) can be found by the tool in 250 iterations. The q -factor is therefore larger than 1. It is to be noted that the results are dependent on the size of the ocean area in relation to the number of WECs, as mentioned previously.

The gridded code shows a slightly higher efficiency in finding the configuration with the highest power output. It's also worth noticing that destructive interaction influences the total power absorption to a larger extent than positive interaction effects; the worst layouts have 14-21% lower power absorption as compared to WECs in isolation, whereas the optimal layouts have an improved power absorption of 0-9%.

Given that all the buoys and generators in the array are identical, maximizing the power output is equivalent to optimizing the q -factor. Numerical values of power obtained from the model are also reported in Tables 2 and 3, together with the q -factor.

In order to verify the accuracy of the model and the solutions obtained, some simulations with different parameters have been performed. In particular, regarding the 9 WECs array, simulations with a higher number of iterations and a *double GA* have been implemented. Double GA means that the final solution of one GA

Table 2: Best and worst results of the optimization code A (gridded GA).

Number of WECs	Best Solutions		Worst Solutions	
	P_{tot} [kW]	q	P_{tot} [kW]	q
4	47	1.07	38	0.86
5	59.5	1.08	47.5	0.86
7	82.5	1.07	64	0.83
9	104.5	1.06	80	0.81
14	149.5	0.97	122	0.79

Table 3: Best and worst results of the optimization code B (continuous GA).

Number of WECs	Best Solutions		Worst Solutions	
	P_{tot} [kW]	q	P_{tot} [kW]	q
4	48	1.09	38	0.86
5	59.5	1.08	48.5	0.88
7	80.5	1.05	62.5	0.81
9	99.5	1.01	83.5	0.84
14	143.5	0.93	125.5	0.81

simulation (Code A, 500 iterations) was forced to be the initial population of one other GA run of 500 iterations with $I = 150$. Results didn't improve and the same solution was kept as the best one (Fig.8).

To better validate the results from the GA optimization, the array model was run with some fixed park configurations (locations of the WECs and ocean area size). Output from the GA code are plotted in Fig. 9 b) and d), while Fig. 9 a), c) and e) are arbitrary simulated layouts. The q -factor value is indicated at the top of each sub-plot.

When the ocean area width (80 m) allows alignment along the incident wave crest (Fig. 9 c), the power output is maximized, as has already been found for smaller parks. In Fig. 9 a) a layout with 3 shifted lines has been simulated: the number of shadowed WECs is still 3 (as in the GA solution), but the distance between WECs is higher; therefore one could a priori think that this configuration would produce a higher power output, which is not the case. Solution b), which is found by the GA code, performs better in terms of power output and occupies less marine area.

Fig. 9 d) shows the results from the GA code A after 250 iterations for an array of 14 WECs. The width of the area has been set to 80 m, in order to keep the ratio between the number of WECs and the area width comparable (referred to 9 WECs in 50 m). The trend for optimal layout is again the alignment of the devices in 2 lines. A simulation with the same geometrical structure obtained for 7 and 9 WECs was done for 14 WECs (Fig. 9 e). The power result is higher than for any other layout found by the GA. This is due to the few number of iterations performed in relation to the solution space. If $MaxIt$ had been much higher, the GA tool would most likely have found this solution. In the present study $MaxIt$ has been chosen as a compromise between a low CPU costs, which permits computations of large numbers of layouts and cases, and high reliability and repeatability of the results.

4 DISCUSSION

Two different versions of the code have been developed and the results compared. Both codes A and B have advantages and disadvantages; code A allows to search for solutions in a smaller solution space, implying that

Fig. 8: Solution of the first and second GA simulations.

Fig. 9: Comparison between q -factor of GA results (b and d) and three other arbitrary layouts (a, c and e). From a) to c): 9 WECs; d), e): 14 WECs.

convergence is faster and output layouts are regular. The limitation is that the results depend on the arbitrary choice of a fixed grid. Code B has the pros of finding the best separation distance between devices, but, as soon as the number of WECs becomes higher than 5, the number of required iterations becomes very large in order to reach the same solution of code A. The two codes can be efficiently combined by using code B to find the best separation distance (even for a small park), and using the input in a gridded GA for faster optimization convergence.

Considering that code A has always led to a layout with almost equal (in case of 4 WECs) or higher power production than code B, it is suggested that the gridded code is practically more suitable to solve this kind of problems, due to its efficiency (it requires less iterations) and modular regular output (it can lead also to an easier design of electric cables network, mooring etc.).

To characterize the evolution of the layouts through the GA iterations, the following coefficients have been calculated for every layouts and iterations:

$$S = \frac{\sum ShadowDistance + 1}{Nb} \quad (4)$$

$$D = \frac{d_{tot}}{Nb} \quad (5)$$

$$T = S \cdot D \quad (6)$$

S is a measure of the shadowing effects within the park, and is given by the sum of all the distances between shadowed buoys (*Shadow Distance*) divided by the total number of WECs in the park (Nb). D is the ratio between the distance from all the WECs to a point that minimizes the total distance (d_{tot}), and the number of buoys. It gives an indication of how much the park is spread out in the available marine area. Since cable cost is a major installation cost for a wave energy park, a minimized D -value is desired also from economical considerations. T is the overall coefficient given by the product of S and D , accounting for both effects.

The mean values over the best three (*elitism rate*) layouts for every iteration is shown in Fig. 10. For parks of 4, 5 and 7 devices, computations have been performed up to 250 iterations. For easier comparison with the larger arrays, the value at iteration 250 has been extended to the end of the graph. As the algorithm proceeds, the shadowing coefficient shows, for every park size, a decreasing trend until a steady value is reached. This value is the minimum shadowing distance feasible according to the number of WECs and the area size. The final solution has the lowest shadow distance of all the parks evaluated. Distance coefficient D has also a decreasing trend, meaning that the WECs don't need to be spread apart to get the maximum of the power output. The results therefore show that it is possible to reduce the ocean area occupied by the park without losing power output.

As can be seen from Fig. 6, the same trends for optimal layouts are visible in all studied cases, independent of the number of devices, where the WECs align perpendicular to the incident wave direction. This can be compared to the results of [17], [15] and [10], although a straightforward comparison is obstructed by the fact that different models and parameter spaces have been used in the different studies. Nevertheless, the optimal layouts in [17], [15] and [10] show a similar tendency towards alignment perpendicular to the incident wave with a small offset angle and the WECs in the optimal layouts are staggered in maximum two rows along the wave direction, which is similar to the results presented in this paper. Despite the differences between the methods used, the overall trends in the optimal layouts and the obtained q -factors are consistent, although a slightly better power performance improvement has been obtained here.

Fig. 10: Coefficients for different park sizes: a) S , b) D , c) T .

5 CONCLUSIONS

An optimization model for the parameters of a wave energy converter device was presented and validated against parameter sweep. Results have shown a very good agreement between the two approaches and the efficiency of the method was established.

Two layout optimization routines for arrays of point-absorber wave energy converters were presented and their applicability and efficiency tested for different trial park sizes. Results from the simulations have shown that the custom GA tool is able to find, within a small number of iterations (less than 500), a layout that avoids destructive interactions and has an increased power output. It was also possible to extrapolate general rules for layout deployment in relation to the size of the WEC and the ocean area.

From an engineering point of view, the real gain from collective behaviour of WECs in a park is anyhow not likely to happen (or at least is yet to be proven by real data), due to all simplifications included in modelling approaches and secondary effects related to real working conditions.

With that in mind, and considering the complexity of the problem, the tool developed in this study can be a useful and practical help in designing a configuration with the target value of the q -factor $\simeq 1$. Given a specific wave climate, the wave energy converter can first be optimized internally (parameters); subsequently, an array layout optimization can be performed avoiding a negative park effect and keeping the q -factor close to 1.

It has to be noted that variability of the wave climate is an important factor for array performance, but has not been considered in the present study. The irregular waves used as input to the model are unidirectional and it can be expected that the results could change in omnidirectional waves [23], which would be interesting for further studies.

The GA tool was created and tested with layouts of identical devices and has the potential to be applied in optimization of parks with different WECs geometry and generators, where results in terms of hydrodynamic interference are so complex that a decisional support tool for effective deployment is needed.

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