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A MULTI-OBJECTIVE REAL-CODED GENETIC ALGORITHM METHOD FOR WAVE ENERGY CONVERTER ARRAY OPTIMIZATION

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ABSTRACT

For consumers residing near a coastline, and especially for those living or working in remote coastal areas, ocean energy is a promising source of electricity that has the potential to serve as a primary energy source. Over the last decade, many wave energy converter (WEC) designs have been developed for extracting energy from the ocean waves, and with the progression of these devices' ocean deployment, the industry is looking ahead to the integration of arrays of devices into the grid. Due to the many factors that can potentially influence the configuration of an array (such as device interaction and system cost) optimal positioning of WECs in an array has yet to be well understood. This paper presents the results of a novel real-coded genetic algorithm created to determine ideal array configurations in a non-discretized space such that both power and cost are included in the objective. Power is calculated such that the wave interactions between devices are considered and cost is calculated using an analytical model derived from Sandia National Laboratory's Reference Model Project. The resulting layouts are compared against previous array optimization results, using the same constraints as previous work to facilitate algorithm comparison. With the development of an algorithm that dictates device placement in a continuous space so that optimal array configurations are achieved, the results presented in this paper demonstrate progression towards an open-source method that the wave energy industry can use to more efficiently extract energy from the ocean's vast supply through the creation of array designs that consider the many elements of a WEC array.

INTRODUCTION

The United States, in addition to countries around the world, is actively supporting avenues for expanding its energy portfolio to include sources that are renewable and locally accessible. The White House and Department of Energy (DOE) have set guidelines for reducing dependence on foreign oil and better implementing water power methods. More specifically, the U.S. is seeking to generate 80% of its energy using renewable sources by 2035 and to achieve an 80% reduction in carbon emissions by 2050 [1]. Consequently, with over 50% of the U.S. population living in close proximity to an ocean coastline [2], research and development has been ongoing in the realm of ocean energy – specifically in regards to the extracting of energy from ocean waves.

The estimated global amount of energy in ocean waves is between 16,000 TWh per year and 18,500 TWh per year [3]. Quantified, one terawatt-hour of generated electricity is roughly the amount of energy that 9,000 U.S. homes use over the course of a year [4]. Furthermore, in the United States, the recoverable ocean wave resource is estimated to be approximately 1,170 TWh per year [5] which could provide the electricity needed by over one million homes. In Hawaii, Alaska, and Oregon, states with prime wave resources, wave energy could potentially supply 100%, 100%, and 57% of these states' respective energy needs [1].

Due to the number of individuals residing near an ocean, the push to develop and implement renewable energy sources, and the quantity of energy to be extracted from the ocean, wave energy is a promising source of electricity for which there are many devices under development that are nearing the point of full-scale ocean deployment. Following ocean deployment of individual devices, developers are planning the implementation of arrays of devices to provide grid-connected power to a large consumer base with many needs. The process of developing wave energy converter (WEC) arrays involves comprehending and overcoming associated challenges such as volatile sea states and associated costs. As it is vital that the industry be well-informed regarding the potential deployment of WEC arrays to ensure survival and future competitiveness, determining optimal array configurations at this stage in research is essential.

The work presented in this paper details a methodology that utilizes an optimization method for suggesting arrangements where developed power is maximized and cost is minimized. To begin, previous work relating to WEC array optimization will be discussed. Next, the developed real-coded genetic algorithm (GA) method used in this work is presented, followed by explanations of the associated objective function, models, and defined parameters. Lastly, the optimal layouts obtained are presented, discussed and compared against previous research.

PREVIOUS WORK

Wave energy converters in the ocean affect the wave field through radiated waves (waves that ripple out from a device) and diffracted waves (the bending of the incident wave around a device). Unlike wind energy farms – where placing turbines too close to one another results in negative interactions between turbines and a decrease in power production – WECs have the potential to generate more power when placed in an array than the combined power that the same number of devices would produce acting in isolation [6]. This ratio is described using the interaction factor, q, shown in Eq. 1

$$q = \frac{P_{array}}{N \cdot P_{isolated}} \tag{1}$$

where P_{array} is the power generated by an array of devices, $P_{isolated}$ is the power generated by a single isolated device, and N is the number of devices in the array [6]. Having focused on finding arrays where this interaction factor is greater than one, previous research has noted that there are many elements which influence the power produced by an array, including sea state, wave directionality, and array configuration [7]. However, the impact that these factors have on an array's power production is yet to be well quantified.

Research in array configuration design has primarily focused on pre-determined layouts and their resulting q factors. Examples of layout shapes that have been considered include squares, triangles, single rows, parallel offset rows, and hexagons [8–12]. Additional research has observed that beyond layout configuration, individual device and global control schemes would greatly improve power production [13–15]. Ricci et al. suggested that the benefit a device can experience from a neighbor degrades as distance between devices increases. From a configuration study where heaving point absorbers are theoretically placed off the coast of Portugal, the distance proposed at which interaction effects become negligible is four times the WEC radius [16].

Several researchers have utilized optimization methods for determining layouts that maximize the interaction factor. Snyder & Moarefdoost used a two-phase heuristic algorithm that assumes a unidirectional wave in combination with a convex optimization solver and is dependent on an assumption of symmetry [17]. More recently, McGuinness & Thomas developed an analytical method for determining optimal spacing between devices when placed in a single row parallel to the oncoming wave; in this work, arrays are optimized based on a maximization of the mean of the interaction factor rather than just maximizing the interaction factor itself [18].

Using a unidirectional, regular sea state and a set number of point absorber type devices constrained in the vertical or heave direction, Child & Venugopal implement two methodologies to generate layout configurations: Parabolic Intersection and MATLAB's GA toolbox [19–21]. Parabolic intersection assumes that the diffracted waves around a WEC take the shape of a parabola and so, once the first device is placed, following devices are then placed to benefit from the higher wave heights in the parabolic shaped diffracted waves generated by the first device. The GA method, using reactively-tuned devices, returned the highest interaction factor of the two methodologies. Figure 1 show examples of generated arrays from the two methods.

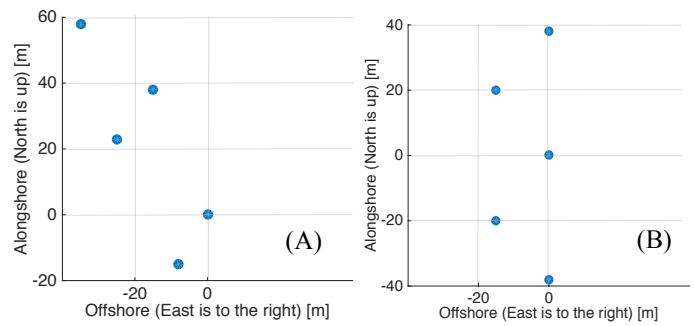

FIGURE 1: LAYOUTS GENERATED BY (A) USING MATLAB'S GA TOOLBOX AND (B) THE PARABOLIC INTERSECTION METHOD [20]

The private company DNV-GL is also working on the creation of an optimization tool, WaveFarmer [22]. In available DNV-GL research, an array consisting of four devices is placed in a square formation such that the WEC positions are constrained and the individual device's power take-off systems are controlled. A ten-device array is also considered, using a Brettschneider spectrum wave field input, and optimal WEC layout is determined using MATLAB'S GA toolbox. The ten-device array is arranged in two offset parallel lines that are generally perpendicular to the oncoming incident waves with five devices in each row as shown in Fig. 2. For each of the evaluated cases an interaction factor greater than one was reported.

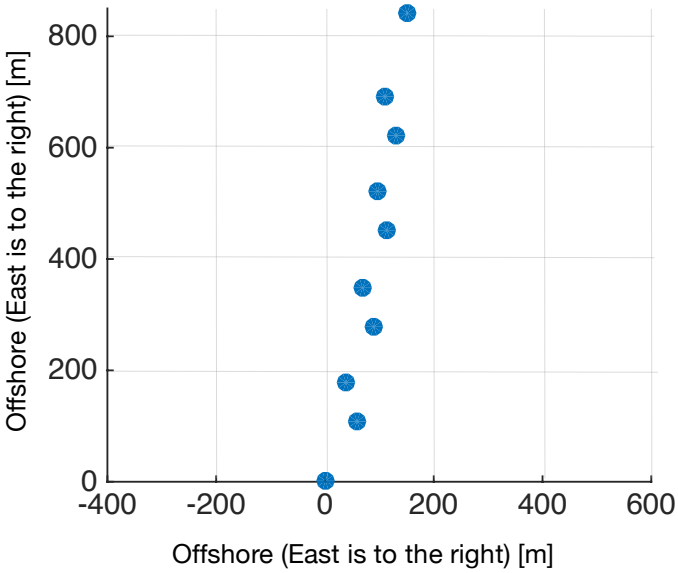

FIGURE 2: LAYOUT GENERATE BY DNV-GL [20]

The potential for determining a layout that would provide an interaction factor greater than one is promising; however, developers are ultimately interested in reducing the cost of energy, which helps drive down barriers of new, renewable energy source implementation. Consequently, economics must be considered during the computational WEC array design process. Vicente et al. and Balitsky et al. both note that array costs will affect the configuration of WEC arrays [9,15]. However, we have found no reported work, excluding our own, that incorporates cost into the objective or as an objective.

Through an implementation of a binary genetic algorithm, the authors' previous work in WEC array optimization introduced cost into the objective function in addition to generated power [23,24]. This initial work examined the effects of device spacing on the optimal layout of one-meter radius truncated cylindrical point absorbers constrained in heave (similar to those used in [20]), and found that a defined minimum separation distance dictated whether radiated waves or diffracted waves improved the interaction factor. Figure 3 shows the result for a fixed three-meter minimum separation distance, which essentially means that the devices are allowed to get within one meter edge-to-edge. With this proximity, the devices take advantage of neighboring devices' radiated waves.

When a further minimum separation distance of six-meters (four meters edge to edge) is required, the interaction factor is found to improve through the use of diffracted waves. The best-found layout given this minimum separation distance is shown in Fig. 4. This work demonstrates the potential ability of WECs to benefit from being placed in relative close proximity.

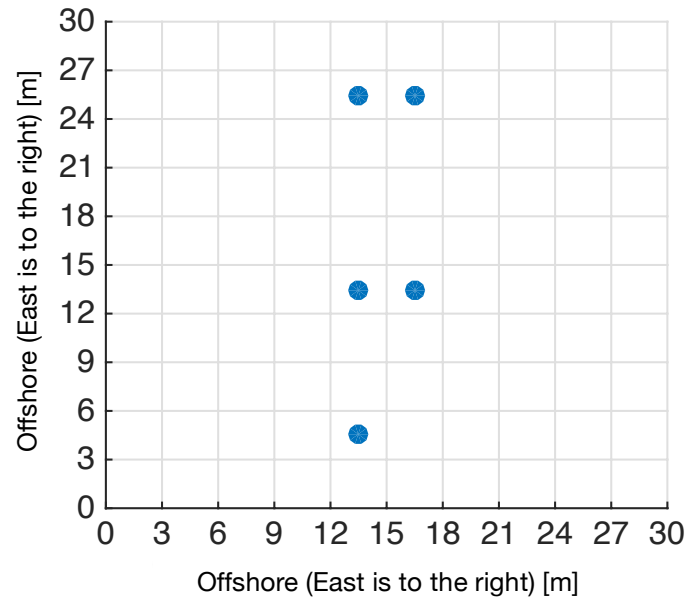

FIGURE 3: LAYOUT GENERATED BY A BINARY GA WITH A MINIMUM SEPARATION DISTANCE OF THREE METERS [24]

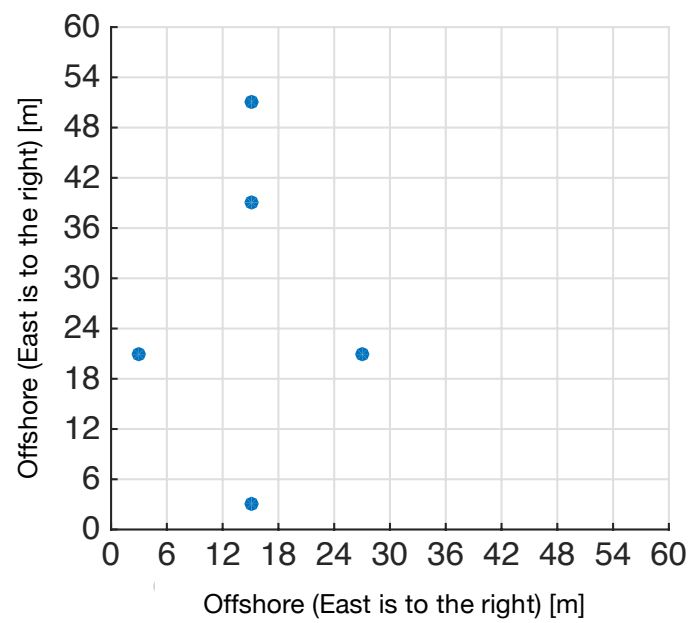

FIGURE 4: LAYOUT GENERATED BY A BINARY GA WITH A MINIMUM SEPARATION DISTANCE OF SIX METERS [24]

The results from the binary GA demonstrate the need for further investigation regarding the optimal placement of WECs in an array since the best placement may be somewhere between stipulated minimum separation distance values. Accordingly, this paper describes the process of a real-coded (also referred to as continuous) GA and the results found using this method.

REAL-CODED GENETIC ALGORITHM OVERVIEW

A real-coded genetic algorithm (GA) approach was created to determine optimal WEC array designs that incorporate cost information in addition to generated power. Prior work (using a discretized GA method) preliminarily explored the effects of device spacing. In continuation, this paper presents a previously unexplored real-coded approach that allows for the optimization of device spacing in a continuous space.

A real-coded GA generates potentially optimal solutions via a representation of the biological reproduction process, wherein children solutions are comprised of components of the parent solutions and are potentially subject to prescribed mutation. The methodology of the real-coded GA is similar to that of the binary GA with several key differences. This process will now be described.

First, the initial parent population, or generation zero, is created by randomly scattering a number of devices into the solution space. To facilitate comparison to previous work, the space is defined as a 60-meter by 60-meter square and the number of devices is limited to 5. Each WEC location is specified by a random X and Y coordinate that is confined within the space. Throughout the entire execution of the algorithm, device placement is not accepted unless no physical overlap exists with any devices already in the space. Once the initial parents are generated, their objective function evaluations are evaluated and they are sorted from lowest (best) to highest (worst), at which point the reproduction phase begins.

In the presented continuous GA, there are several stages that occur to build the children set – elitism, crossover and mutation, and random solution generation. Elitism begins by cloning an upper percentage of the parent solutions directly into the children solution set. Doing so means that the global best solutions in the parent population will not be lost due the reproduction process. In addition to these cloned solutions, a mutated set of cloned solutions is also added to the children set; the mutation process is is described later in this section.

After elitism is complete, crossover and mutation is conducted on a defined upper percentage of the parent solution set. Since previous research (including previous binary GA work conducted by the authors) has included a fixed number of devices, crossover is performed such that the number of devices is retained. To accomplish this, pairs of parents are found using rank roulette selection as described in [25]. Once the crossover and mutation pool has been filled with the selected parent pairs, children are created as follows. First, based on a set probability, child solutions are made by combining device locations from two selected parents. In other words, the two children solutions created by a parent solution pair contain locations of devices from each of the parents. Only non-overlapping devices are eligible for crossover in order to avoid a device being placed in physical contact with another pre-existing device.

Figure 5 demonstrates the utilized method of crossover. In this scenario all points in both parent solutions are available for crossover and two points will be swapped – the second and fourth points from the first parent and the first and second points from the second parent. Thus, the first child is comprised of points one, three and five from the first parent as well as points one and two from the second parent. Conversely, the second child contains points three, four and five from the second parent and points two and four from the first parent.

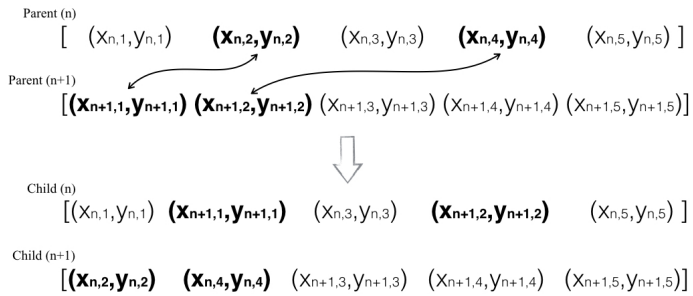

FIGURE 5: IMPLEMENTED CROSSOVER METHOD

Second, once the children are created, they are potentially subject to mutation. If selected for mutation, based on a set probability, a number of devices in a child solution (up to a defined fractional amount of the total number of devices) are moved to new random locations in the solution space. The implementation of prescribed mutation, combined with crossover, allows the algorithm to better explore the solution space to avoid being stuck in local minima.

The children set is now comprised of the elite group, the mutated elite group, and the solutions generated from crossover and mutation. The final stage of the reproduction phase is the introduction of random solutions. These solutions are created in the same manner as the initial parent population and are incorporated into the children population to again allow the algorithm the opportunity to further explore the solution space and avoid being caught in local minima. For the results presented here, the elitism rate and crossover rates were set specifically to allow the same number of random generated solutions as the number of solutions that that were cloned.

Throughout the execution of the algorithm, new solutions (unique to a generation) are tracked so that only their objective functions need be evaluated. In this manner, the number of function evaluations is reduced by not evaluating solutions that have not changed from the previous generation. With a children solution set created, the objective function is evaluated for each solution and a check for convergence is conducted.

Convergence is determined by the number of generations without improvement. Once this criterion is satisfied, the best solution will be reported; however, until convergence is found, the children set becomes a parent set and the process continues. An overview of the algorithm is represented in Fig. 6.

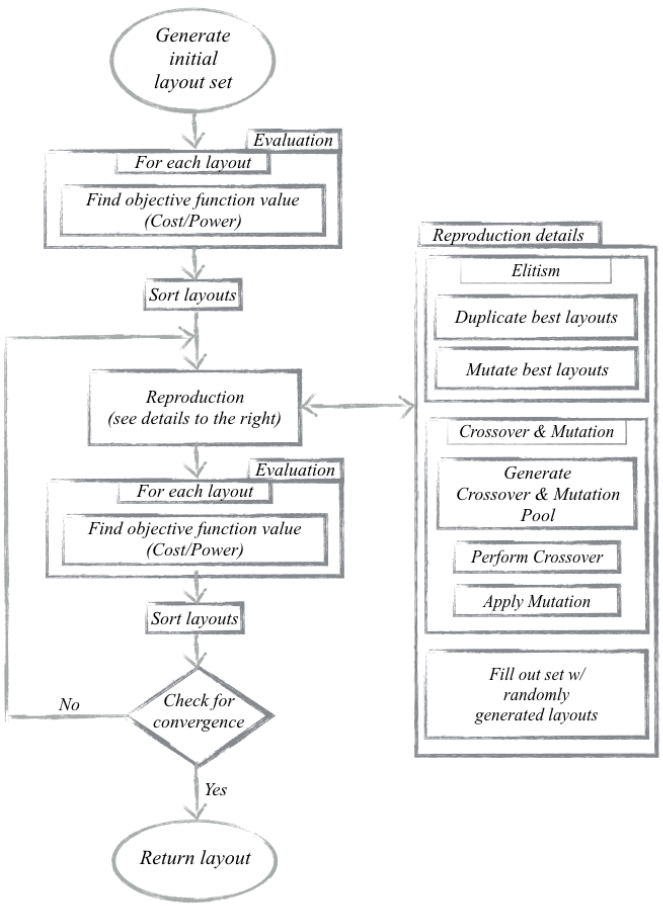

FIGURE 6: REAL-CODED GA FLOWCHART

OBJECTIVE FUNCTION FORMULATION

The objective function used in the work presented here includes cost in addition to power and is shown in Eq. 2

$$Objective\ Function = \frac{Cost}{P_{20}} \tag{2}$$

where P_{20} represents an array's generated power over an assumed 20-year lifetime and *Cost* represents the cost of the array over 20 years.

To calculate power, the behavior of an isolated device is first considered using the linear wave-body software WAMIT [26]. The device is subjected to incident waves from multiple directions in a sea-state with a limited water depth and a range of wave periods. With the hydrodynamic information of the single device obtained from WAMIT, the diffraction coefficient matrix, force transfer matrix, and radiated wave coefficients are found for the single device. Figure 7 shows a single device's effect on a wave field, where yellow indicates an increase in wave height as compared to the incident wave height, and dark blue indicates a decrease in compared wave height. Essentially, Fig. 7 shows the effect of wave diffraction when an incident wave experiences a WEC in the ocean – the waves "pile up" and bend around the obstructing device.

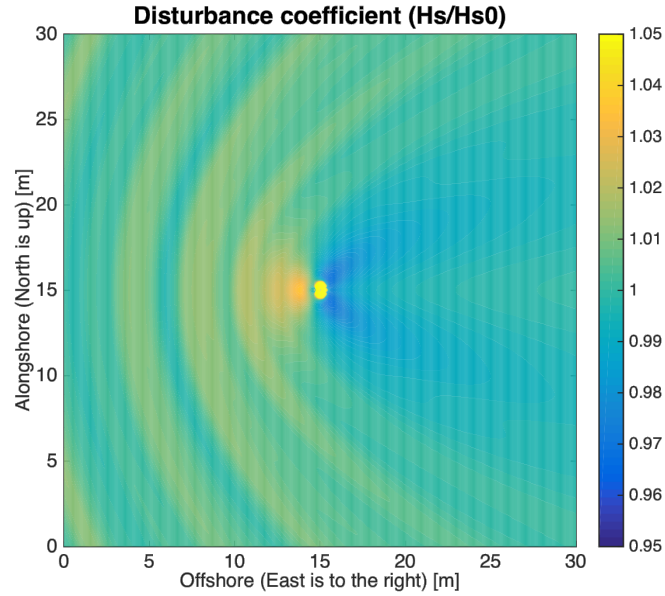

FIGURE 7: EFFECT OF A SINGLE DEVICE ON A WAVE FIELD DEMONSTRATED BY A CHANGE IN WAVE HEIGHT

To find the power generated by an array, the isolated WEC's hydrodynamic behavior, individual device orientation, wave diffraction, and wave radiation are required. This information is used to calculate each WEC's excitation force as well as the total array's added mass and damping. The power is then found using Eq. 3

$$P = \frac{1}{8}\mathbb{X}^{*}\boldsymbol{B}^{-1}\mathbb{X} \tag{3}$$

where $\boldsymbol{B}^{-1}$ represents the damping and $\mathbb{X}$ represents the complex excitation force [27]. This process is described in detail in [28].

With the total power development for the array found, the next component of the objective function to determine is the cost associated with an array of WECs. As the authors note in [29], the particulars to be included in array economic calculations lack specificity due to limited deployment data. As such, models that exist for determining array costs need further development to provide realistic results. The authors chose to use Sandia National Lab's Reference Model Project (RMP) as it is the most comprehensive model found, and because it provides information for arrays with differing numbers of devices [30].

In general, research separates array economics into capital costs (CAPEX) and operations and maintenance costs (O&M) as shown in Figs. 8 and 9.

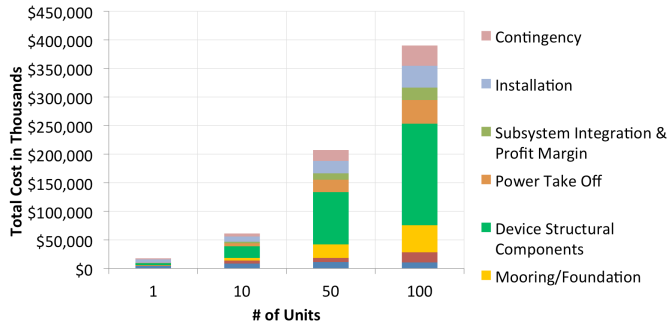

FIGURE 8: CAPEX COSTS ASSOCIATED WITH ARRAYS FOR DIFFERING NUMBERS OF DEVICES [30]

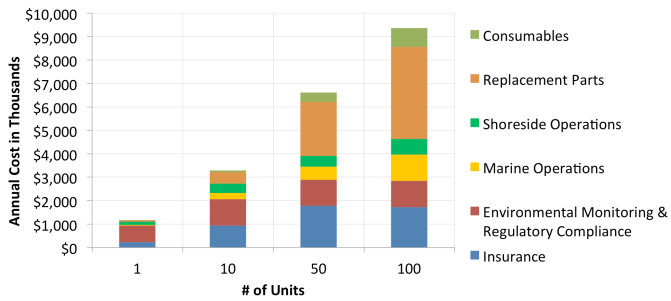

FIGURE 9: O&M COSTS ASSOCIATED WITH ARRAYS FOR DIFFERING NUMBERS OF DEVICES [30]

The information provided by the RMP was used to generate an equation for estimating array cost based on the number of devices in the array, *N,* with an assumed lifetime of 20 years.

$$Cost = 3(10)^7 \cdot N^{0.6735} \tag{4}$$

Eqation 4 serves as a preliminary means of estimating WEC arrays costs; however, it is understood that these costs are dependent on additional factors such as array location, distance to shore, location in the water column, mooring configuration, and electrical cabling. Though basic, an equation such as Eq. 4 is consistent with other energy system optimization scenarios in their early stages of development [31].

PROBLEM FORMULATION

The WEC device used in this research is the same device as is modeled in [23,24], and is consistent with the device used in previous work [20]. This device is a truncated cylinder constrained in the vertical direction (heave) with a diameter of two meters and a draft of one meter. Placed in water with a depth of eight meters, these parameters are a scaled representation of an array of 10-meter diameter devices in a water depth of 40 meters [20]. Figure 10 shows the portion of the truncated cylinder below the water surface.

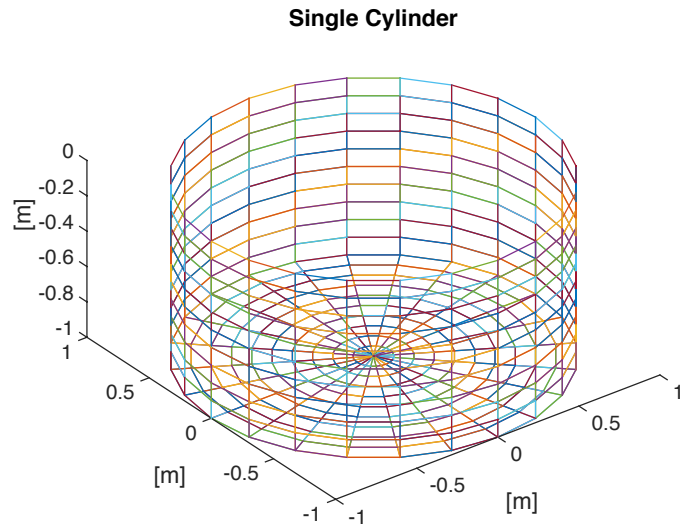

FIGURE 10: PORTION OF MODELED DEVICE BELOW THE WATER SURFACE

When placed in an array, the devices experience unidirectional, irregular waves defined by a Bretschneider spectrum. This spectrum is generated with a significant wave height of two meters, a modal frequency of 0.2 Hertz, and periods, in half second increments, distributed between 4 and 8 seconds.

Two different test scenarios, each with 5 devices, are conducted. The first allows the WECs to be placed anywhere in the solution space with the only requirement being that no physical overlap occurs. Additionally, since devices deployed in the ocean will most likely need to be separated from neighboring devices to allow O&M access and to minimize harmful physical interaction, the second scenario imposes a minimum separation distance of three times the diameter (six meters center-to-center) as is proposed in [13]. Tables 1 and 2 define the tunable parameters for both scenarios.

TABLE 1: TEST SCENARIO PARAMETERS PARAMETERS

Scenario	# Of WECs	Size of Solution Space (alongshore x offshore)	Minimum Separation Distance
1	5	60 m x 60 m	--
2	5	60 m x 60 m	6 m

Beyond tuning the scenario parameters, the GA must also be tuned in order avoid converging to quickly or never converging. For the problem presented here, with a small and constant number of devices in a relatively large space, the main parameters that were tuned to achieve the presented results are the elitism rate (and consequently the crossover and mutation rate), the probability of mutation, and, to a small extent, the probability of crossover. The convergence requirement was empirically determined, and set at 75 generations without improvement.

TABLE 2: TUNABLE GA PARAMETERS

	Scenario 1	Scenario 2
# Of Parents	100	100
Elitism Rate	3%	5%
Crossover & Mutation Rate	81%	75%
Probability of Crossover	95%	95%
Probability of Mutation	35%	35%
Maximum number of WECs to Mutate	2/5	2/5
Convergence Requirement (generations without improvement)	75	75

Using five devices allows for results which can be readily compared against previous work that use the same number of devices. The size of the solution space is defined to match the maximum sized space from the binary GA work.

RESULTS AND DISCUSSION

As genetic algorithms are inherently stochastic and the number of potential array arrangements infinite, each scenario was conducted multiple times and the best results – based on the objective function evaluation – are reported here.

The first scenario achieved the overall best result between the two scenarios and is shown in Fig. 11. For all following images the unidirectional incident waves are traveling due East (from left to right).

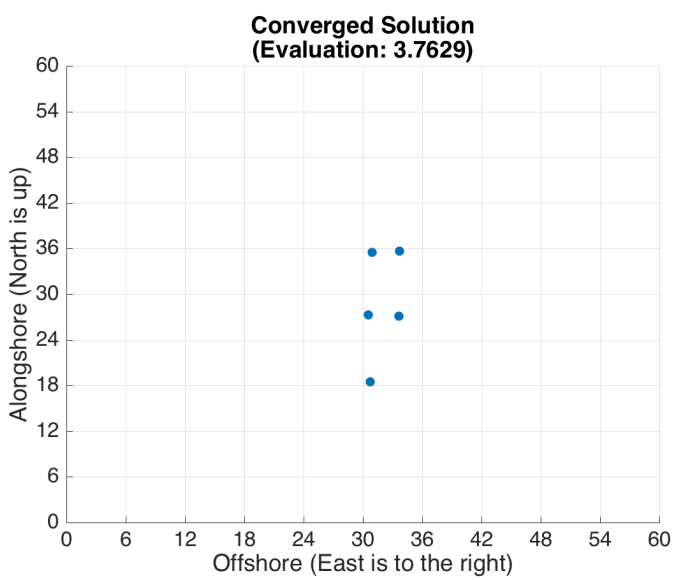

FIGURE 11: OPTIMAL LAYOUT, FIRST SCENARIO

With no minimum separation distance imposed, the best layout is achieved when the devices line themselves up in pairs, parallel to the oncoming incident wave. This layout is similar to the best layout found by the three-meter minimum separation distance case of the binary GA (as shown in Fig. 3). The effect of this layout on the wave field is portrayed in Fig. 12.

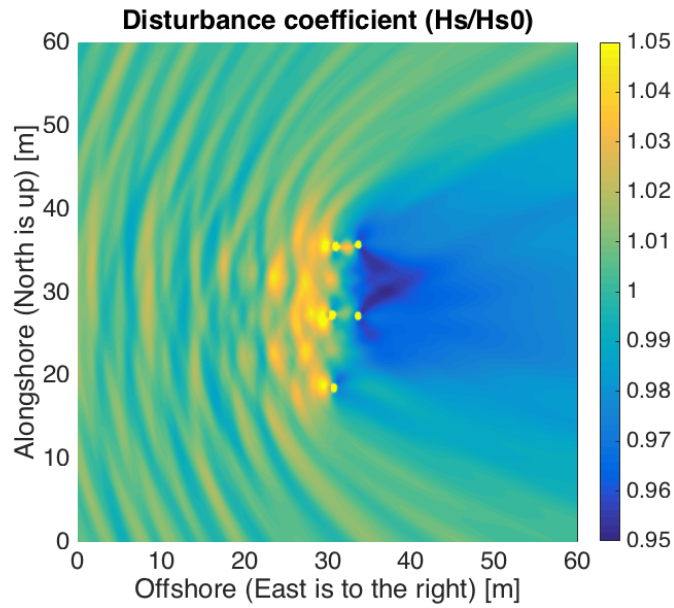

FIGURE 12: EFFECT ON THE WAVE FIELD OF THE BEST LAYOUT FROM SCENARIO 1

With the incident waves approaching from the left, the center-to-center distance between paired devices in the offshore direction is approximately three meters and the center-to-center distance between up-wave devices in the alongshore direction is about eight and one-half meters. While this scenario allows the devices to be closer than three meters (unlike in the binary case) the optimal result is found when the devices are separated from each other by a small amount in the offshore direction in order to take advantage of the radiated waves, and far enough apart in the alongshore direction to benefit from the diffracted waves.

The next scenario considered involves the addition of a minimum separation distance in order to model realistic array deployment and to compare against the results from the scenario with no spacing constraint. For this scenario, the two layouts with the best function evaluations will be examined. As with the binary GA, when the devices are required to stay a certain distance apart, the resulting device placement transitions away from capitalizing on radiated waves to solely taking advantage of the diffracted waves. Figure 13 shows the layout with the best objective function evaluation given the spacing constraint. Figure 14 demonstrates the effect that this layout has on the wave field.

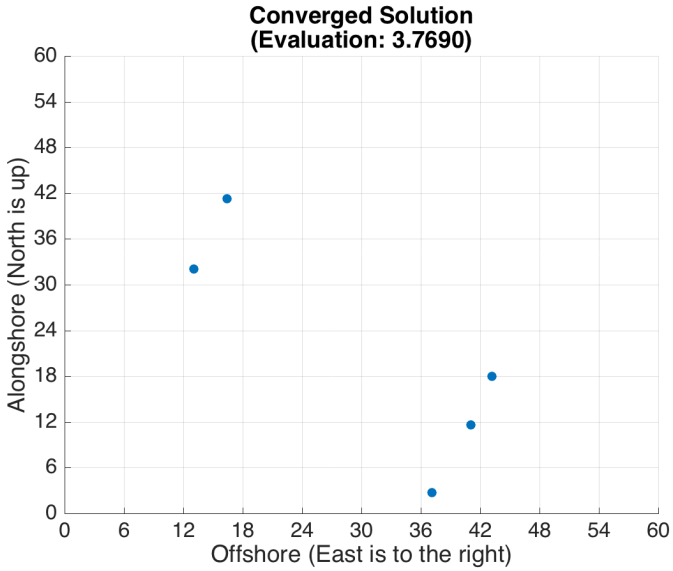

FIGURE 13: BEST LAYOUT ACHIEVED FOR THE SECOND SCENARIO

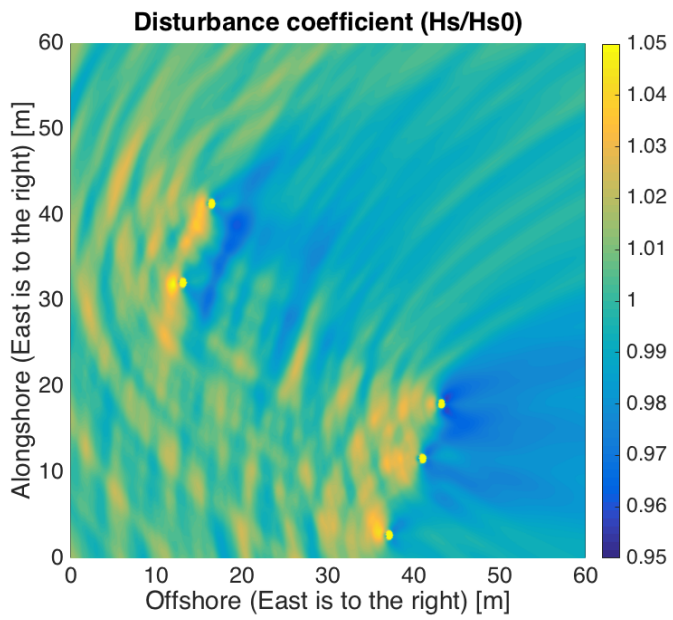

FIGURE 14: EFFECT ON THE WAVE FIELD OF THE BEST LAYOUT FROM SCENARIO 2

Examining the wave field effect, it is observed that within the two subgroupings, devices benefit from each other's diffracted waves and that, in addition, the group of devices further down-wave also benefits from the up-wave pair of devices.

It is worth noting that the layout that achieves the second best objective function evaluation, with the spacing constraint imposed, demonstrates the general shape of a layout that occurs relatively often between both scenarios.

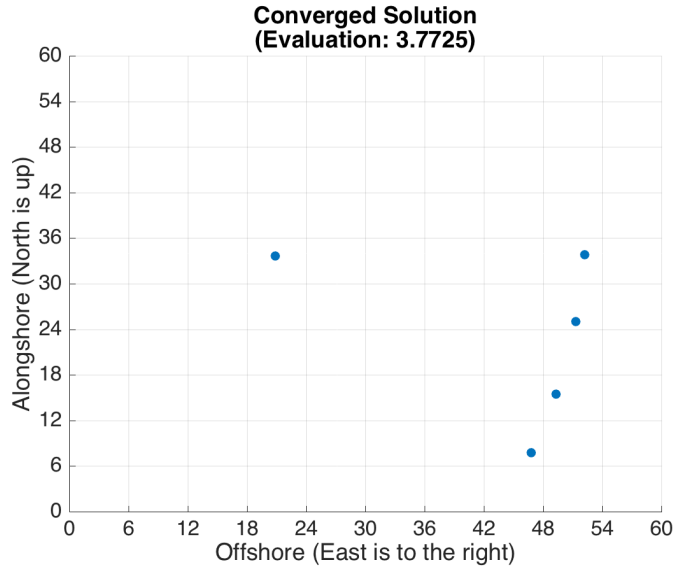

FIGURE 15: SECOND BEST LAYOUT ACHIEVED FOR THE SECOND SCENARIO

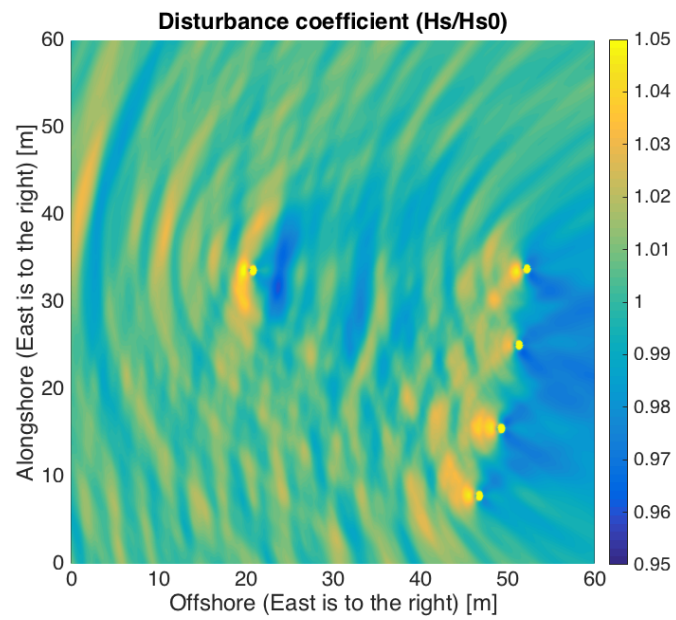

FIGURE 16: EFFECT ON THE WAVE FIELD OF THE SECOND BEST LAYOUT FROM SCENARIO 2

The grouping of four devices, close to equally spaced, at an angle slightly offset from the perpendicular to the incident wave occurs often in the results. Of this type of result, the best, and the second overall best for the second scenario, has a 0.09 percentage difference in objective function evaluation when compared to the second scenario's best overall result. Comparatively, the worst of this type of layout has only a 0.48 percent difference when compared to the function evaluation of the second scenario's overall best. The angled alignment of the grouped devices is allowing an improved cascading interaction effect due to diffracted waves. Since the potential locations for

WECs is infinite, if the devices line up exactly perpendicular to the incident wave, they would need precise placement in order to benefit from the diffracted waves of neighboring WECs. However, with the angled placement shown, the devices further down-wave can capture the diffracted waves of more up-wave devices. This offset angle is also observed in the results of Child and Venugopal and DNV-GL [13,20].

The isolated fifth device in the array seems to be deemed unnecessary by the algorithm in regards to array design. The variation in function evaluation between similar layouts appears to be primarily affected by the grouped devices and less dependent on the isolated fifth device.

Table 3 shows the objective function evaluations and the interaction factors for the presented results of both scenarios.

TABLE 3: OBJECTIVE FUNCTION EVALUATIONS AND INTERACTION FACTORS OF PRESENTED RESULTS

	Scenario 1	Scenario 2a	Scenario 2b
Objective Function Evaluation	3.7629	3.7690	3.7725
Interaction Factor (q)	1.0269	1.0252	1.0243

If the device spacing is left unconstrained, then the algorithm finds a layout that has a power improvement of 2.7% when compared to the power produced by five devices acting in isolation. Once a spacing constraint is put in place, then the algorithm returns a layout with a 2.5% power increase.

Table 4 compares the results presented here with the interaction factors of previous work. For the results shown from the parabolic intersection method and MATLAB's GA, the layouts obtained from [20] (shown in Figs. 1 and 2 respectively) were calculated using the method presented in this paper for a more accurate comparison.

TABLE 4: OBJECTIVE FUNCTION EVALUATIONS AND INTERACTION FACTORS OF PRESENTED RESULTS

	Objective Function Evaluation	Interaction Factor (q)	Power Increase
MATLAB's GA	3.8864	0.9942	-0.6%
Parabolic Intersection	3.8793	0.9961	-0.4%
Binary GA (6m minimum spacing)	3.7920	1.0190	1.9%
Binary GA (3m minimum spacing)	3.7737	1.0239	2.4%
Scenario 2 (6m minimum spacing)	3.7690	1.0252	2.5%
Scenario 1 (no spacing constraint)	3.7629	1.0269	2.7%

The table shows clear improvement with the introduction of the real-coded GA. The results of the two scenarios found layouts that obtain a better increase in power production when compared to the best performing binary GA result. In fact, across all the runs conducted, both scenarios consistently achieved layouts with better results than their counterparts in the binary GA.

CONCLUSION

With the vast amount of energy to be captured in the ocean waves and the size of the population living and working near a coastline, developers have focused on the creation of devices to access this prime source of electricity. Now nearing the point of ocean deployment, the industry is looking ahead to future deployment of arrays and optimal methods of implementation. As such, a method which considers all contributing facets, such as developed power and required cost, and returns information that aids in maximizing investment returns is vital to the industry's success.

Research in array configuration design has solely focused on maximizing power production and only mentions the need for incorporating cost. Additionally, implemented methods have primarily been based on user-decided layouts which are dependent on many assumptions that are yet to be well understood or quantified.

Previous work by the authors presents the use of a binary genetic algorithm that includes array cost in the objective function. These preliminary results indicate that devices needed the opportunity to be placed anywhere in the solution space.

Consequently, the real-coded GA presented here demonstrates the advantage of implementing non-discretized space. Allowing devices to select any location in the stipulated space, the best overall layout achieves a 2.7% increase in power over the power that would have been produced if the five devices were acting alone. This is a 12.5% increase over the best result found using the binary GA method. Even when a six-meter spacing constraint is set in place around the devices, the real-coded GA obtains an array that performs 4.2% better than the best result from the Binary GA.

Similar to the binary GA, when the minimum separation distance is small or nonexistent, the WECs take advantage of neighboring devices' radiated waves, but transition to capitalizing on diffracted waves when imposed with minimum spacing requirements. When the objective function evaluations and interaction factors are compared to other research in array design, the real-coded GA outperforms in both the unconstrained and constrained scenarios.

The layout configurations from the algorithm vary due to a highly multi-modal solution space. Due to seemingly minor differences in device positioning, results from two different runs can have similar looking layouts, but different objective function evaluations. However, for the layouts from the second scenario with groupings of four, the results have a low percentage difference from the global best solution. This points towards a more robust design than the global best layout.

In the second scenario's second best layout (shown in Fig. 15), with the minimum spacing constraint in place, the fifth device does not find a manner of incorporating itself into the array. This indicates the need for allowing a variable number of devices in order to find the optimal number for a defined space. Additionally, constraining the number of devices to a set value loses relational device information in the implemented crossover method, but allowing for a variable number of devices and implementing multi-point crossover would help alleviate this issue.

Finally, with the constant number of devices, cost isn't able to influence the layout configuration with the current objective function equation.

Through better inclusion and investigation of influencing elements, the application of a continuous algorithm is advantageous for determining the optimal spacing of WEC arrays, through the ability of the algorithm to dictate the optimal device placement in the solution space.

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