Parameter Optimization in Wave Energy Design by a Genetic Algorithm

Marianna Giassi*, Malin Göteman

Department of Engineering Sciences, Uppsala University, Uppsala, Sweden Email address of presenting author: marianna.giassi@angstrom.uu.se

HIGHLIGHTS

- A tool for optimization of parameters of a single wave energy converter using a genetic algorithm was developed and validated against a parameter sweep optimization of the variables.
- The procedure combines the genetic algorithm with a multiple scattering method for the calculation of the hydrodynamics (Göteman M. et al., 2015), providing fast computational time.
- The method was then modified and applied to optimization of the spatial layout of a wave power array of identical devices, that interact hydrodynamically by scattered and radiated waves. The resulting optimal park layouts avoid destructive interactions and get a q-factor slightly above 1.

1 INTRODUCTION

Wave energy conversion is one of the promising renewable energy technologies that is now facing the challenging steps towards early commercialization. Many of the technologies developed consist of small devices that are designed to be deployed in large parks of many units to produce a considerable amount of power. The wave energy converter (WEC) developed at Uppsala University belongs to this group of technologies; it consists of a floating buoy connected to a linear direct-driven permanent magnet generator on the seabed (Leijon M. et al., 2009). When deployed, the devices interact with each other, both hydrodynamically by scattered and radiated waves, and electrically, leading to an increase or decrease of the power production depending on many parameters such as park layout, number of devices, separating distance, wave direction, etc.

This paper focuses on the development and implementation of a tool able to optimize some of the principal parameters (buoy's radius, buoy's draft and damping coefficient of the generator) of a single point absorber WEC using a genetic algorithm (GA). After validation of the method against parameter sweep (PS), the tool has been improved to optimize the spatial layout of a park of WECs.

Research in wave energy park optimization by means of a genetic algorithm has been carried out by Child B.F.M. & Venugopal V. (2010), Child B.F.M. et al. (2011) and Sharp C. & DuPont B. (2016). Child B.F.M. & Venugopal V. (2010) used parabolic intersection and genetic algorithm with different kind of tuning of the devices and optimized the spatial configuration of 5 identical devices upon power output of the array; Sharp C. & DuPont B. created a model to determine array configurations and included both power output and costs in the evaluation function, both with binary and continuous GA. Child B.F.M. et al. (2011) included optimization of power take off characteristics given a fixed layout and optimization of array layout of 10 identical WECs, given fixed power take off coefficients.

2 METHOD

A genetic algorithm is one method among the more generic evolutionary algorithms which are based on the theory of biological evolution. In this kind of routines, the optimization depends on an "evolution" of a set of solutions, "genetically developing" every iteration towards the optimum. 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 (Haupt R.L. & Haupt S.E., 2004).

After definition of the GA parameters (see Table 1), a first *population* is generated by randomly sampling from a pool of defined values; this is the first set of *chromosome* (nPop), each of them



Fig. 1: 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 (d) show a zoom of the GA results (diamonds) with parameter sweep optimum (cross).

consisting in a number (nVar) of different genes (nGene). Then, the first population is evaluated and ranked, and the convergence criteria are checked. The following convergence criteria were implemented in the code: 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 (cut off) of iterations. As long as convergence is not reached, reproduction is performed, where some of the chromosomes chosen as parents will be coupled to generate a new part of the population called offspring. Reproduction is executed in several steps: natural selection, pairing, mating or crossover, mutation.

In the presented study two slightly different GAs were implemented in MATLAB coupled with an analytical fast multiple scattering method for the calculation of the hydrodynamic parameters of the fully hydrodynamically coupled WECs developed by Göteman M. et al. (2015). The input to the model consists of time series of irregular waves measured off-shore at the west coast of Sweden.

2.1 Genetic algorithm for a single device

The goal of the single WEC genetic algorithm tool is 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 described above; consequently, the number of different genes (nGene) in every chromosome is three: R, d, γ . The evaluation function computes the total mean absorbed power of the WEC over an hour of time; the negative of this value will then be minimized to find the optimum solution. The parameter space is discretized so that solution values are placed on a grid; the resolution and wideness of this grid is customizable and depends on the range of initial set parameters.

Natural selection determines which percentage (selection rate) of the individuals will survive and

Parameter	Description	1 WEC	Array
Nb	Number of WEC	1	4,5,7,9
nPop	Initial population size (number of chromosomes)	16	12
nGene	Number of different genes	3	1
Nvar	Number of genes in every chromosome	3	$Nb \cdot nGene$
MaxIt	Maximum number of iteration/generation	100	250
selection rate	Fraction of nPop that is selected for mating	0.5	0.5
mutation rate	% of population to be mutated	0.2 - 0.3	0.2
elitism rate	Number of best solutions kept unaltered in the next generation	1	3
cut off	Iteration needed to converge if solution doesn't improve	25	_

Table 1: Genetic algorithm parameters settings.

continue to the next generation; this fraction of the chromosomes is selected after the population has been ranked from the best to the worst objective function value. Afterwards, the chromosomes in the survived population are paired in order to mate and reproduce two offsprings. During *crossover*, one gene is randomly chosen as "crossover point" and then swapped between the two parents chromosomes, so that distinctive genes from both individuals are inherited by every child. Finally, new genetic material is introduced by *mutation*, which randomly changes a chosen percentage of variables in the population. *Elitism* keeps the first set percentage of the ranked population unchanged in the following generation, to preserve the best solutions from potentially negative mutations.

2.2 Extension of the method for an array

After validation, the algorithm has been modified to perform layout optimization of a park of many units. This enables multiple parameter optimization in wave energy parks, where the parameter space is so large so that a parameter sweep optimization becomes computationally unfeasible. The single devices are allowed to take their coordinates inside a fixed gridded ocean area. In this case the number of different genes (*nGene*) is equal to one (couple of coordinates $[x_i, y_i]$, where *i* is the i-th device in the park). Therefore, there will be $Nb \cdot nGen$ genes in every chromosome (*Nvar*), where *Nb* is the number of WECs in the array. *Natural selection* and *mating* are performed in the same way as described for the single WEC. *Crossover* is performed by choosing a random variable as "crossover point" that divides the chromosome in two parts; these are then swapped between the two parents individuals.

3 RESULTS

3.1 Single device parameter optimization

In the single device GA optimization performed, the parameters are allowed to assume the following range of values: R = 1: 0.5: 5 m, d = 0.2: 0.05: 0.4 m and $\gamma = 15: 1: 2000$ kNs/m. The model input is a time series of irregular waves characterized by significant wave height $H_s = 1.53$ m and energy period $T_e = 5.01$ s. The maximum number of iterations is set to 100 and the *cut off* iteration equal to 25. Mutation rate is 20%. 20 different simulations have been performed and 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. 1.

The agreement between the PS computation and the GA simulations is very good: all the solutions found by the GA (colored diamonds) are located in the region of maximum power output calculated by parameters sweep (surfaces); the differences between the PS optimum value and the GA results has been, in all 20 simulations, less than 0.2% regarding the final average power output of the WEC. Optimal radius and draft were found in 100% of the simulations and the difference between γ coefficients found by the GA and the optimum PS value is less than 8%. This is most likely related to the number of iterations that the tool was allowed to perform.

Even though the GA model of the single WEC is simple, the saving in computational time is important. One run of PS with the previous mentioned parameter space took 87.2 min, while 85%



Fig. 2: Results of GA optimization after 250 iterations.

of the GA runs took less than 10 min to reach convergence. Is worth noticing that, in almost all the cases, convergence of type 3 was reached, meaning that the actual solution was found a *cut off* number of iterations (in this case 25) before maximum number of iterations (100). Simulations were performed on a desktop PC with 16 parallel Intel(R) Xeon(R) 2.40 GHz processors and 32 GB RAM.

3.2 Wave energy arrays layout optimization

Simulations of arrays of 4-9 devices were performed; each WEC has the same design characteristics $(R = 3 \text{ m}, d = 0.45 \text{ m} \text{ and } \gamma = 140 \text{ kNs/m})$. The ocean area is 2500 m², gridded every 10 m both in x and y directions; devices are allowed to take coordinates on this grid. Unidirectional irregular waves are moving along the x axis. Fig. 2 shows layout results obtained for different park sizes, after 250 GA iterations. As expected, the best configuration for 4 and 5 WECs in such a large area is the perfect alignment of the park with the incoming wave front. When the ocean area and the separation distance do not allow a complete alignment (i.e. for 7 and 9 WECs), the optimal power is produced by adding to the complete line a supplemental front line with buoys located every second spot. The power production found by the GA has an increase of the output between 3% and 7%, depending on the number of WECs; the q-factor for the resulting layouts is slightly above 1, meaning that destructive hydrodynamical interaction is avoided and slight positive interaction is gained.

4 CONCLUSIONS

The work presented here has shown the potentiality of GA implementation for wave energy design: optimization method for single WEC's parameters gave accurate results in little computational time, compared to PS. Moreover, the results have been successfully validated. Then, given specified parameters of a wave energy converter's array (i.e. size of the WECs and power take-off characteristics, ocean area and distance required between the devices), the genetic algorithm implemented was able to find a spatial configuration which avoid destructive hydrodynamical interactions (q-factor of the array slightly > 1). The solutions are in some sense independent from the number of WECs and consist of a regular geometrical pattern. This would enable a fast pre-evaluation of the hydrodynamic interactions before the array's deployment process starts. Moreover, different runs of the GA tool with a sufficient number of iterations have led to the same configurations results.

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