Optimization of a wave energy park using a spectral wave model and a binary genetic algorithm.

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Keywords—**Wave energy park, optimization, genetic alhorithms**

I. Introduction

Globally, the main motivations for research into alternative energies have been the fossil fuel crisis, climate change, and energy security. In addition, the production of fossil fuels is expected to fall by the end of this century. Regionally, the peninsula of Baja California, Mexico is isolated from the national electrical system of the country and has a deficit in the production of electricity. On the other hand, near the coast of Baja California the waves are the most energetic of the country. The use of such energy can be done through wave energy converters (WEC) parks. Optimization of wave parks is one of the priorities in current wave energy research.

[1] presented a methodology based on statistical methods to evaluate different WEC arrays. For this purpose, they used historical wave climate simulations using the Simulating WAves in Nearshore (SWAN) model in the Gulf of Cadiz. In this work they considered WECs as obstacles. They concluded that an arrow shape array is the most efficient in terms of maintenance and operation.

[2] derives optimal designs for linear WEC arrays in front of a vertical wall that maximize the absorbed energy. They used a numerical optimization framework based on the WAMIT hydrodynamic model in conjunction with a genetic algorithm, and used SWAN to determine, the climatological characteristics of waves in the Aegean Sea. They conclude that the largest annual wave energy absorption is observed in the near-wall array.

[3] studied how to optimize the dimensions of the individual WECs and the size of the park for certain wave conditions, using flat bottom in their study. They used a genetic algorithm that optimize the devices and the park by means of a levelized cost of energy function. Their results show that the hydrodynamic interaction has a significant impact on the optimal WECs array of the parks and that the length of the intra-array cable is not significant in the optimization routine.

According to [4], Wave energy is at a stage where large-scale facilities are being planned, so research in WEC park optimization is an active area. In their review, after analysing various optimization methods, they conclude that comparisons are challenging, but WECs tend to align along several lines. Their configurations are the result from single objective functions, optimizing power production.

A recent review [5] mention single-target optimization results in regular layouts (perpendicular lines). However, when a multi-objective function must be applied for design optimization, it results in non-obvious fixes. One trend in WEC park design optimization is the application of computational intelligence. However, a large number of elements and multi-objective optimization have high computational requirements. This could be simplified by introducing machine learning approximations and techniques. However, each simplification implies data loss, which must be handled very carefully due to non-linearities and parameter complexities.

In their review [6] mentions that staggered and inline model, as well as economic model are appropriate for large-scale WEC array optimization, which can be beneficially combined with machine learning to further improve the optimization performance. This problem has been approached by computational intelligence algorithms like Genetic Algorithms, Hybrid Co-evolution and k-means. While the first two are optimization Heuristics with strong optimization abilities, k-mean, as a Machine Learning method, can be combined with them for more complex modelling of the problem. As for now, optimization heuristics like Genetic Algorithms are among the best alternatives for WEC array optimization, at least for relatively small sizes and number of objectives.

In this paper we analysed how to optimize a wave energy converter farm considering a variable sea bottom. For this purpose, genetic algorithms such as those developed in the work of [3] are used. By using an objective function that calculates the power and levelized cost of energy a wave park resulting from SWAN numerical model.

II. METHODS

Optimization problems try to find a maximum or minimum of real function. Among the computational methods, there are those known as evolutionary algorithms, which use ideas inspired by nature. One of the most effective evolutionary algorithms are genetic algorithms. They have the ability to distinguish between global and local optima and at the same time to be computationally efficient.

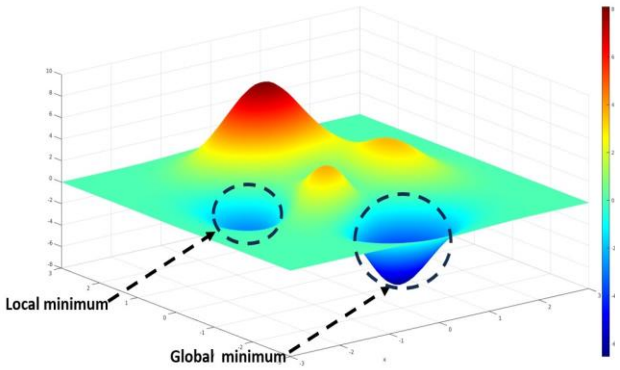

Fig.1. Example of function to minimize.

A. *Genetic algorithm*

Equation (1) shows the idea of optimization where f is the objective function to be optimized, M is the domain of the function and R is the range. When evaluated on the vector x that optimizes the function f, for example, the minimum $minA$ is obtained.

$$f : M \rightarrow \Re,\ f(x) \rightarrow minA \tag{1}$$

Figure 1 shows an example of a function with local minima and maxima, it is important to note that global minima and maxima are also present because computational algorithms may have difficulty discerning between them. To find the optimum, it is necessary to declare an objective function that will be optimized. The objective function depends on variables that represent the genes within the genetic algorithm, a set of variables or individuals, in this case representing the position of the devices of a wave energy farm in the mesh where the waves will be simulated. In this work the individuals are represented by a string of binary numbers. As shown in Figure 2, each row contains 16 bits, 8 bits for the position of the WEC on the x-axis and 8 bits the y-axis, thus an individual is formed by the total positions of the wave energy converter devices. The initial population of the algorithm is formed by n individuals on which the genetic operations are performed.

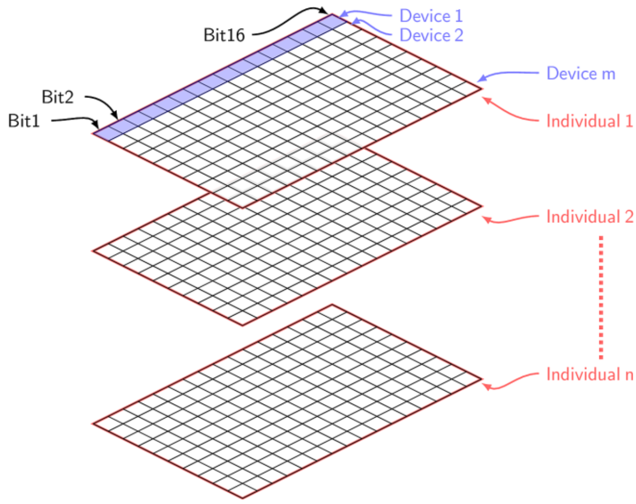

Fig.2. Representation of individuals by bits and a population in this work.

Genetic operations were followed according to the methods described by [7] and [8] as shown in the following diagram, see Fig.3.

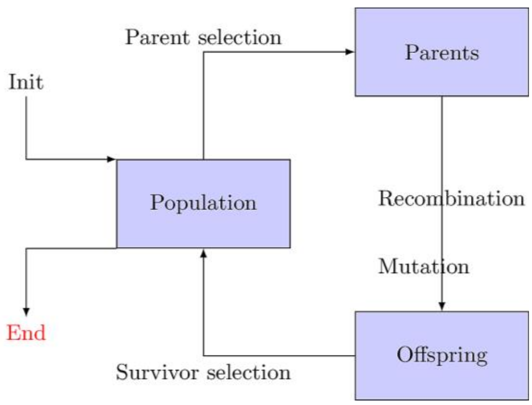

Fig.3. Flowchart of the genetic algorithm.

The genetic algorithm was developed from scratch, run on a computer with a processor intel XEON processor with 8 cores and 16 threads. The objective function calls the external software SNL-SWAN which consumes 90 percent of the computation time.

B. *SNL-SWAN model*

The SWAN model is a spectral wave model based on the wave action equation, which allows the study of waves as a stochastic phenomenon. In addition, the modification known as SNL-SWAN [9], developed by Sandia Laboratories, allows the inclusion of wave converter devices as obstacles that absorb energy at different frequencies.

In this work, SNL-SWAN is used to estimate the power produced by WEC farms which is used to minimize LCoE in the optimization algorithm. For this purpose, SNL-SWAN was run in stationary mode in a subregion of Todos Santos bay of 2800m x 2200m with spatial resolution of 22m and 17m (128 x 128 nodes). Boundary conditions are climatological wave characteristics obtained from a local hindcast of the TSB with a spatial resolution of 250 m.

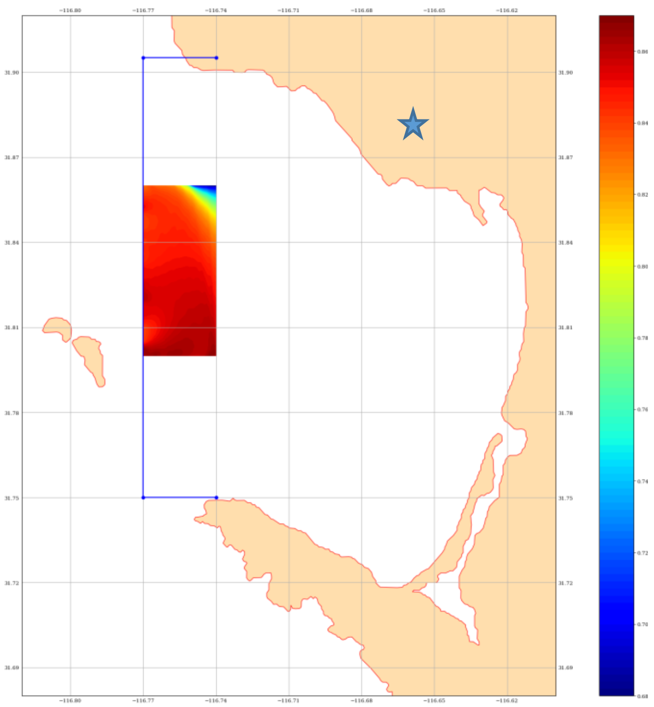

Fig.4. Todos Santos Bay, in Baja California, Mexico. The coloured rectangle is the study subregion where SNL-SWAN is run. The colours represent the significant wave height without WEC devices. The blue star represents the position of the closest onshore electrical substation to the study region.

The power and levelized cost were calculated as proposed by [3], [10], [11] . One offshore substation is considered for the WEC array, its position was calculated by geometric mean of the WECs position. The distance from the farm substation to the onshore power substation is approximately 11 km.

III. RESULTS

Here we show results of a wave park composed of 10 WEC devices. The optimizations were performed with a population of 20 individuals, which allowed to have a good convergence for the levelized cost of energy in 100 iterations. Fig.7. shows the result of the first iteration, where each graph represents an individual of the algorithms. This is how the first 16 individuals are shown at the beginning of the algorithm that maximizes power. In Fig.5., it can be seen that WECs are almost aligned in a straight line when the optimizations are done by maximizing the generated power by the park. Power of the park was calculated from (2). As can be seen in Fig.6. convergence by optimizing generated power is reached after 5 iterations.

$$P_{park} = \sum P_{devices} \tag{2}$$

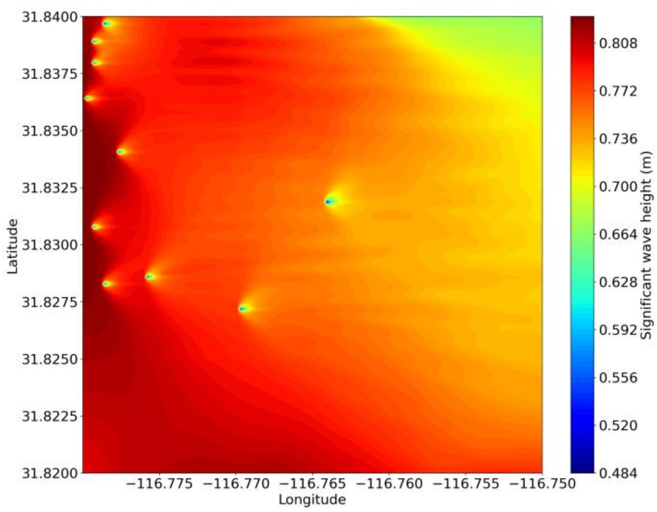

Fig.5. The power-maximizing farm layout. The colours show the significant wave height.

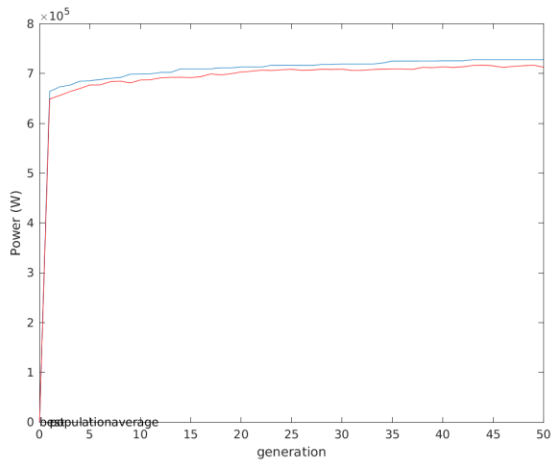

Fig.6. Generated power by WEC farm through the iterations of the genetic algorithm. In blue the highest power per generation and in orange the average power value of the population.

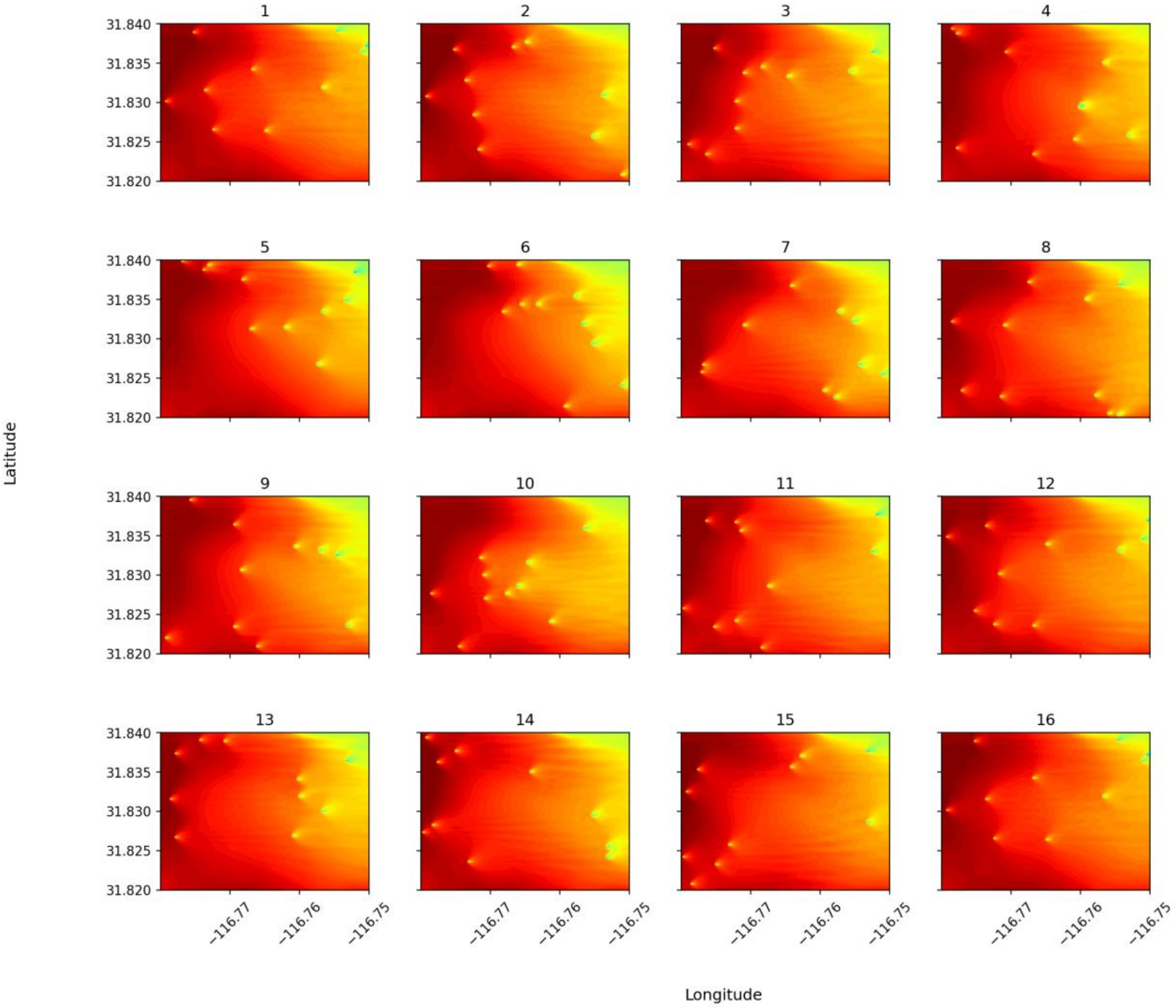

Fig.7. The power-maximizing farm layout. The colours show the significant wave height. The individuals of the first iteration are presented ordered from the highest power to the lowest power absorbed by the array. WEC devices can be seen as yellow dots.

When the optimization is made by minimizing LCoE the WEC park also has a straight shape but much less extended (Fig. 8). It can also be observed that some devices are located too close because no constraint on proximity was considered.

In optimization it is important to check the algorithm convergence in order to know if a suitable solution was found. An important difference between the optimization using generated power and LCoE as objective function is the number of iterations that the algorithm needs to converge. As can be seen in Fig.9. convergence by optimizing of LCoE is reached around 100 iterations.

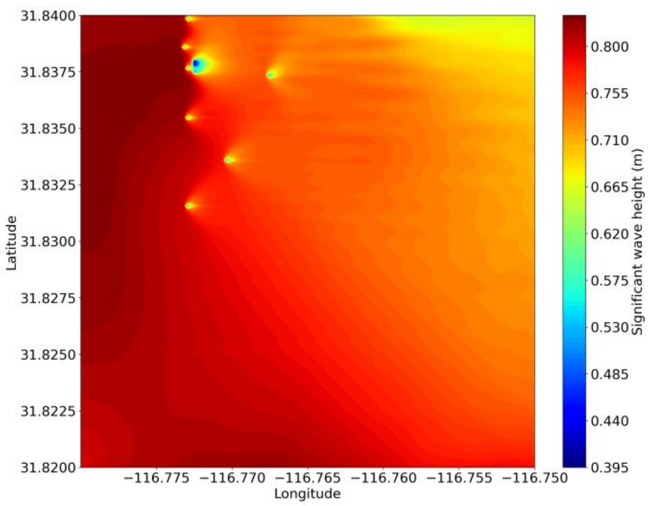

Fig.8. The distribution of a WEC farm that minimizes the levelized cost of energy. The colours show the significant wave height.

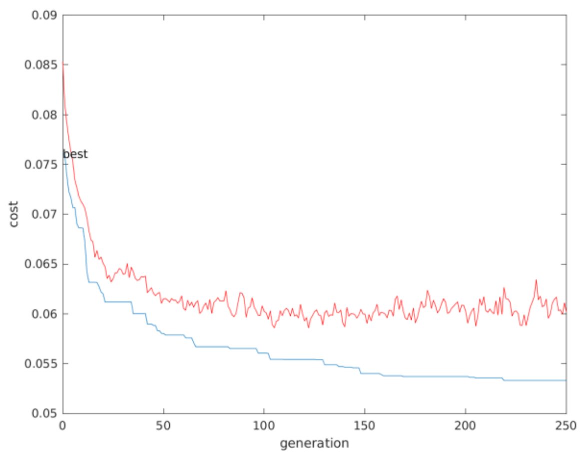

Fig.9. Levelized cost of energy through the generations of the genetic algorithm. In blue the lowest levelized cost of the generation and in orange the average levelized cost of population per generation.

IV. Discussion & Conclusion

This preliminary work shows that the WECs farm is located close to the onshore substation, an area with little lower waves, when optimization is done over LCoE because it reduces costs associated with cable lengths. In both optimizations, of LCoE and of generated power, the genetic algorithm was able to found a WEC array with linear orientation as mentioned by [4]. In order to improve our results, we plan to include proximity and depth restrictions based on WECs capacity to show the effect of the seabed on the spatial distribution of the WEC farm.

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